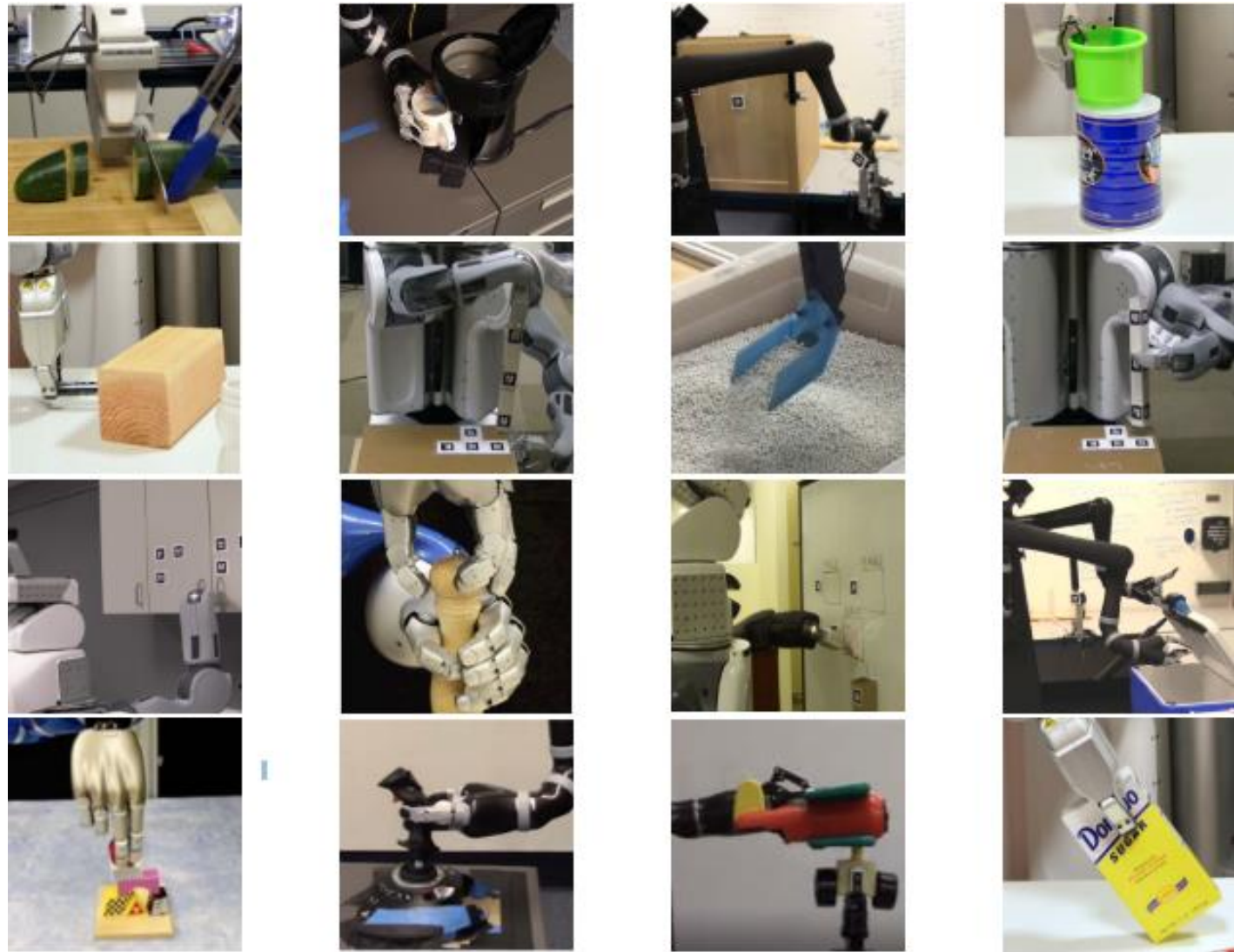
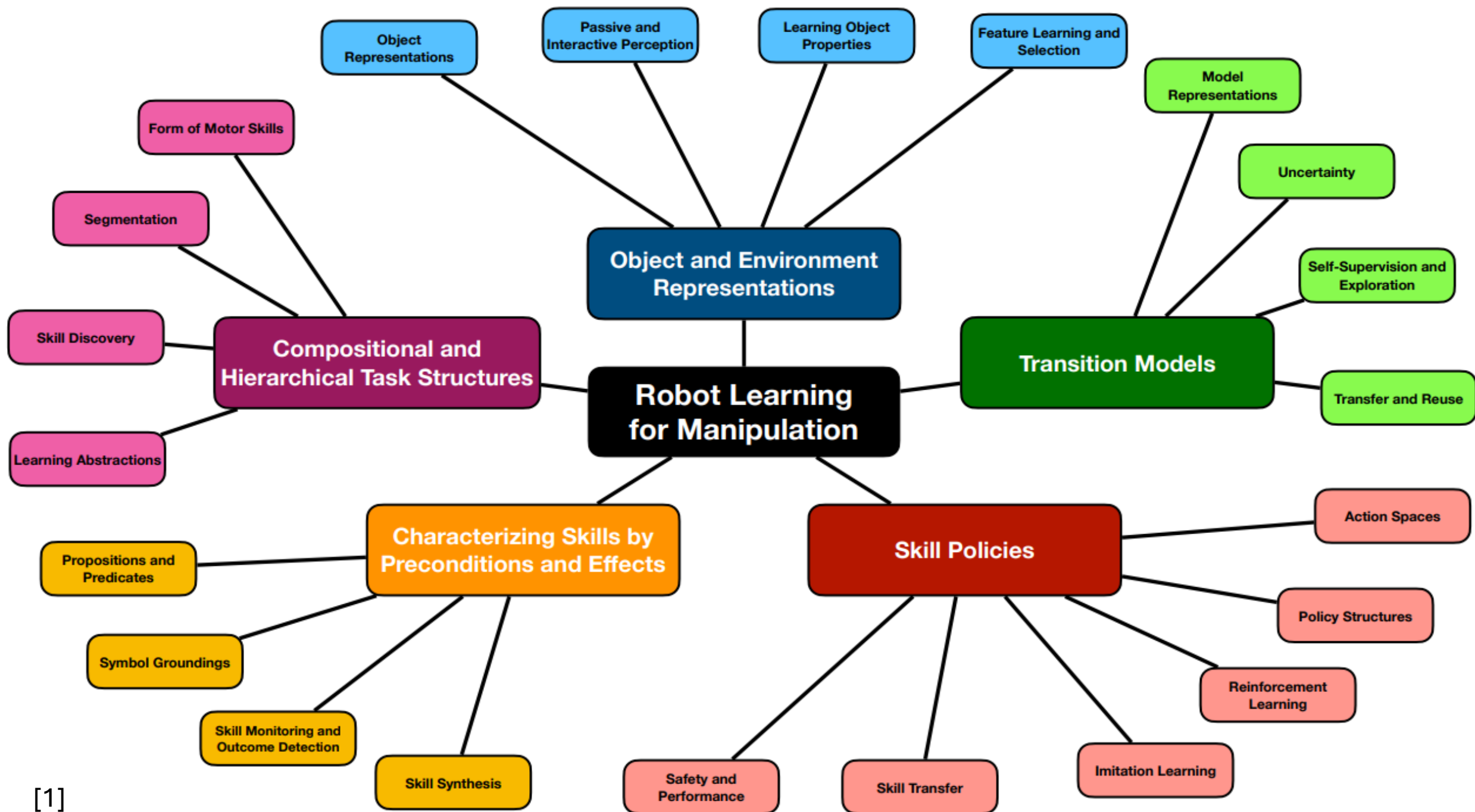


AI for learning tasks / movements

- Ivan Smirnov 22109653
- Vladislav Veselov 22102251
- Maryana Smirnova 22109911



[1] Example manipulation skills including inserting, stacking, opening, pushing, cutting, screwing, pouring, and writing.



Object and Environment Representations

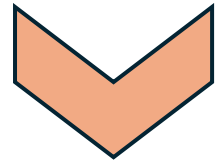
Object Representations

Passive
and Interactive Perception

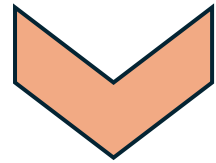
Learning Object Properties

Feature Learning and Selection

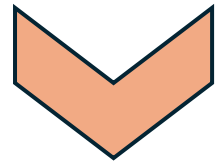
Object Representations



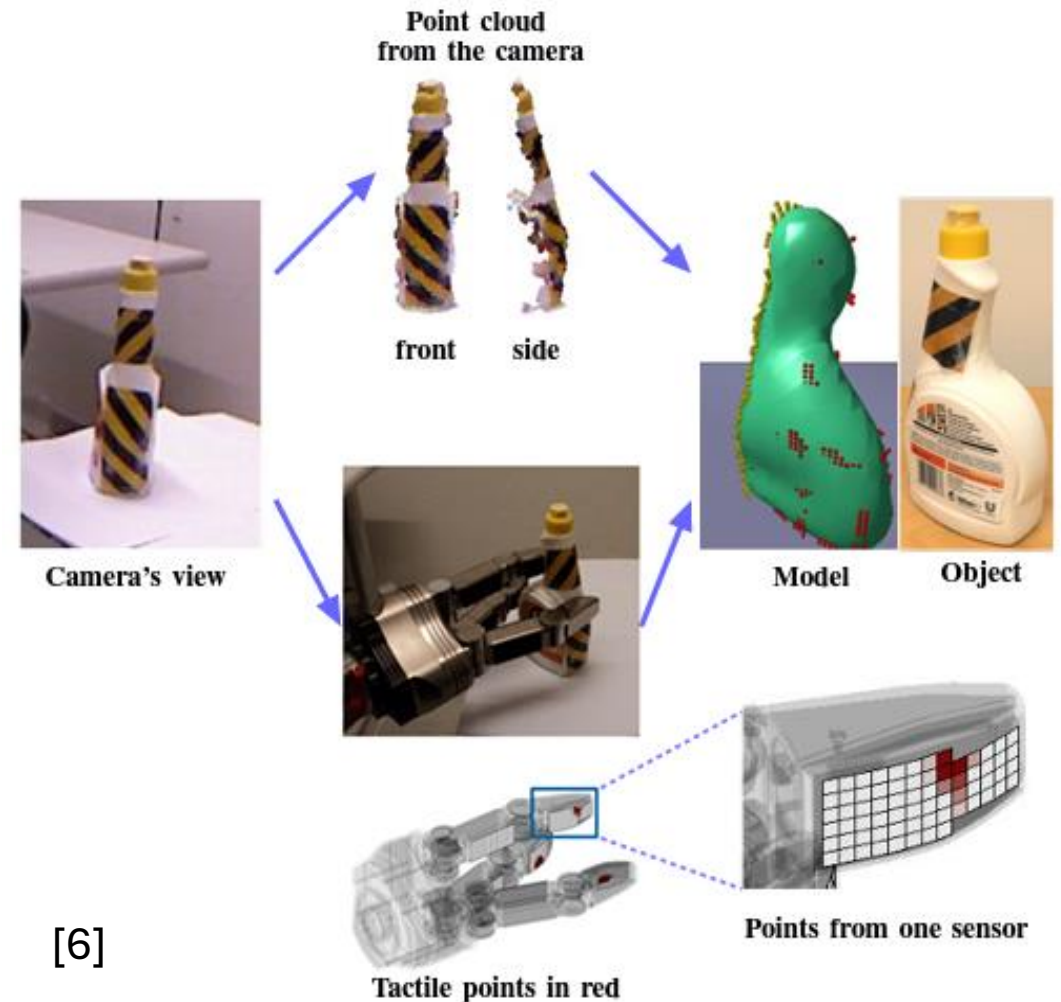
Point Level



Part Level



Object Level



Learning Object Properties

Shape

Pose

Material

Physical
Constraints

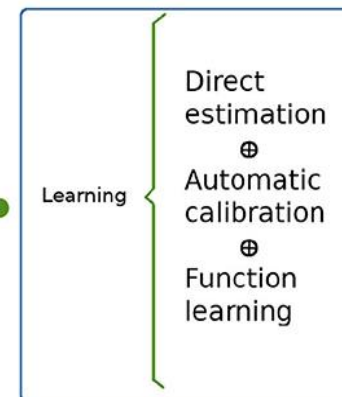
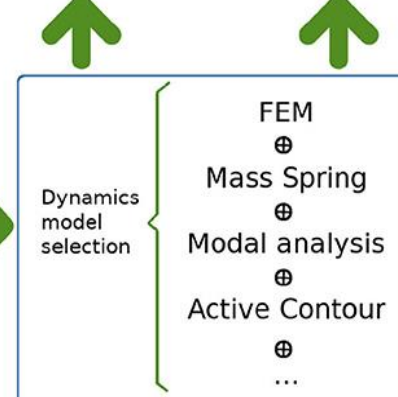
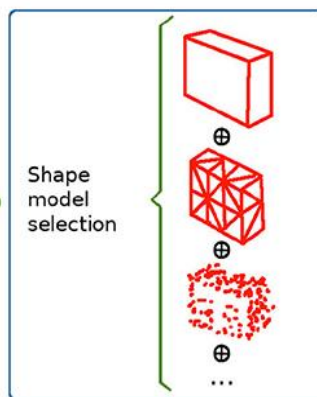
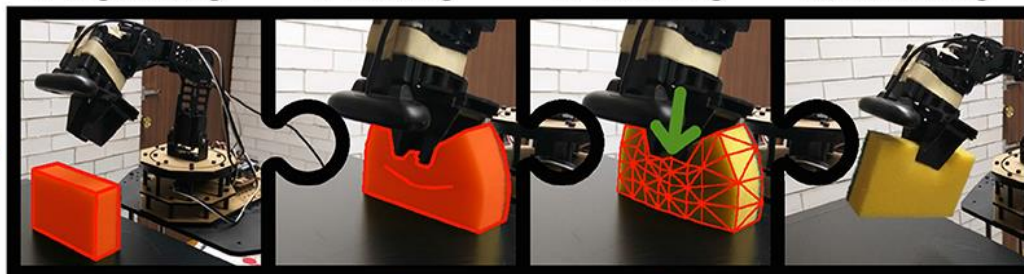
Dynamic
Properties

i) Segmenting

ii) Tracking

iii) Predicting

iv) Controlling

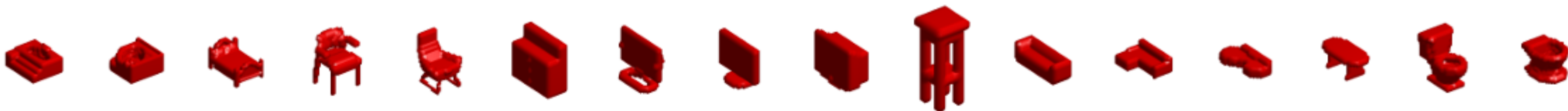


[23]

v) models for shape and dynamics

vi) learning

Ground
Truth



Query



3DShapeNets
Completion



BEO
Completion



[5]

