Foundation Models Meet Embodied Agents

Manling Li
Northwestern

Yunzhu Li
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Jiayuan Mao
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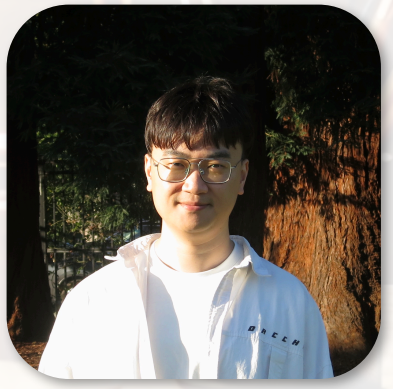


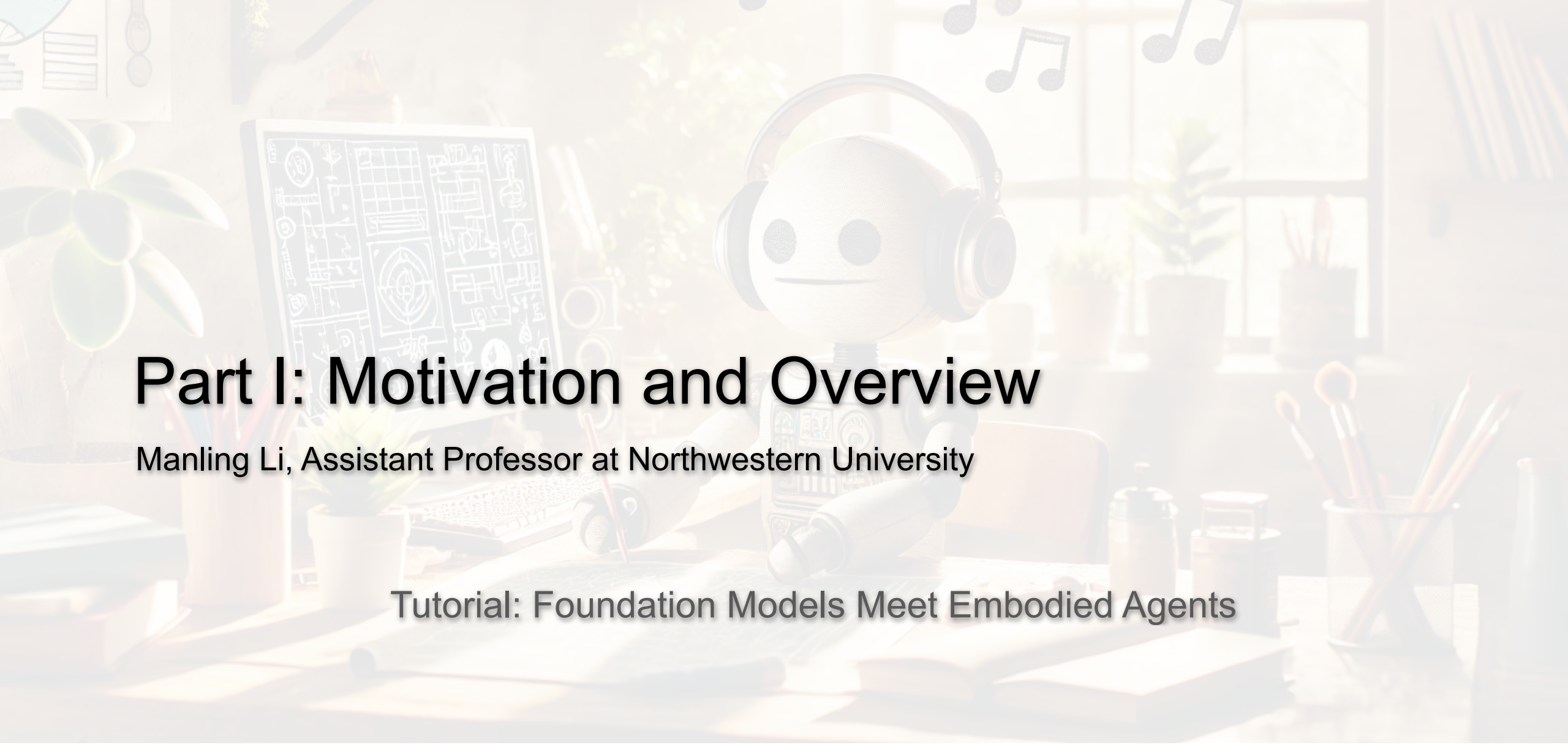
Wenlong Huang
Stanford

Northwestern University

COLUMBIA

MIT

Stanford University



Part I: Motivation and Overview

Manling Li, Assistant Professor at Northwestern University

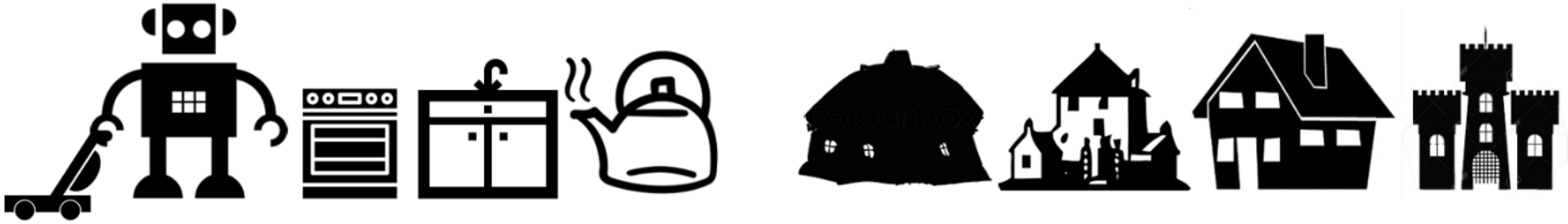
Tutorial: Foundation Models Meet Embodied Agents

Northwestern University

Stanford University

What is a generalist agent?

What is a generalist agent?



Having a robot that can do many tasks, across many environments.

Figure credits: Jiayuan Mao


BEHAVIOR-1K
simulating and benchmarking robot tasks that matter to humans