Passive and Interactive Perception

Passive:



- Using camera to observe the environment
- Moving a camera to a better vantage point
- Observe human performing an action

-  Lots of observation in short time
-  Low effort



Interactive:

- Push a box to obtain its properties
- Haptic, tactile, vision, and audio sensors

-  More specific details
-  Supervisory signal for passive perception

Transition Models

Model Representations

Uncertainty

Self-Supervision and Exploration

Transfer and Reuse

Model Representations

Deterministic Function:

$$T : S \times A \rightarrow S$$

Stochastic Distribution:

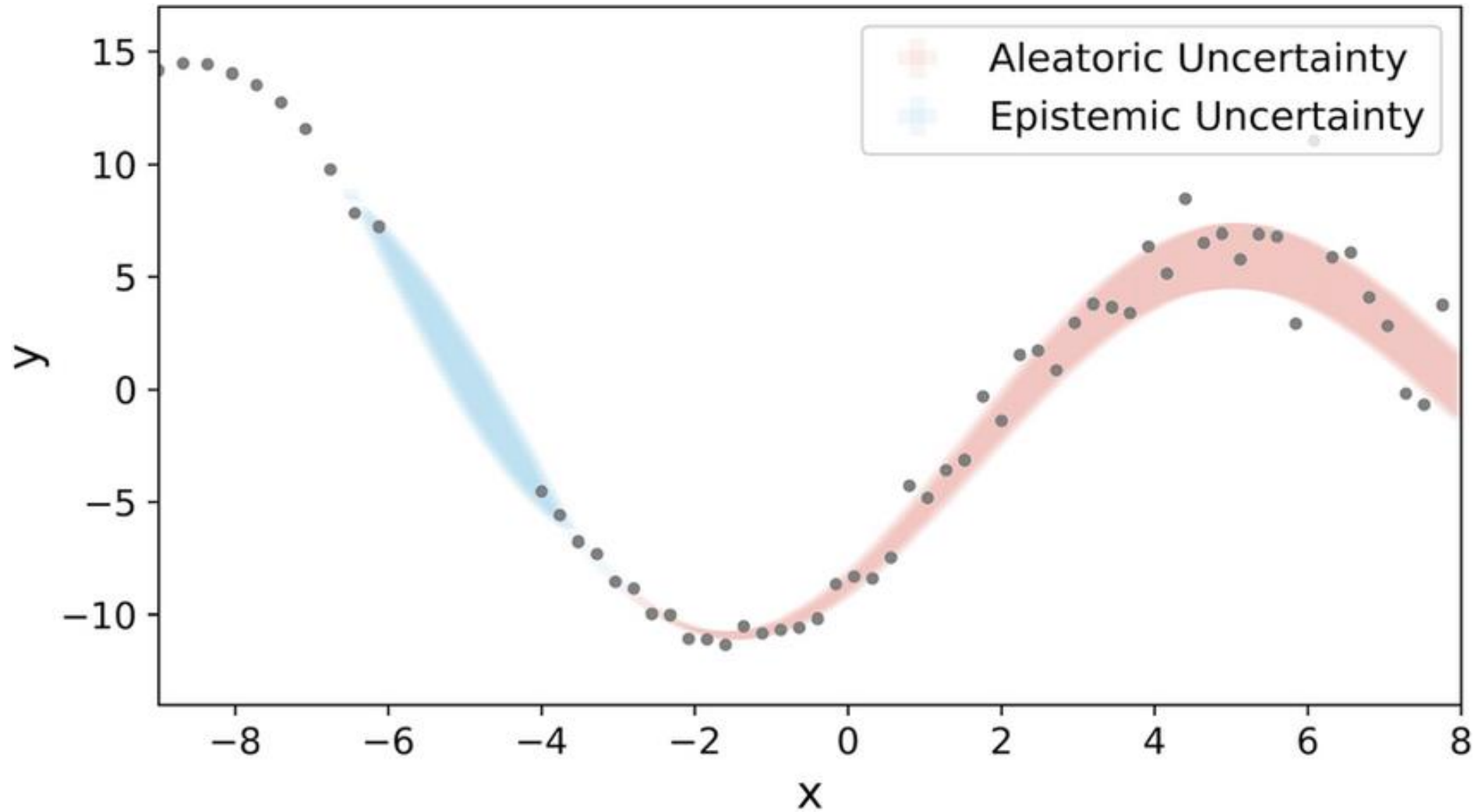
$$T : S \times A \times S \rightarrow \mathcal{R}$$

Continuous Models

Discrete Models

Hybrid Models

Uncertainty



Self-Supervision and Exploration

Random Sampling

Active Sampling

Grid Sampling

Intrinsic Motivation

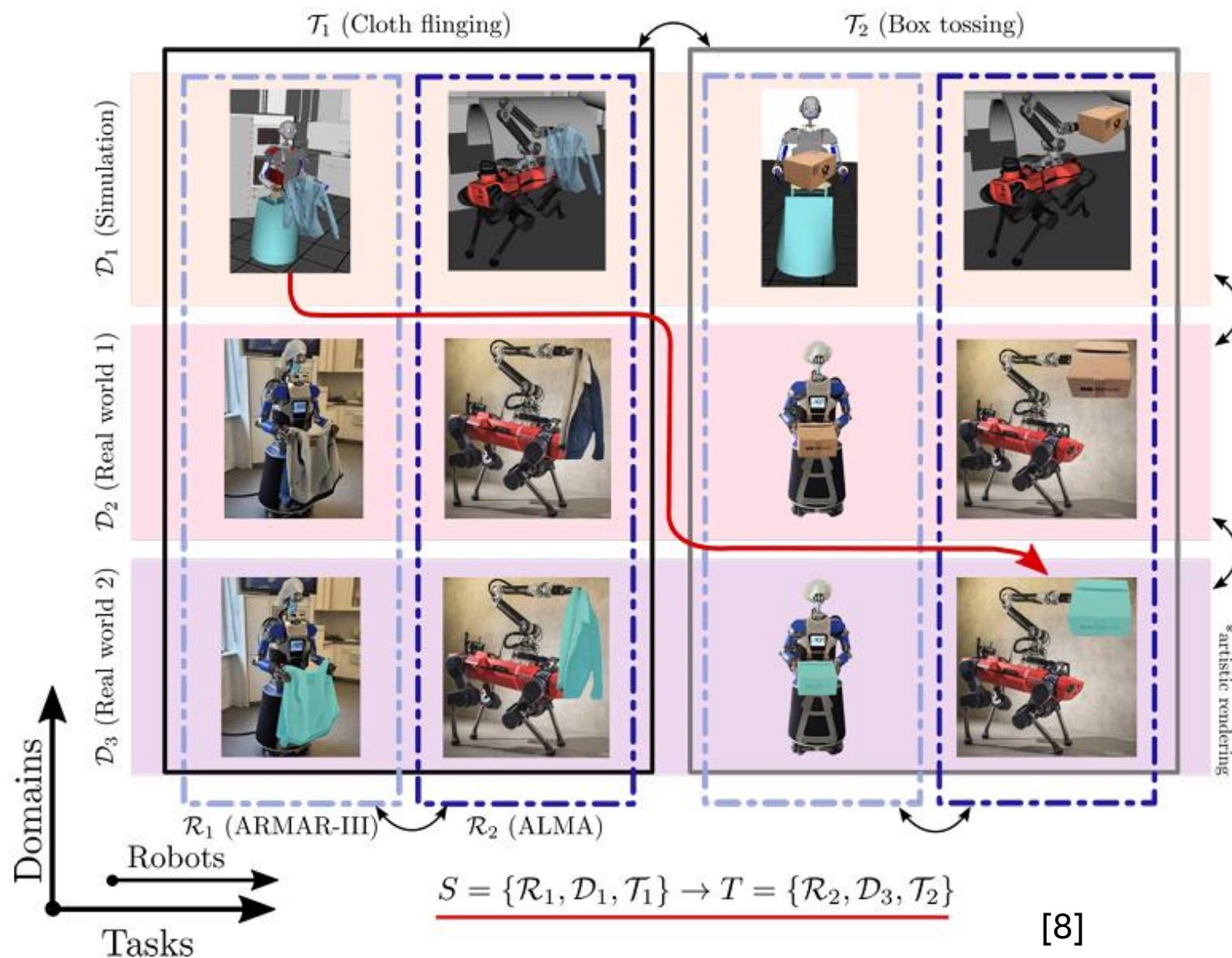
Transfer and Reuse

Conditions for Model Reuse:

- **Compatibility Required:** Same state, action, and context spaces.
- **Mapping Necessity:** If spaces differ, a mapping is required to align them.

Challenges in Model Transfer:

- **Covariate Shift:** Variability in input data distribution between tasks.
- **Dataset Shift:** Variability in both input and output data distributions.



Skill Policies

Action Spaces

Policy Structures

Reinforcement Learning

Imitation Learning

Skill Transfer

Safety and Performance

What are Skill Policies?

- **Goal:** acquire *skill controller*
- Common *skill controller* representation:
State-action pairs mapped to probabilities

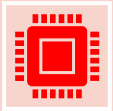
Let's see how to implement skill policies!

Skill Policies: Action Spaces

Action spaces



When implementing Skill Policy, you need to select an Action Space (a set of valid robot actions)



An intermediary controller is often placed between the policy output and actuators (actuators can be, for example, motors)



Intermediary controller translates the Action into specific signals for the actuators



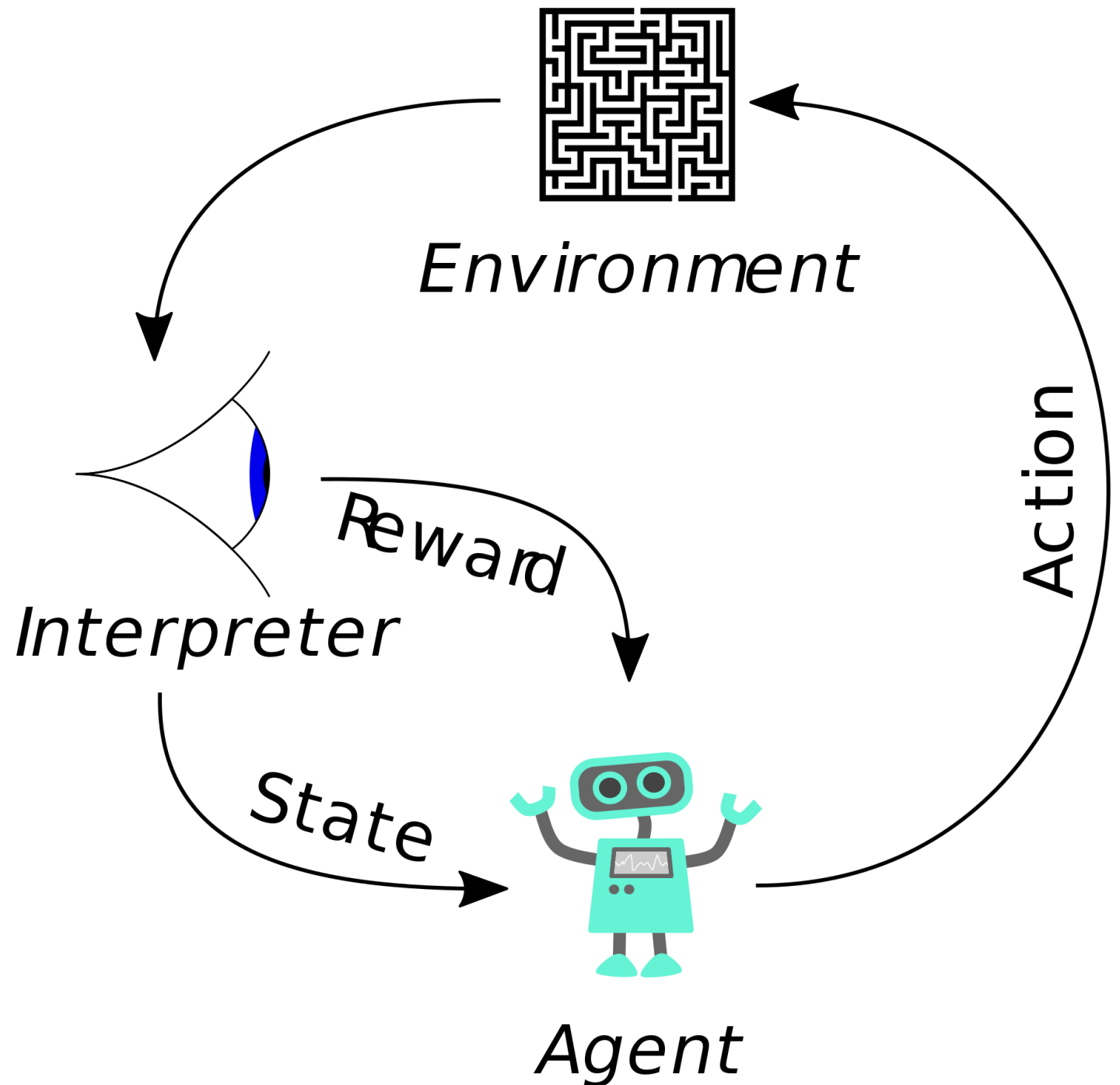
This is necessary for complexity reduction and stability.

Skill Policies:

Reinforcement learning

What is Reinforcement Learning?

Subfield of ML where an agent (robot) learns to make decisions by performing actions in an environment to maximize cumulative reward.



[2]

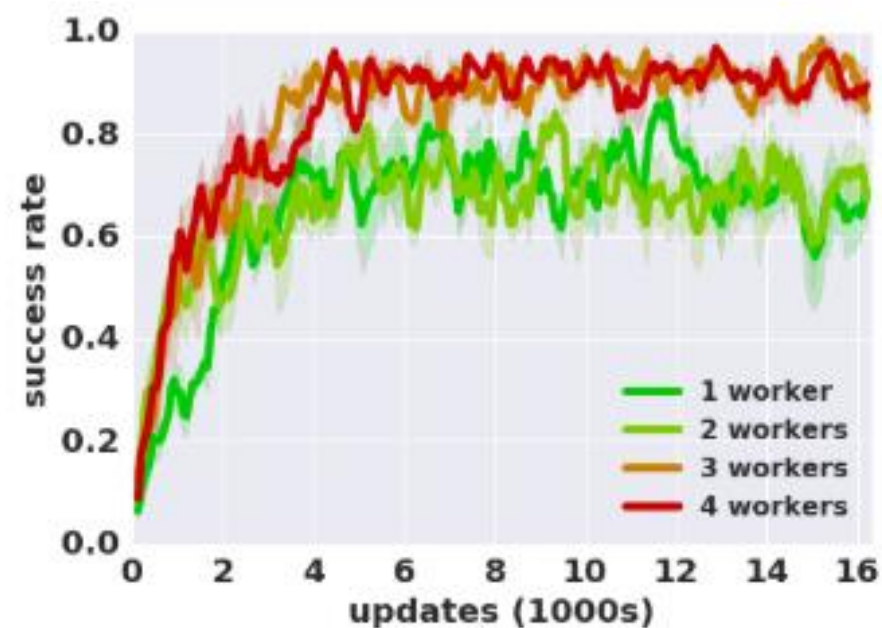


Student-teacher training

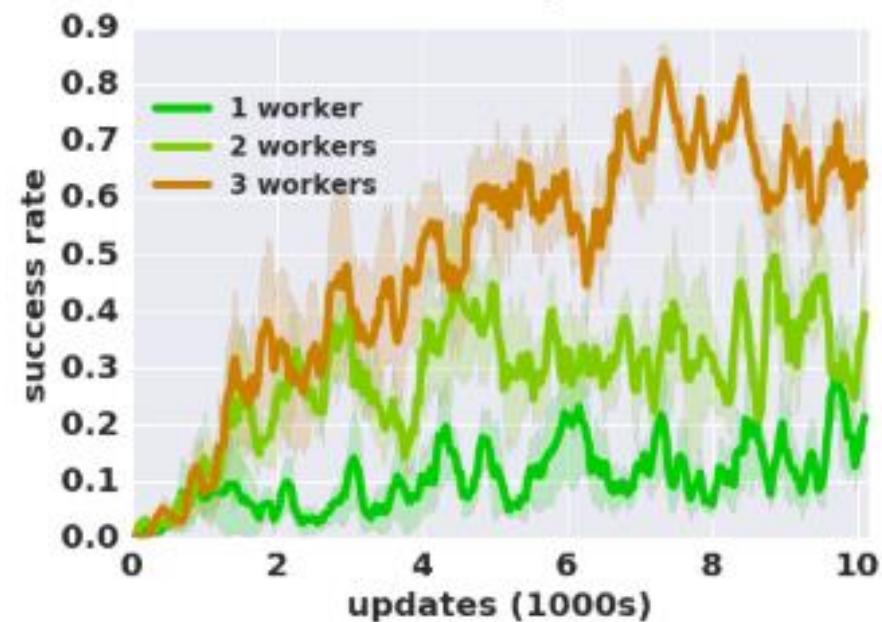
- **Teacher Policy:**
 - Has access to all domain parameters
 - Adapt behaviors based on the specific dynamics of each simulated scenario
- **Student Policy:**
 - No direct access to domain parameters
 - Learns by mimicking the teacher's actions
 - Uses historical sensory data to infer the necessary parameters for decision-making

Asynchronous Training

- The speed of learning in asynchronous training depends on the ratio of data collection speed (by the collectors) to the training speed (by the trainer).
- Multiple robots performing tasks can send back a variety of situational data to a central model for faster learning and adaptation.



(a) Reaching

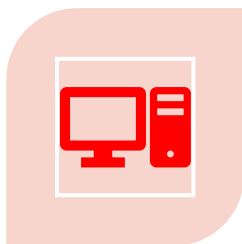


[3] (b) Door Pushing

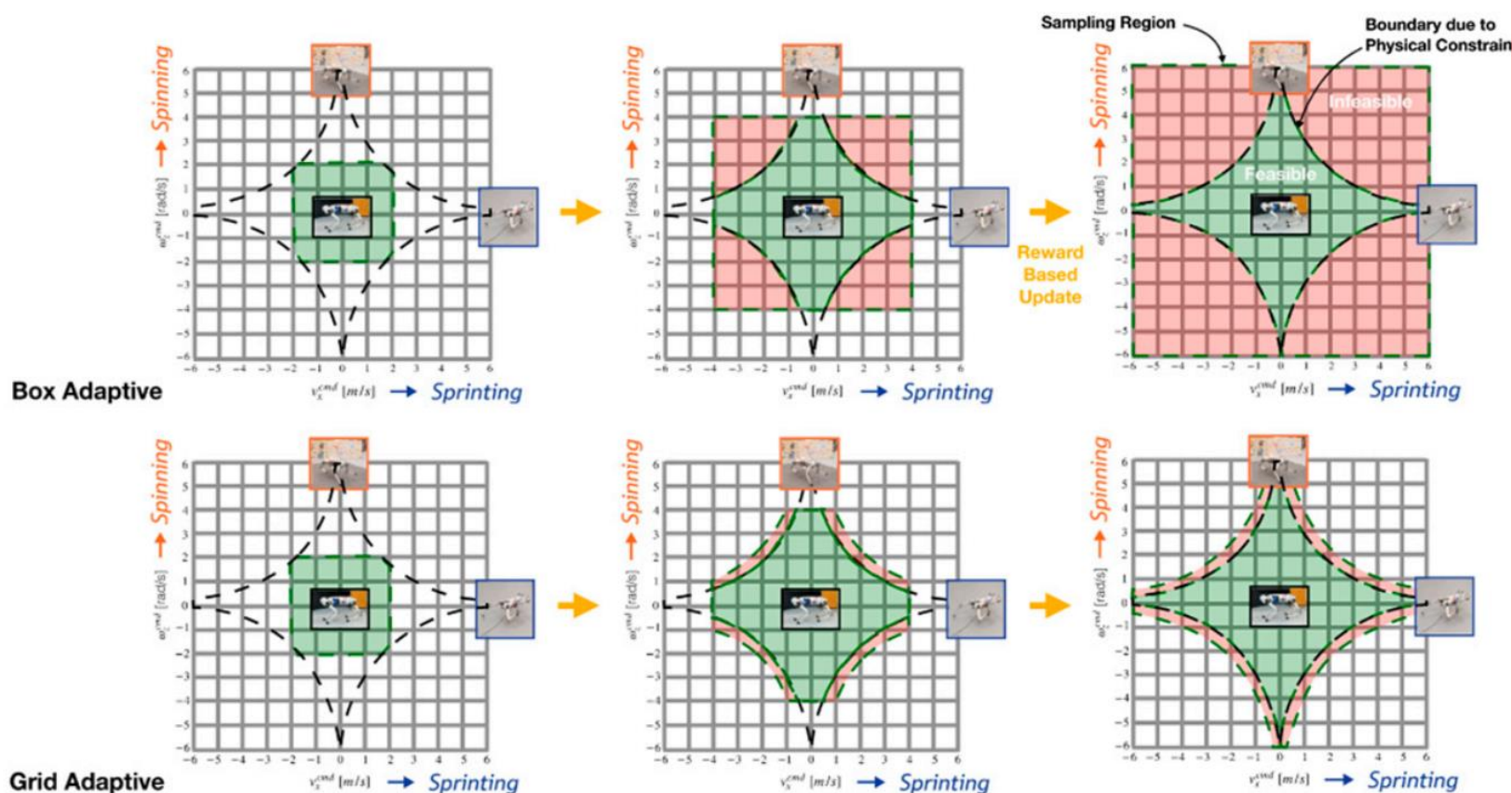
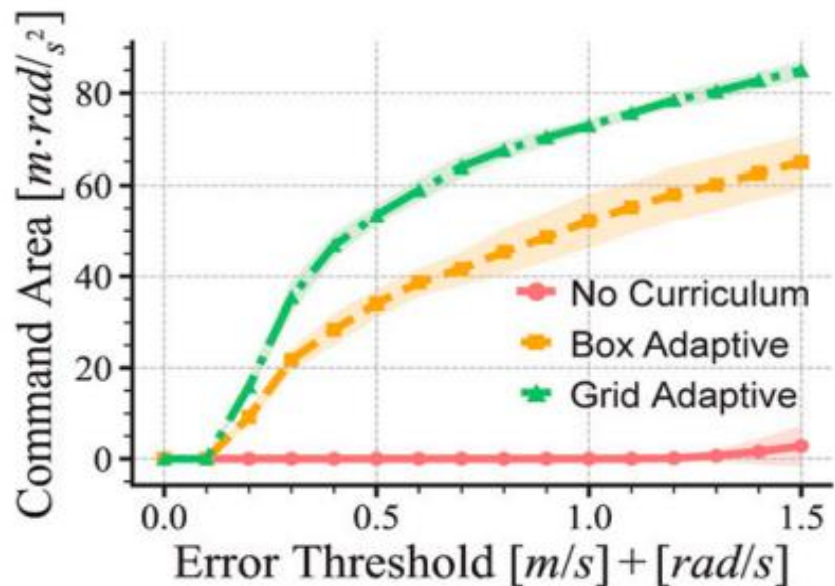
Curriculum Learning



Train the model with a sequence of examples of increasing difficulty



Automated curricula generation using GANs



[2]

Curiosity-Driven Learning



Mechanisms to Guide Exploration:



Expert Demonstrations

Requires predominantly hand-crafted demonstrations



Curriculum Learning

Generation and efficient scheduling of intermediate tasks are still considered unsolved



Intrinsic Motivation (Curiosity)

Learn without external rewards for the pure sake of knowledge gain.

How to incorporate curiosity?

1. Surprise-Based Curiosity

- **Approach:** Model that predicts the environment's forward dynamics. The intrinsic reward is then based on the Euclidean distance between the predicted next state and the observed transition.

2. State Embedding Predictions

- **Approach:** Rather than predicting the complete world state directly, predict a lower-dimensional embedding of the state.

3. Learning Progress and Count-Based Methods

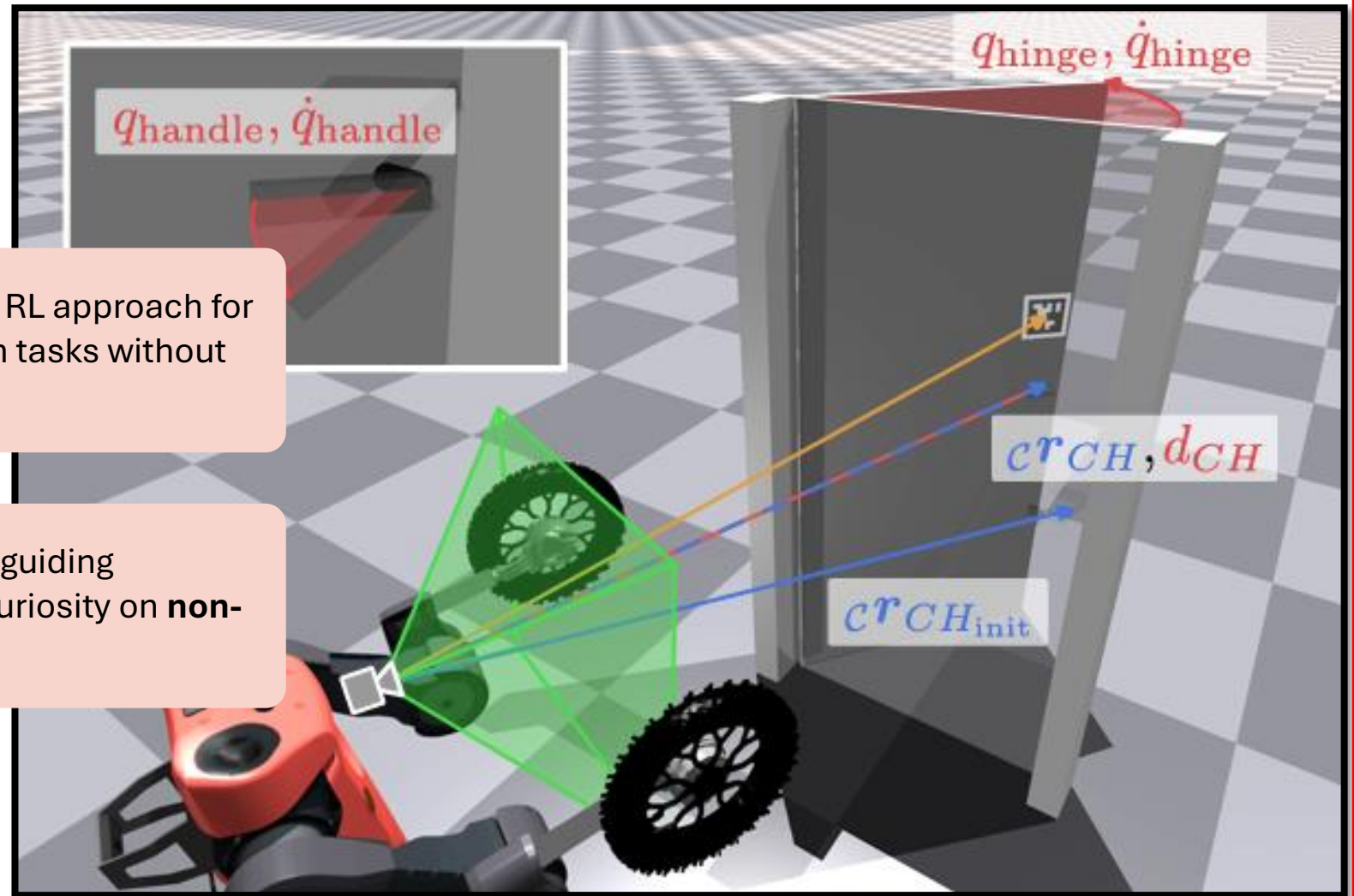
- **Learning Progress:** Intrinsic rewards are given for actions that lead to improvements in the agent's understanding or capability within particular areas of the state space.
- **Count-Based Exploration:** Implements a straightforward count of visits to each state, with a preference for states that have been visited less frequently.