https://behavior.stanford.edu/

What is a generalist agent?

Having a robot that can do many tasks, across many environments.

Figure credits: Jiayuan Mao

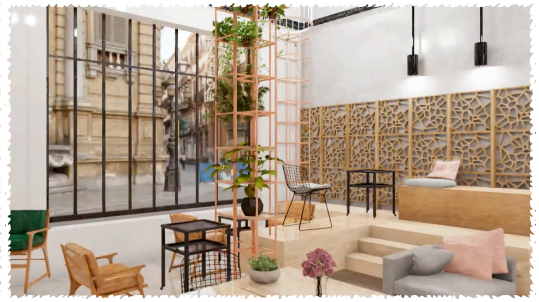
BEHAVIOR-1K

Environment

Observation



State: 3D assets & states

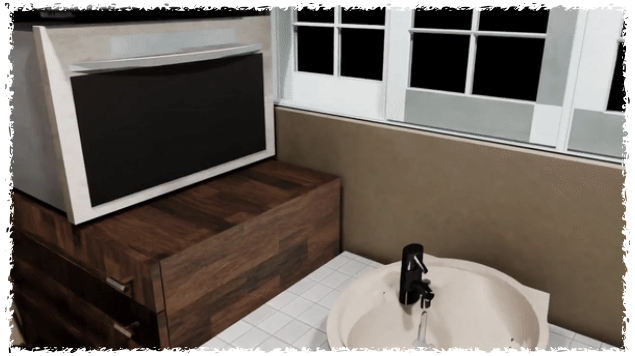







Transition Model





https://behavior.stanford.edu/

What is a generalist agent?

Having a robot that can do many tasks, across many environments.

Figure credits: Jiayuan Mao

tasks that matter

What would you like a robot to help you with?

Cleaning the floor?

Images Generated by DALL-E 3

tasks that matter

What would you like a robot to help you with?

Folding Laundry?

Images Generated by DALL-E 3

tasks that matter

What would you like a robot to help you with?

Cooking Breakfast?