A curiosity-driven **sparse reward** RL approach for learning end-to-end manipulation tasks without **task-specific engineering**



The notion of **curiosity states** as guiding mechanisms, allowing to focus curiosity on **non-directly observable states**



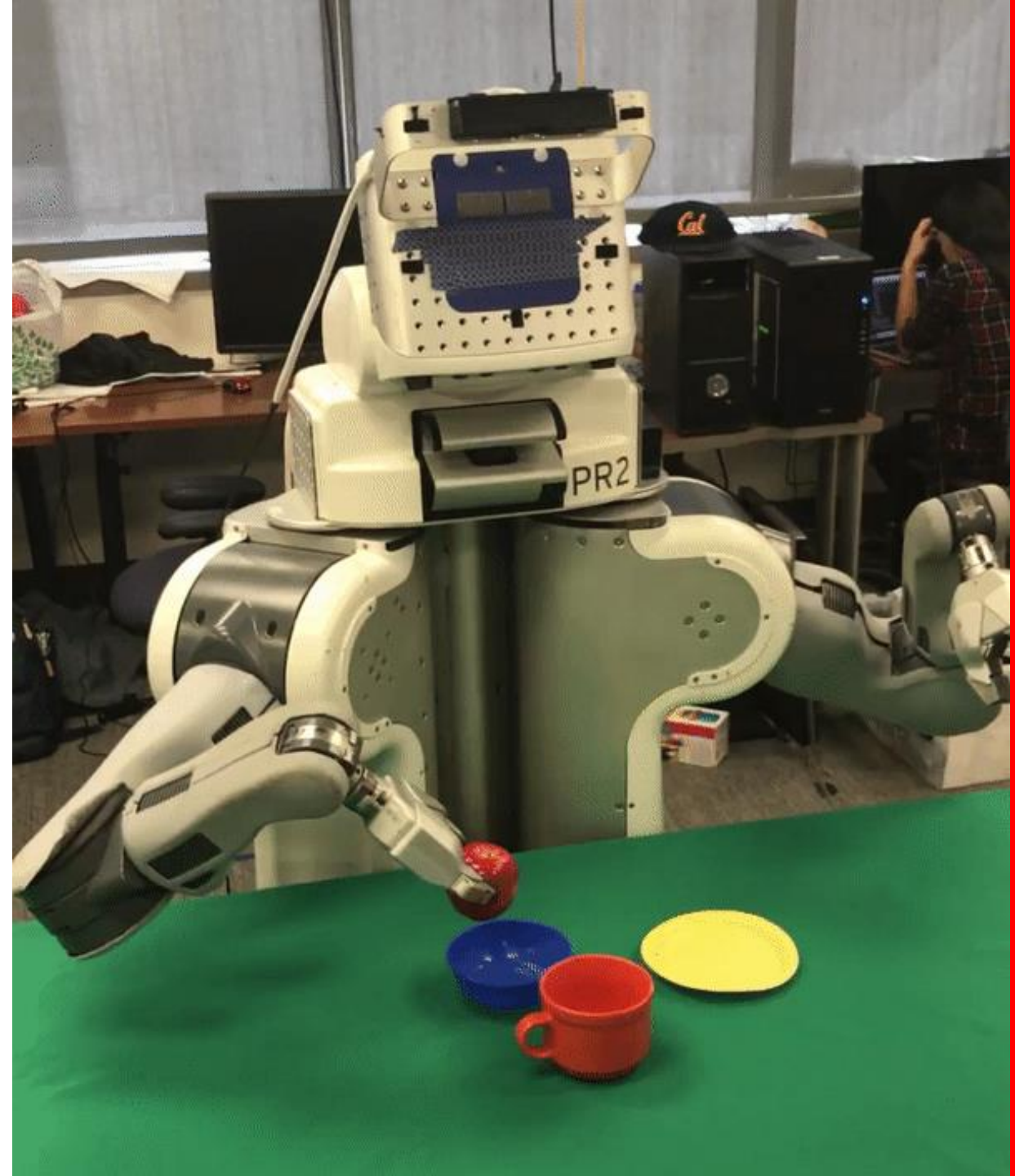


Skill Policies:

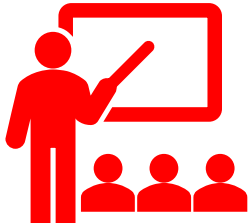
Imitation learning

What is imitation learning?

Subfield of ML where an agent (robot) learns to perform tasks by mimicking human demonstrations



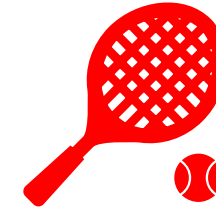
Why imitation learning?



bypass time-consuming exploration
that would be required in a
reinforcement learning setting

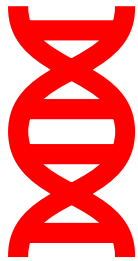


communicate user preferences for
how a task ought to be done

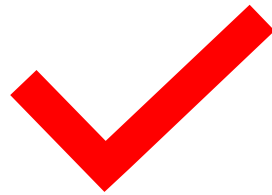


describe concepts, such as a good
tennis swing, that may be difficult to
specify formally or programmatically

Types of Imitation Learning [1]



Behavior Cloning



Direct Policy Learning



Inverse Reinforcement
Learning

Behavior Cloning

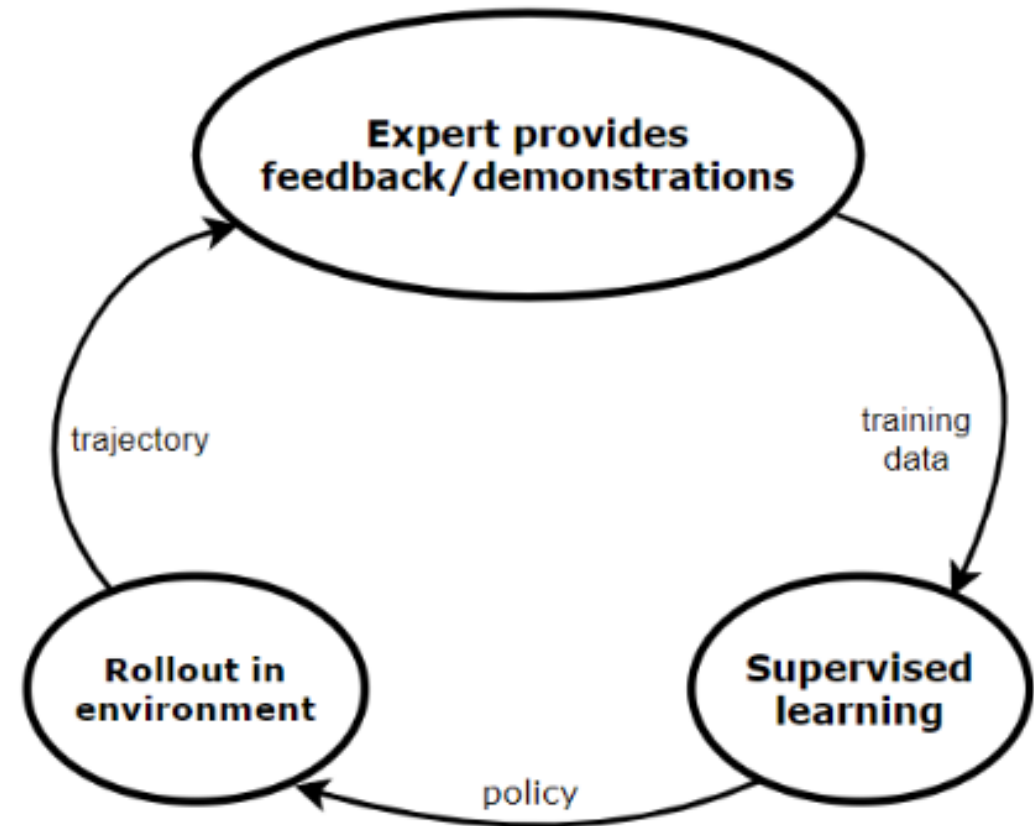
Behavioral Cloning is **Supervised Learning**

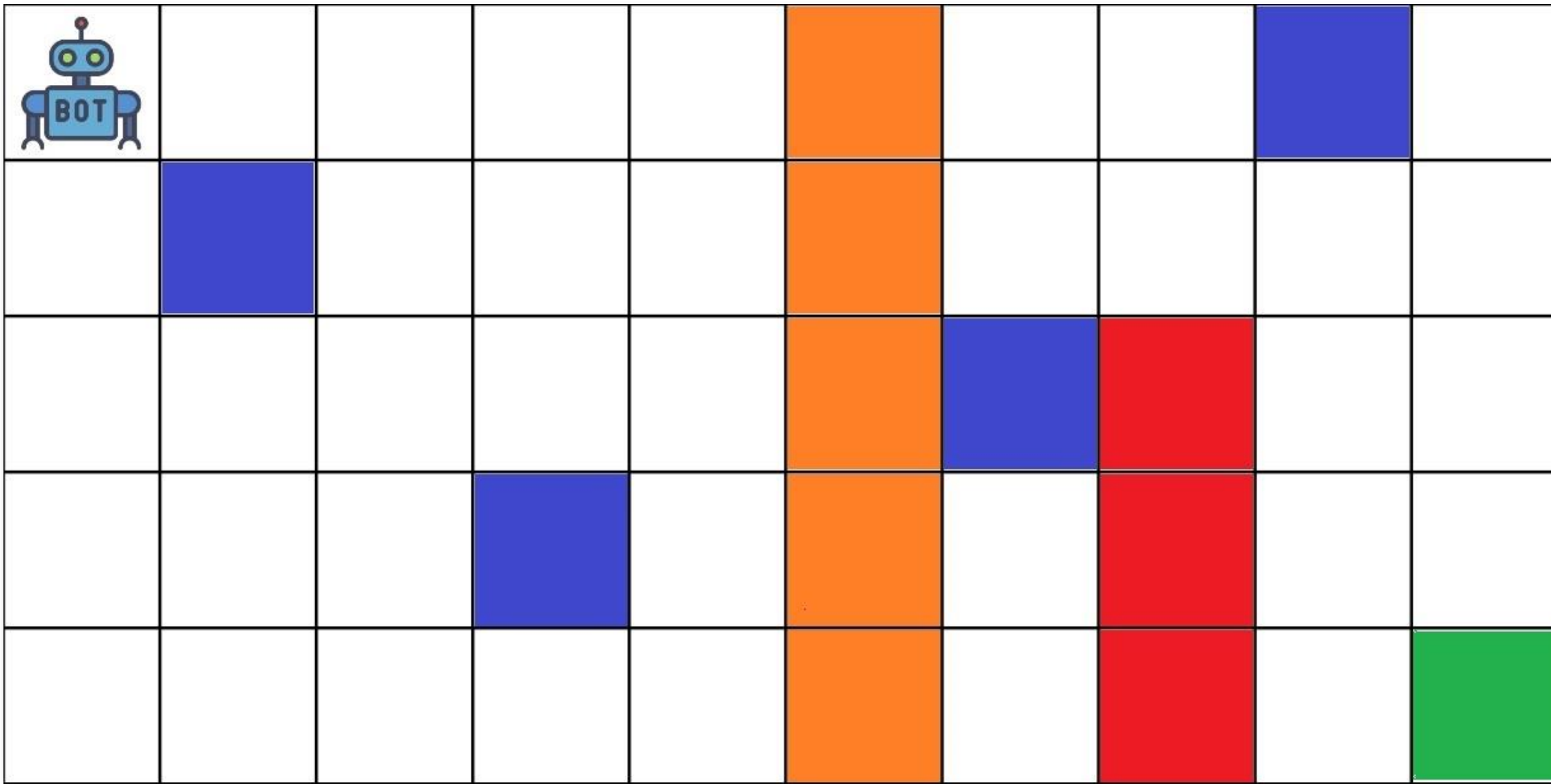
1. Collect demonstration data (state-action pairs)
2. Use state-action pairs as training data for supervised learning
3. Learn by minimizing the loss function

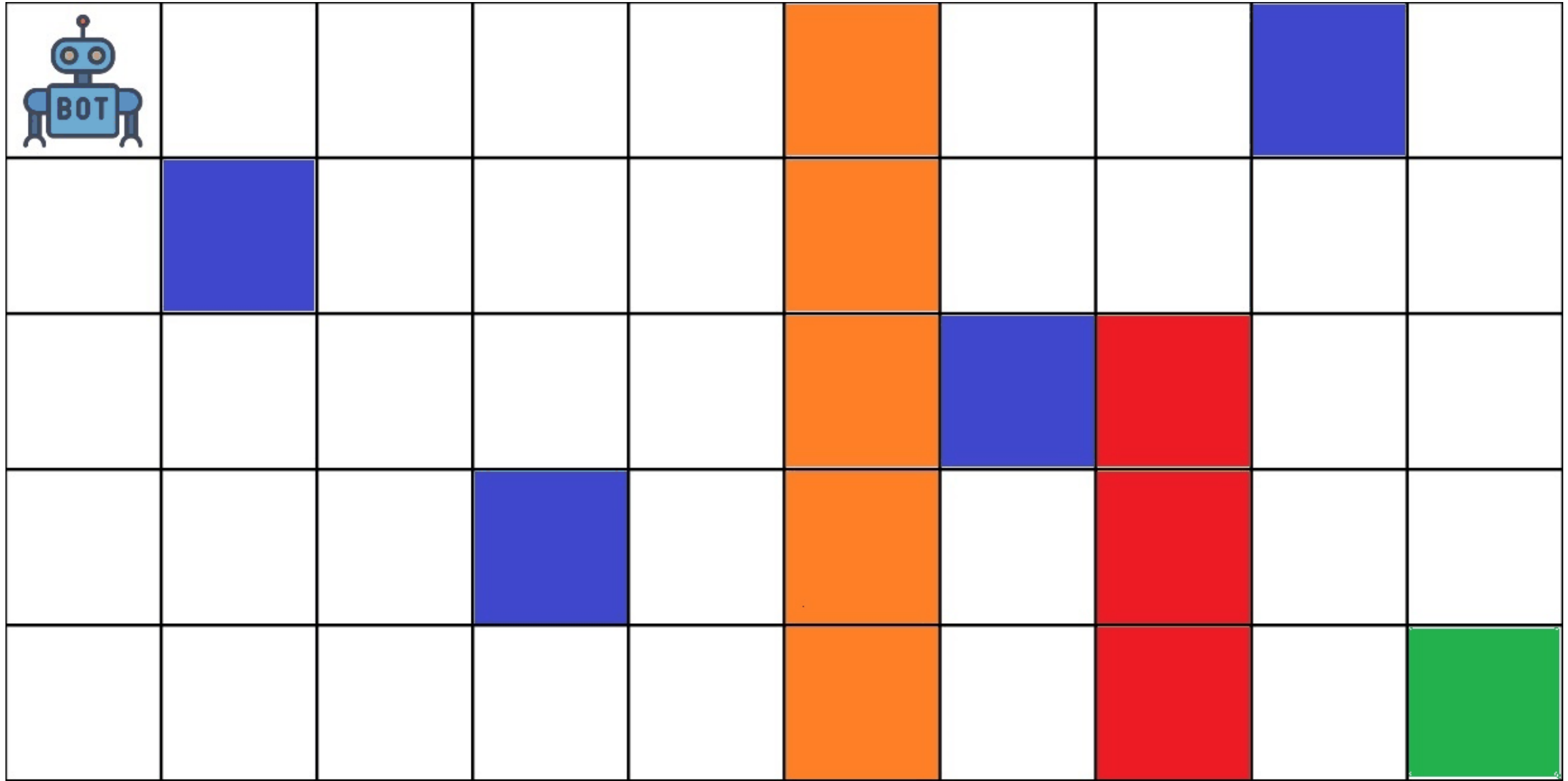
Behavior Cloning demo

Direct Policy Learning

- Improved version of behavior cloning
- Human expert needed during iterative training process
- Each training iteration, human corrects robot behavior
- New state-action pairs are used in the next training iteration







Inverse Reinforcement Learning

Attempt to infer the underlying reward function that the demonstrator was trying to optimize

1. Collect demonstrations of an expert performing a task.
2. Infer the underlying reward function that the expert is optimizing
3. Use reinforcement learning techniques to learn a policy that maximizes the inferred reward function.

Maximum Entropy



INITIALIZE REWARD
WEIGHTS



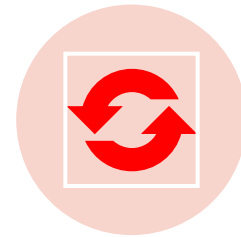
COMPUTE POLICY



COMPUTE STATE
VISITATION
FREQUENCIES



UPDATE REWARD
WEIGHTS



REPEAT

Skill Policies: Skill Transfer

Parameterized Skills [2]

- In certain tasks, only some aspects of the context change, while other properties remain unchanged
- Manifold learning modulates policy parameters based on the changing task parameter

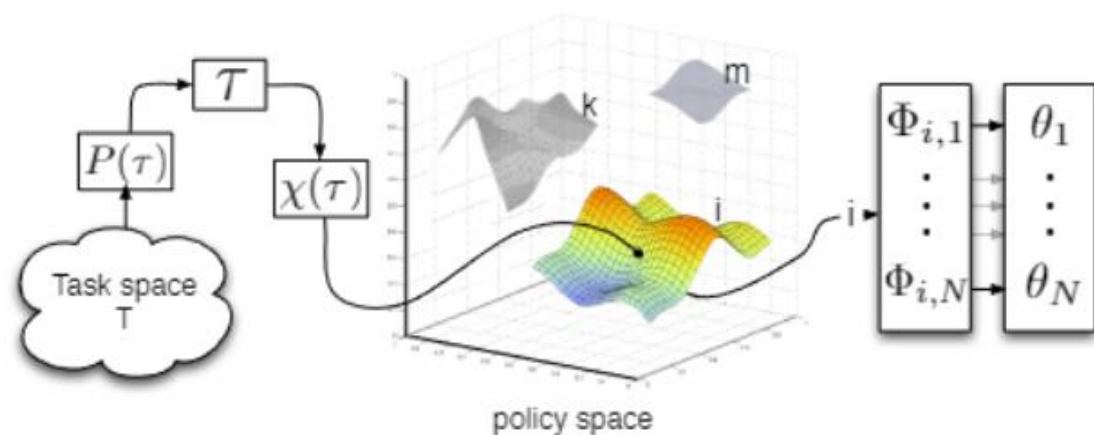


Figure 1. Steps involved in executing a parameterized skill: a task is drawn from the distribution P ; the classifier χ identifies the manifold to which the policy for that task belongs; the corresponding regression models for that manifold map task parameters to policy parameters.

Metalearning [3]

- "Learning to learn"
- Model Agnostic Metalearning (MAML)
 - Given a sequence of tasks, the parameters of a given model are trained such that few iterations of gradient descent with few training data from a new task will lead to good generalization performance on that task. MAML **"trains the model to be easy to fine-tune."**

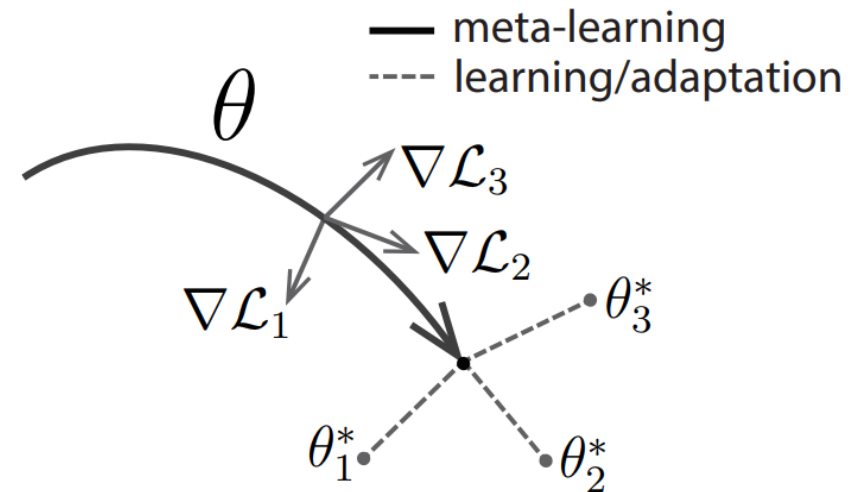
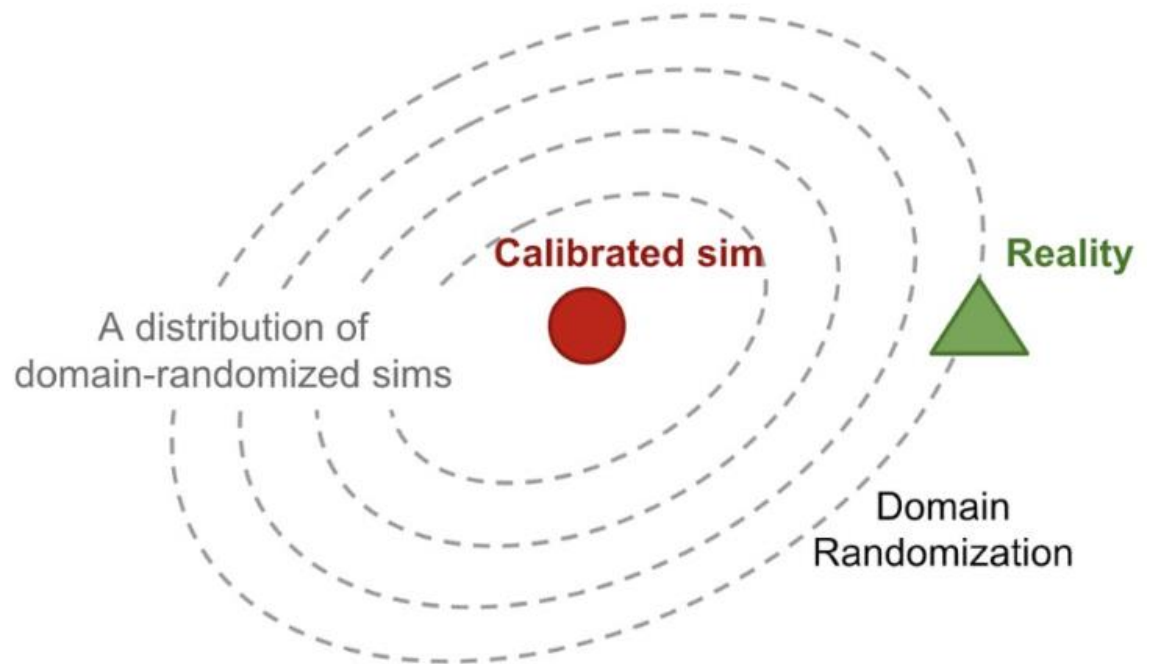


Figure 1. Diagram of our model-agnostic meta-learning algorithm (MAML), which optimizes for a representation θ that can quickly adapt to new tasks.

[18]

Domain Adaptation

- Used when two tasks are the **same at a high level** but **differ in low-level details**
- Example: sim2real task
- Popular method: **Domain Randomization**



[20]

Characterizing skills by Preconditions and Effects

Pre- and Postconditions as
Propositions and Predicates

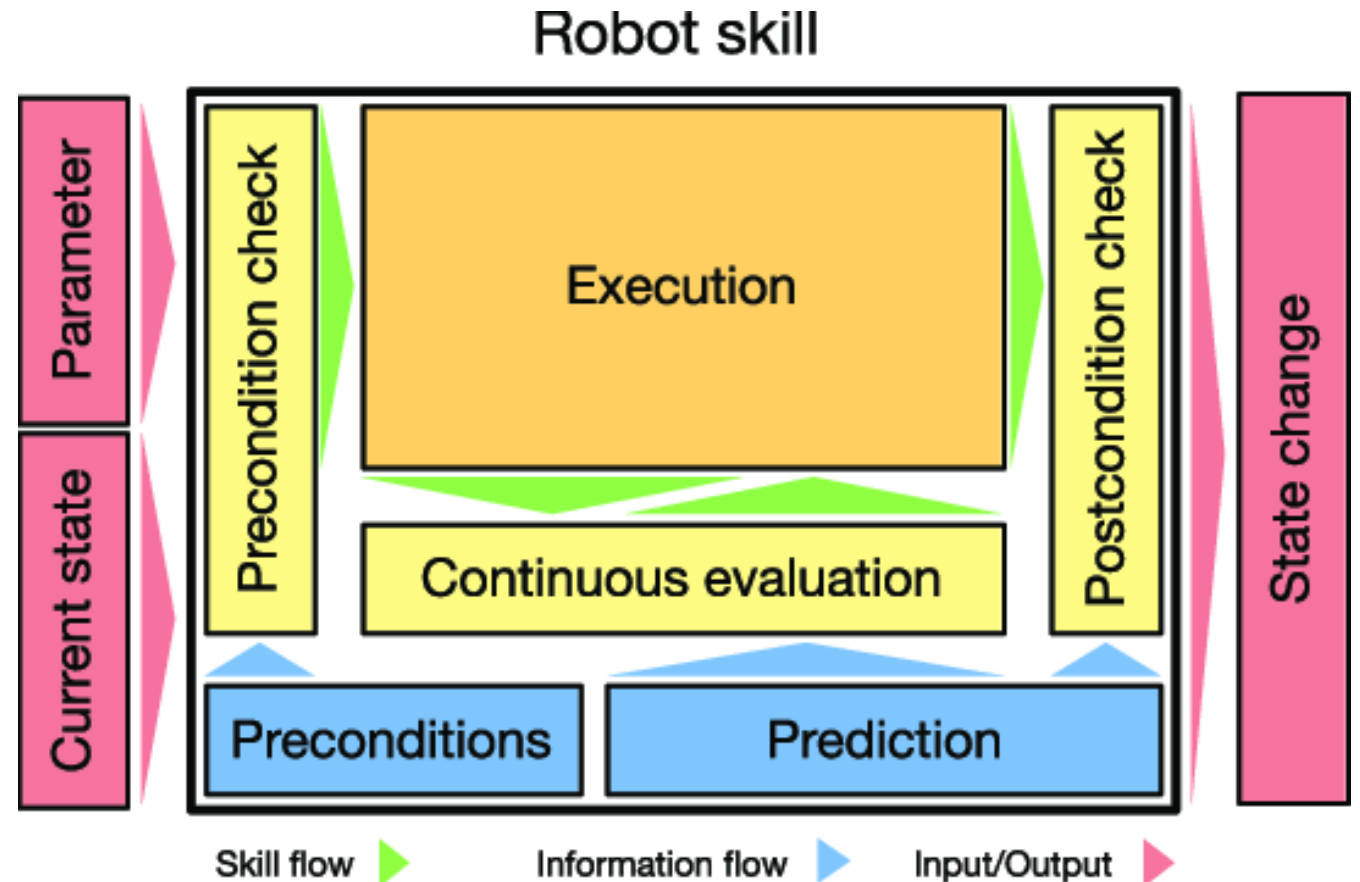
Skill Monitoring and Outcome
Detection

Learning Pre- and Postcondition
Groundings

Predicates and Skill Synthesis

What are Pre- and Post- conditions?

- **Precondition:** A set of conditions that must be met for a robot to successfully execute a particular skill.
- **Postcondition:** A set of conditions describing the state of the environment after a robot has executed a particular skill.



Pre- and Postconditions as Propositions and Predicates

Proposition

AtTableB
GraspedKnifeAwRHand

Predicate

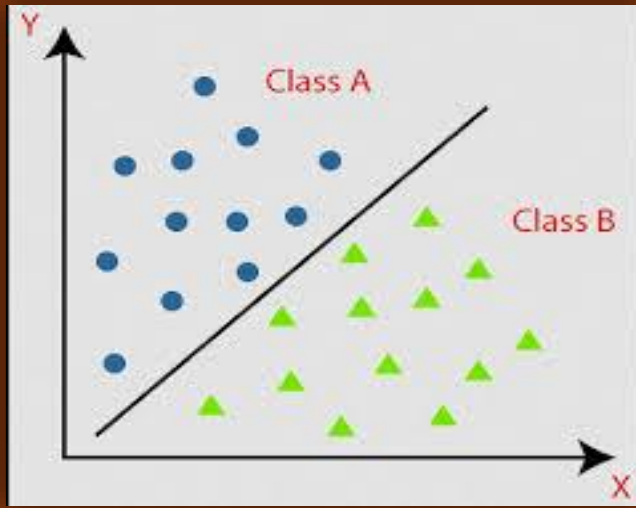
At(TableB)
Grasped(KnifeA, RHand)



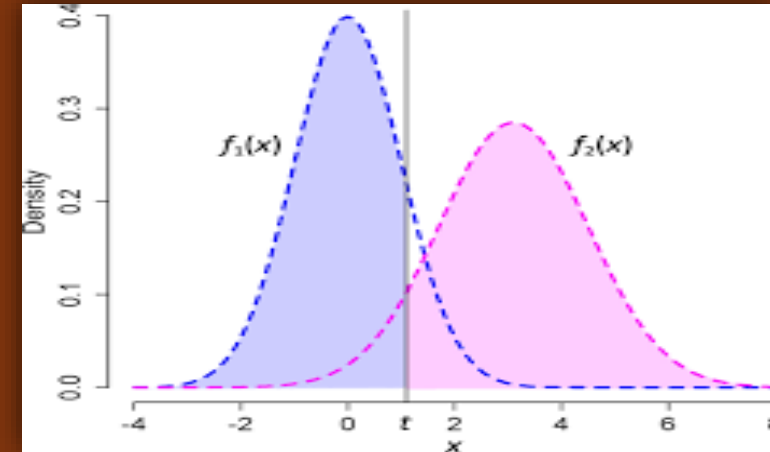
How can a robot map its complex environment to abstract predicates?

Grounding a Predicate is linking abstract symbols or logical expressions to real-world data and conditions.

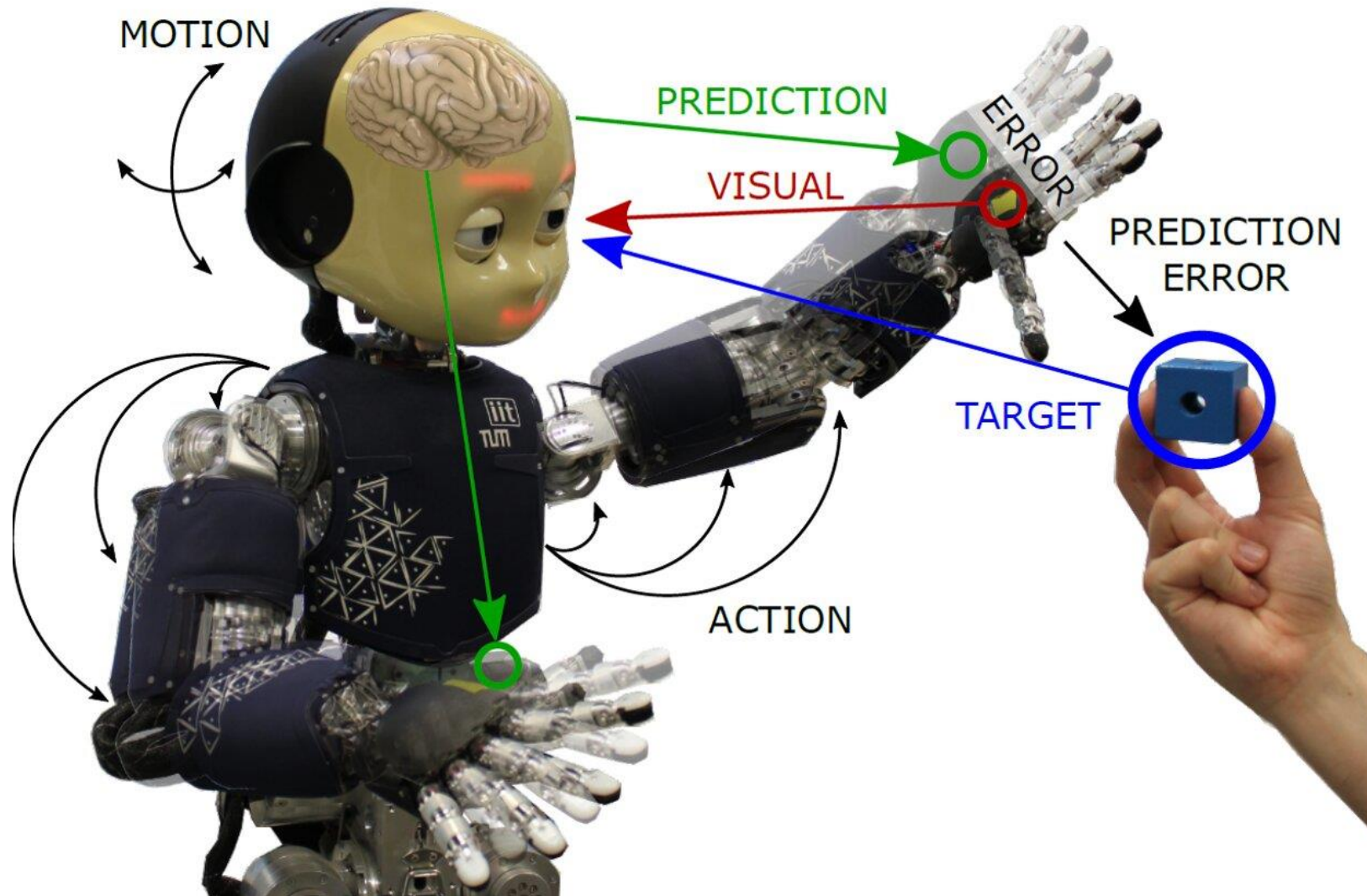
Classifier
Representation:



Distribution
Representation:



Ways to Monitor Outcomes and Errors



1. Learning Goal and Error Classifiers
2. Detecting Deviations from Nominal Sensory Values
3. Verifying Predicates

Compositional and Hierarchical task structures

Compositional
and Hierarchical tasks

Structure of Robotic Skill Execution

Ways to Segment Trajectories into
Component Skills

Skill Discovery While Solving Tasks

Complex tasks

Instruction 1:

Open the drawer.

Instruction 2:

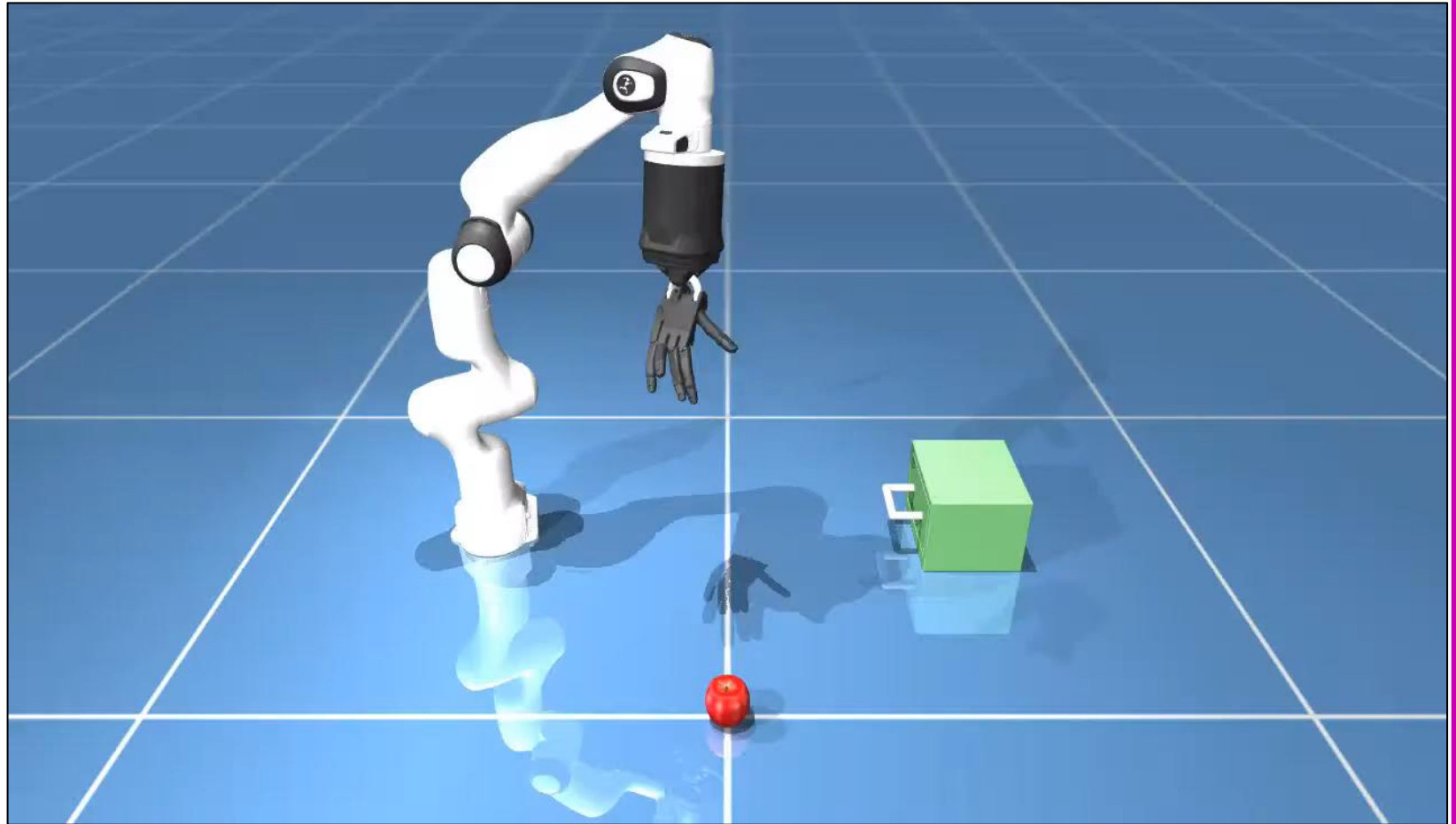
Put the apple inside the drawer while keep it open.

Instruction 3:

Release the apple and move hand away.

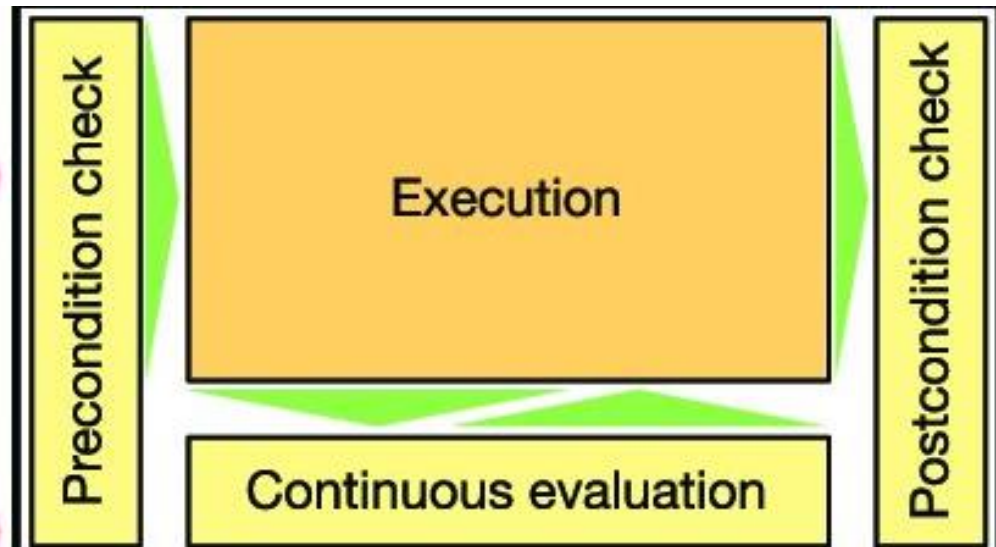
Instruction 4:

Close the drawer.



Structure of Robotic Skill Execution

$$o = (I_o, \beta_o, \pi_o),$$



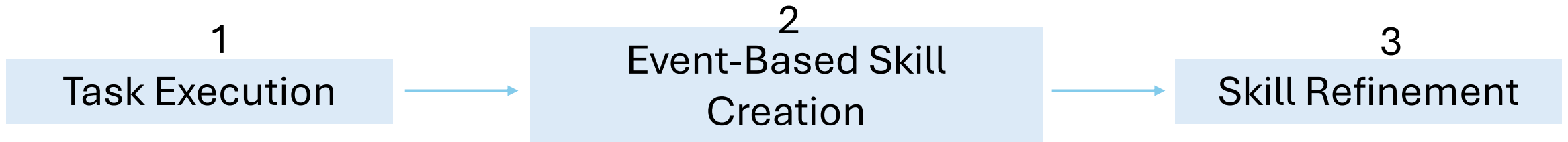
- $I_o : S \rightarrow \{0, 1\}$ initiation set.
- $\beta_o : S \rightarrow [0, 1]$ termination condition.
- π_o option policy.

A **skill library** is a set of reusable skills for a robot.

How to identify skills?

Identifying Skills:

1. Discovering Skills While Solving Tasks



2. Segmenting Trajectories into Component Skills



1. Segmentation Based on Skill Similarity

Ways to measure skill similarity

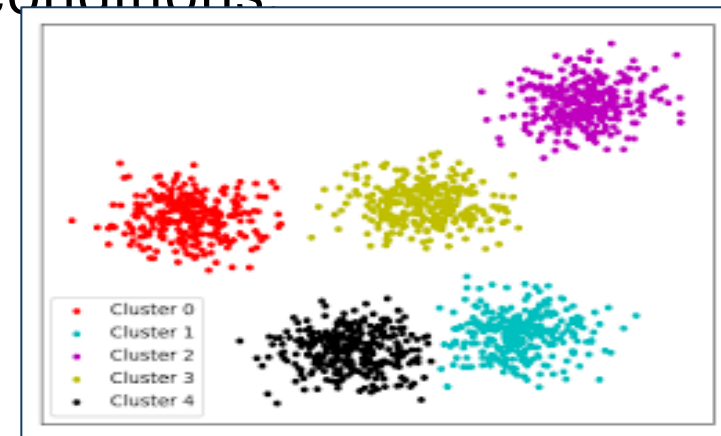
Policy Similarity:

- Measures skill similarity by fitting data to policies and evaluating distance in parameter space.

$$d^*(x, y) = \underbrace{\text{DIST}(\pi^*(x), \pi^*(y))}_{(A)} + \underbrace{\gamma \mathcal{W}_1(d^*)(P^{\pi^*}(\cdot|x), P^{\pi^*}(\cdot|y))}_{(B)}.$$

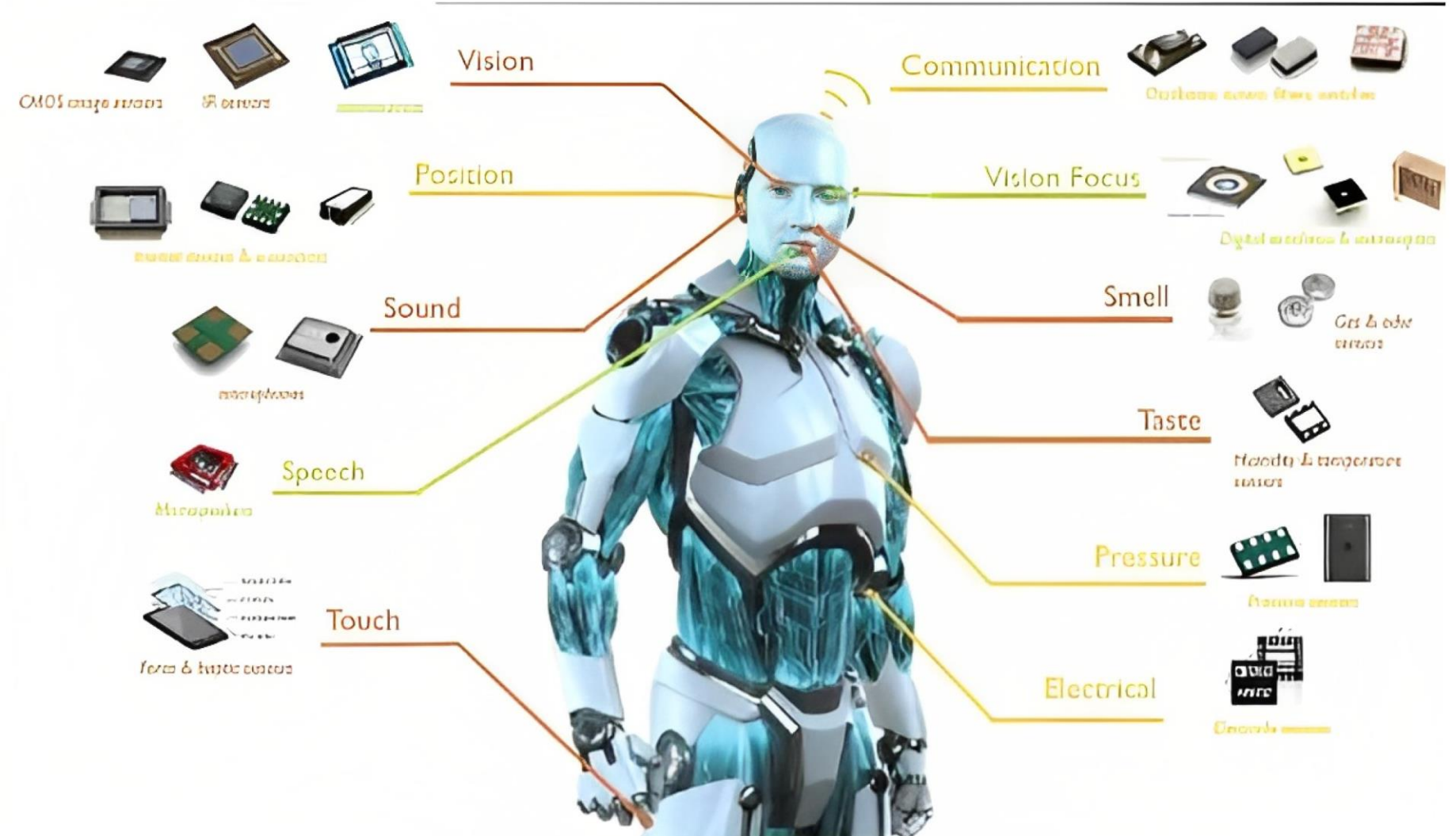
Pre- and Postcondition Similarity:

- Segments skills based on achieving goals from different initial conditions



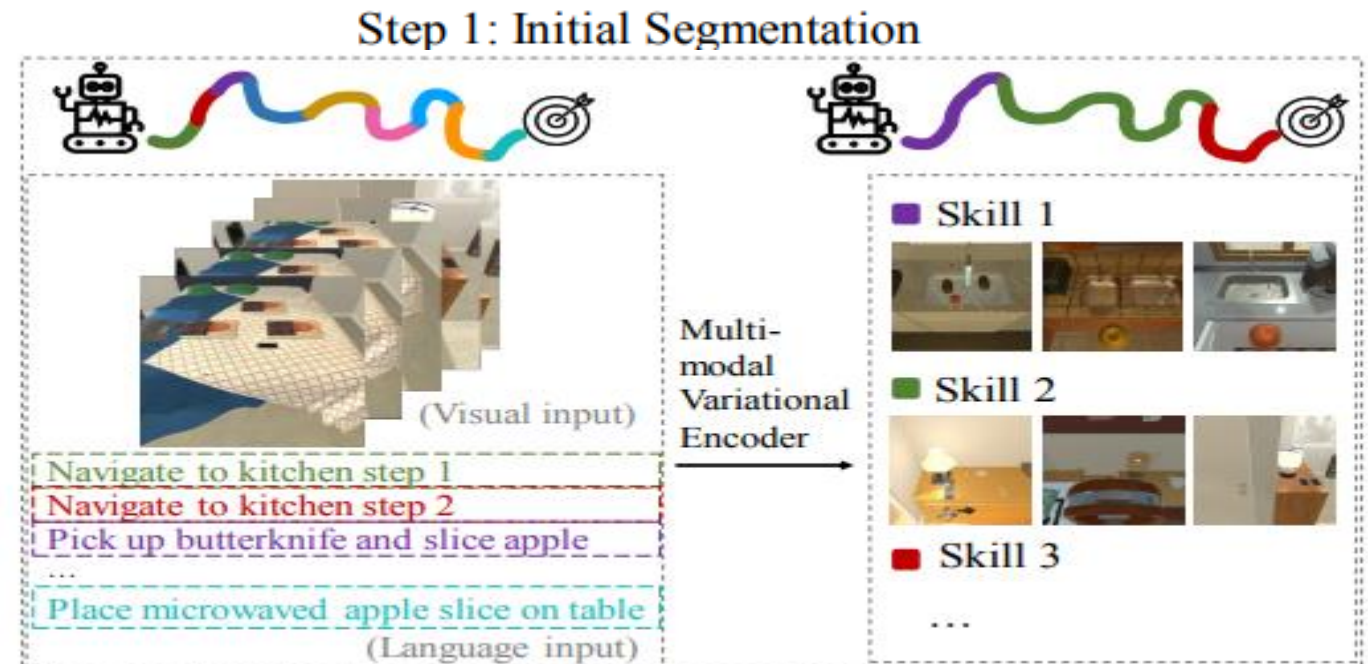
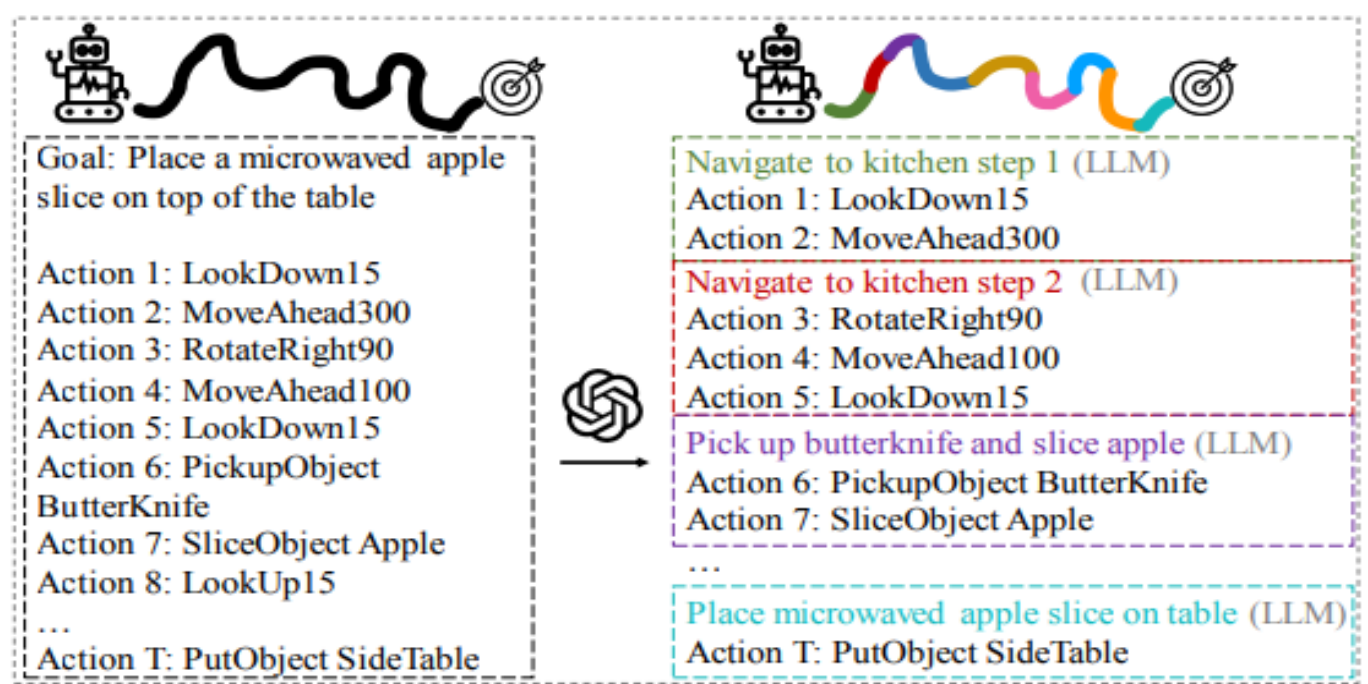
2. Segmentation Based on Specific Events

- Salient sensory events
- Transitioning between modes



Overall framework of LAST

(Language-guided Skill Learning with Temporal Variational Inference)



Language-guided Skill Learning with Temporal Variational Inference

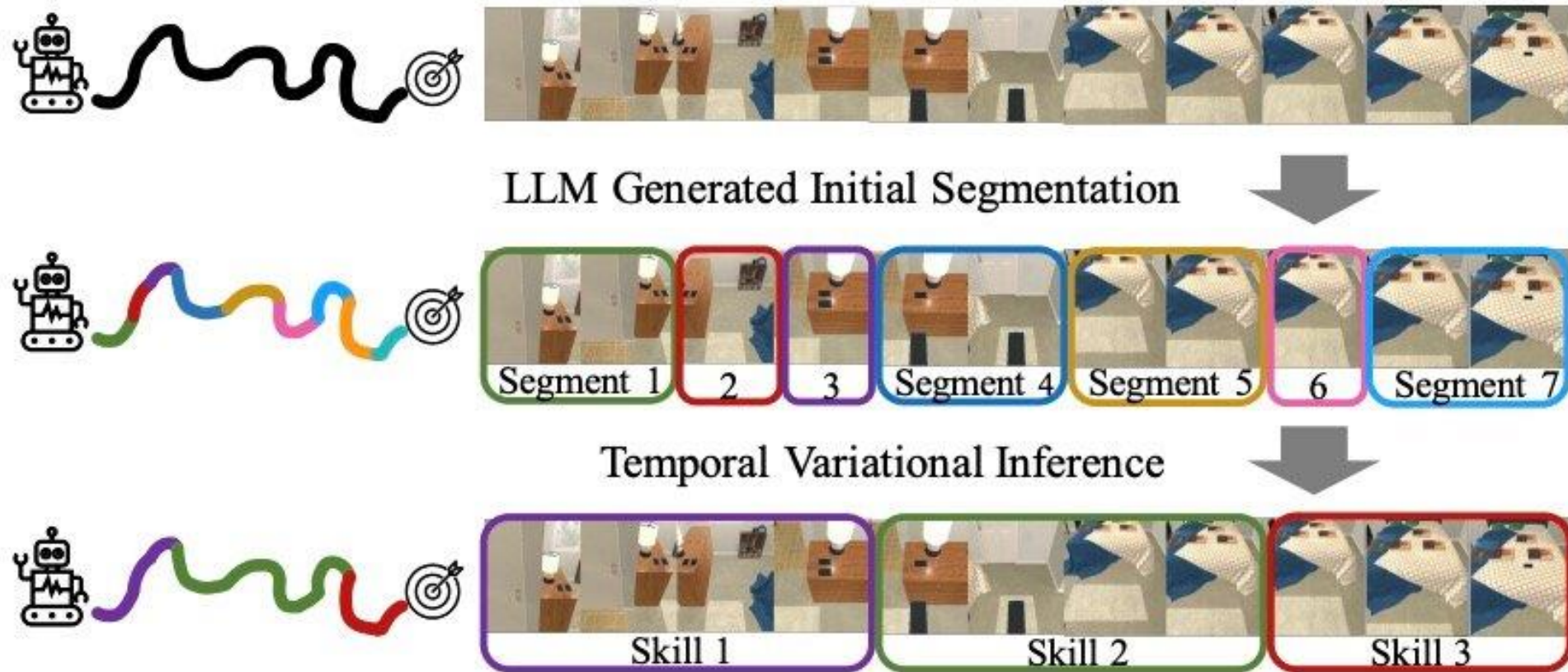
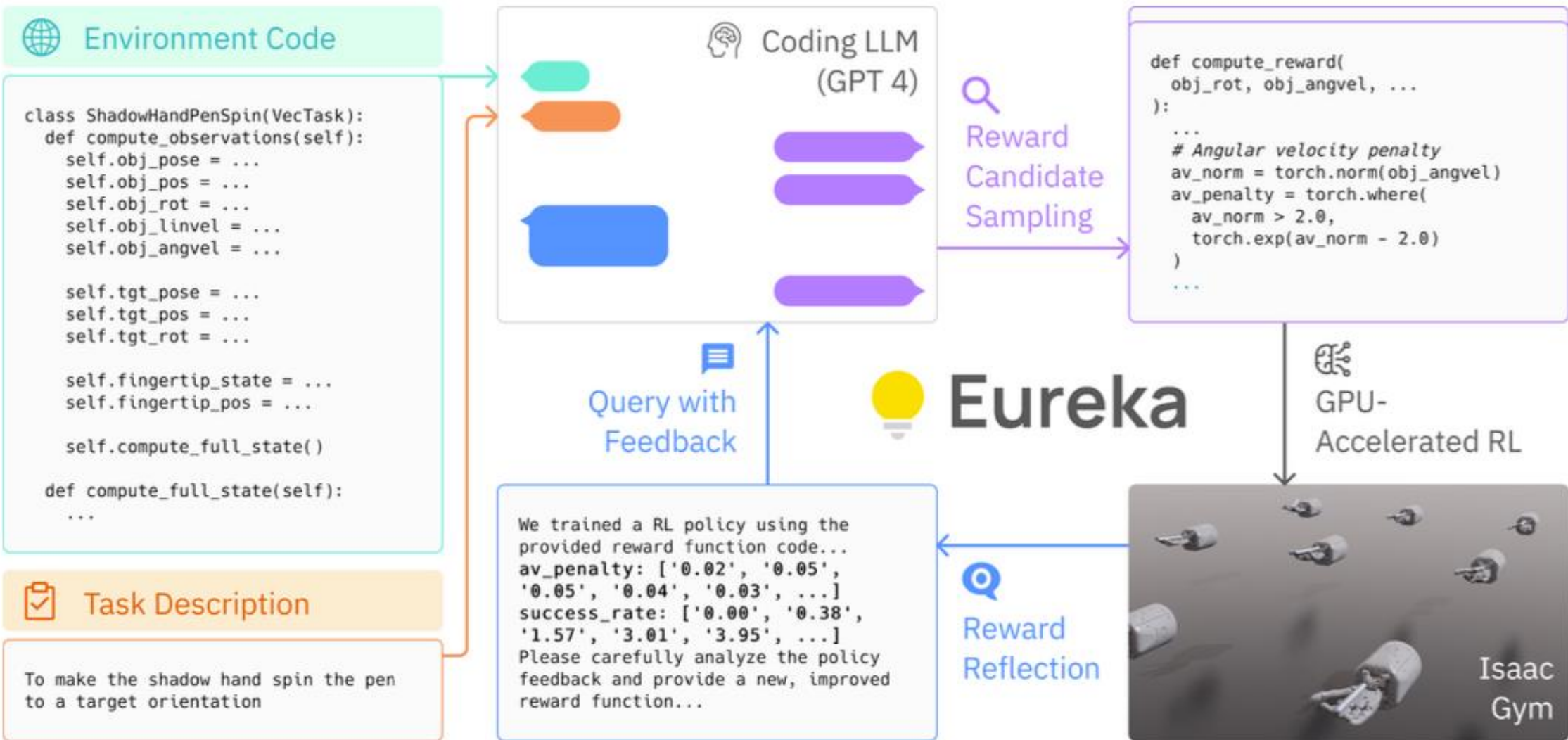
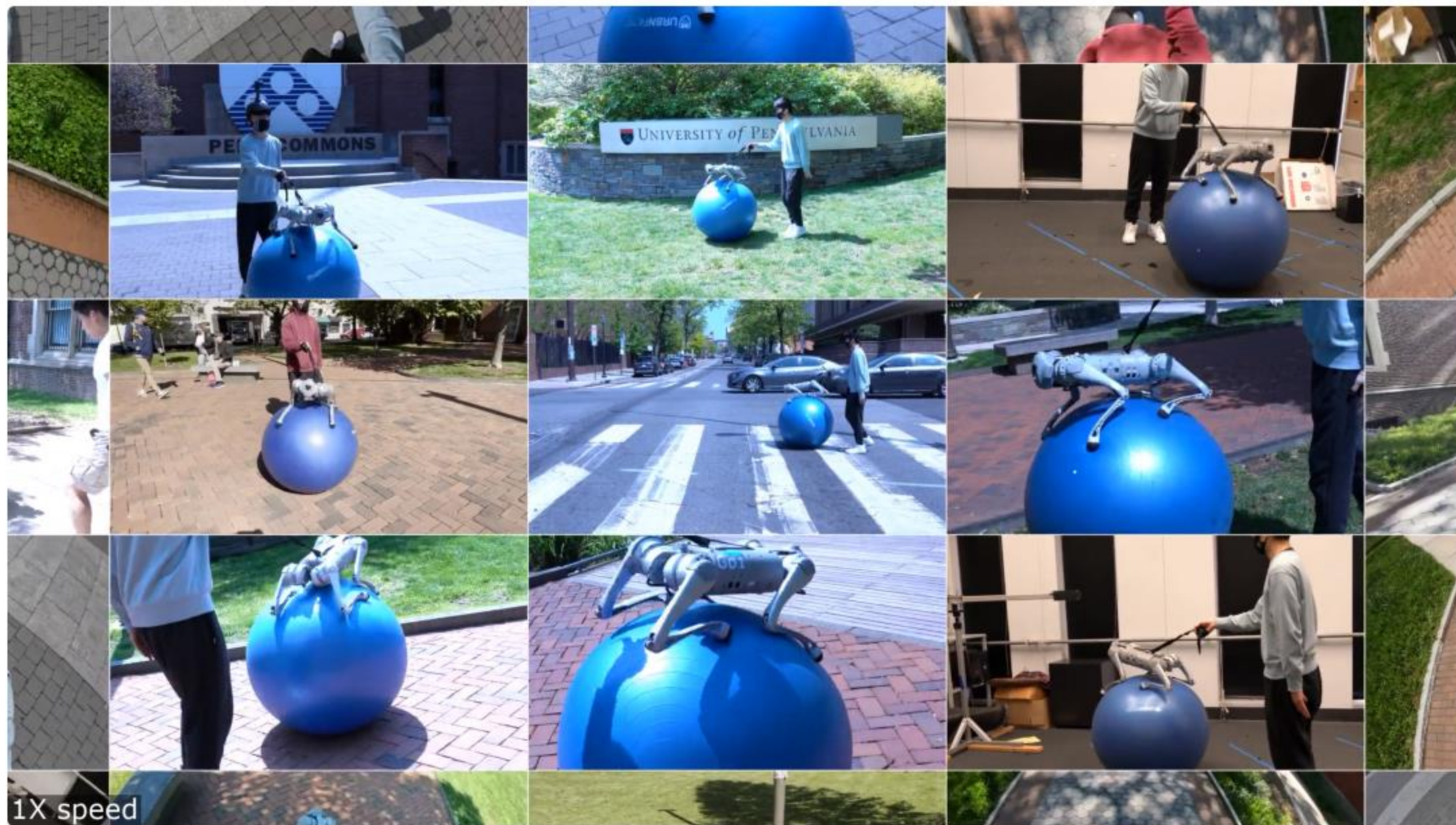


Figure 1. The trajectory segmentation and merging procedure.

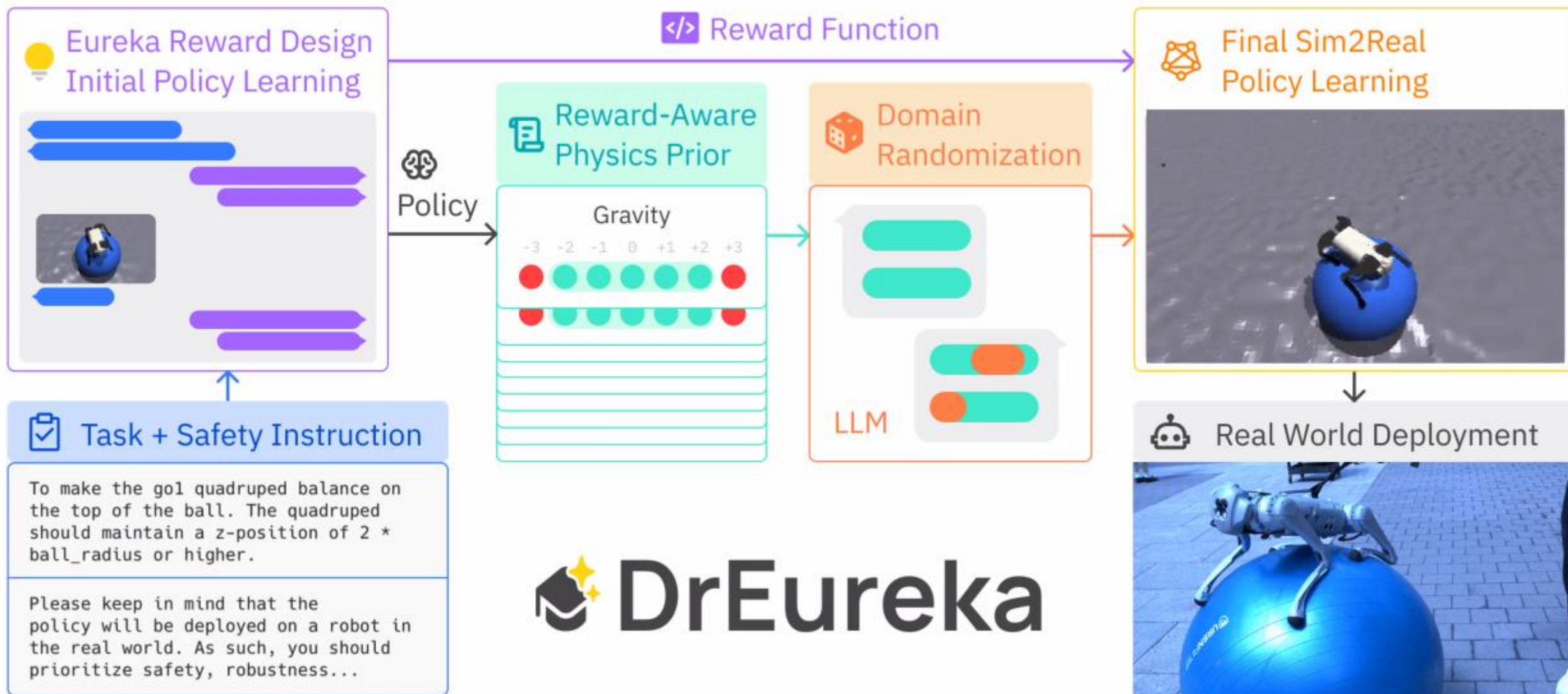
Some relevant Examples

Eureka and DrEureka





[12]



Voyager



Mine Diamond



Gather Cactus



Build Base



Fight Enderman



Build House
with Human Feedback



Mine Gold



Build Nether Portal
with Human Feedback

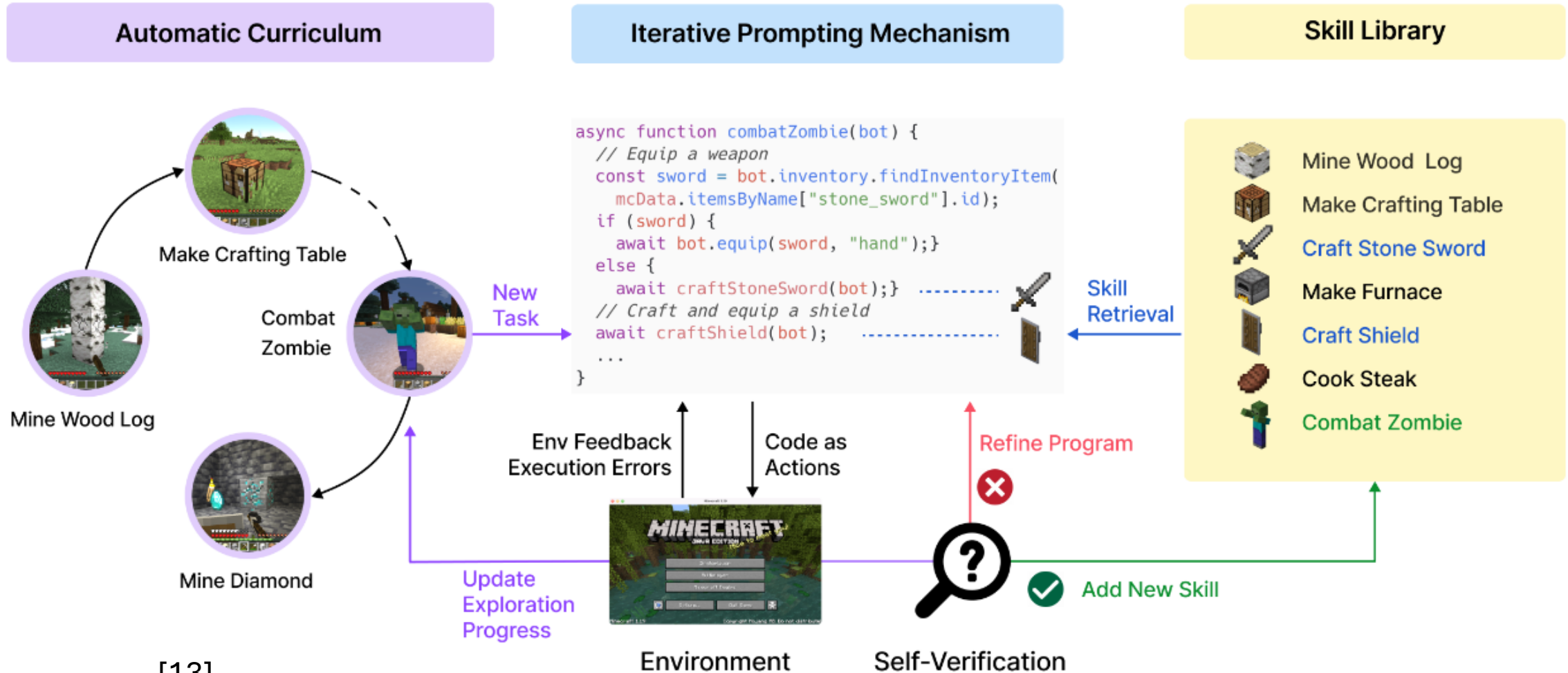


Hunt Pig



Catch Fish

Curiosity learning, curriculum learning, skills



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