Images Generated by DALL-E 3

tasks that matter

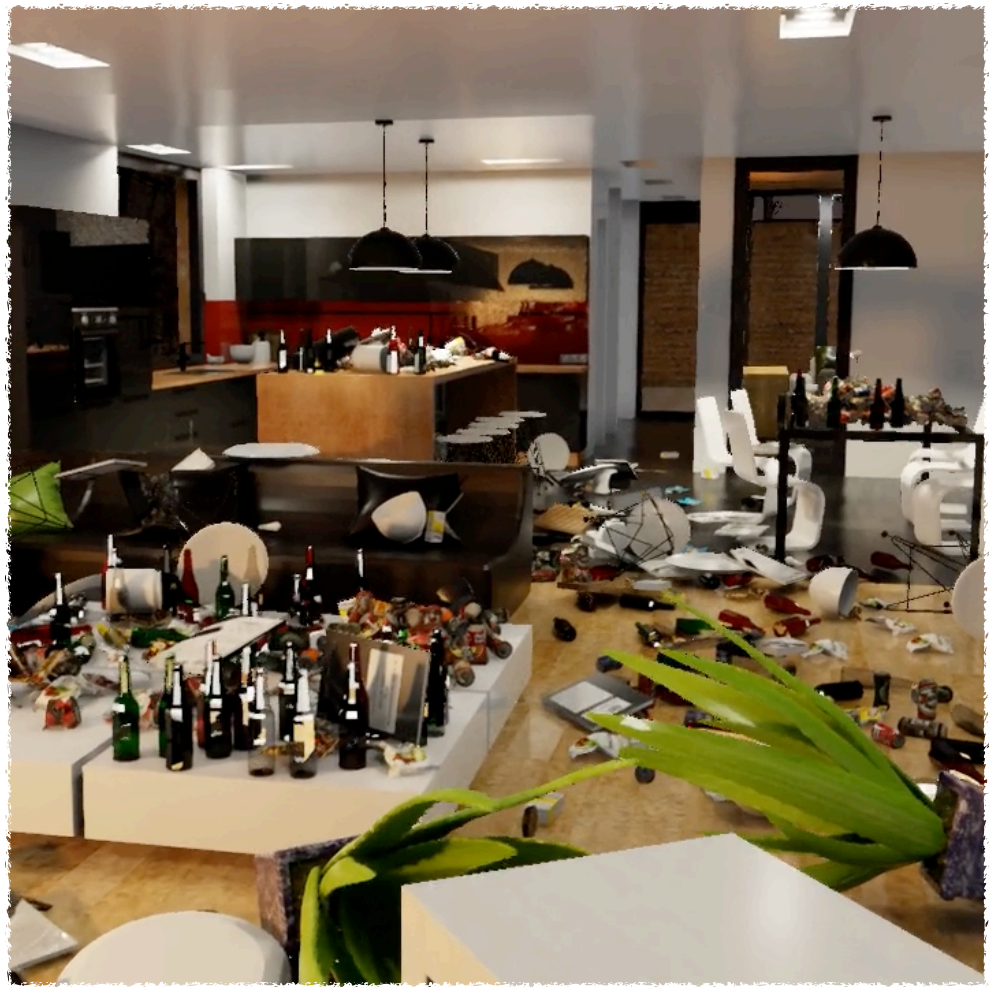
What would you like a robot to help you with?

Opening gifts?

Images Generated by DALL-E 3

tasks that matter

What would you like a robot to help you with?



Cleaning after a wild party?

Images Generated by DALL-E 3

Typical Embodied Agent Tasks

Robotic Manipulation

Human: pack the yoshi figure in the brown box

LEO:

$$P = [0.1, -0.2, 0]$$
$$R = [0, 0, 0, 1]$$

Task Planning

Human: Organize and tidy up the bedroom.

LEO:

1. ***Clean the floor by sweeping to remove …***
2. ***Make the bed …***
3. ***Fold and organize …***

Embodied Navigation

Human: Find the pillow

LEO:

1. ***Move forward***
2. ***Turn right***
3. ***Move forward***
4. …

https://arxiv.org/pdf/2311.12871

To achieve these tasks in these environments

“embodied decision making”

What is “embodied decision making” ?

Can we leverage MDP as a guiding principle to categorize “foundation models”?

Let us go back to MDPs (Markov Decision Processes)

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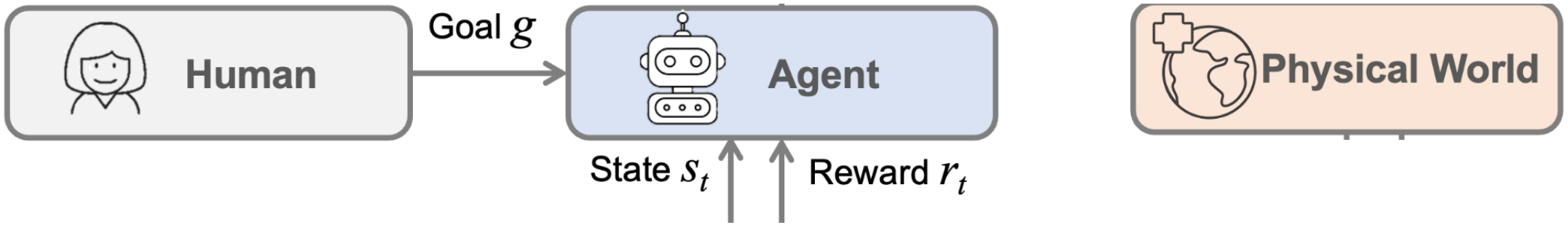

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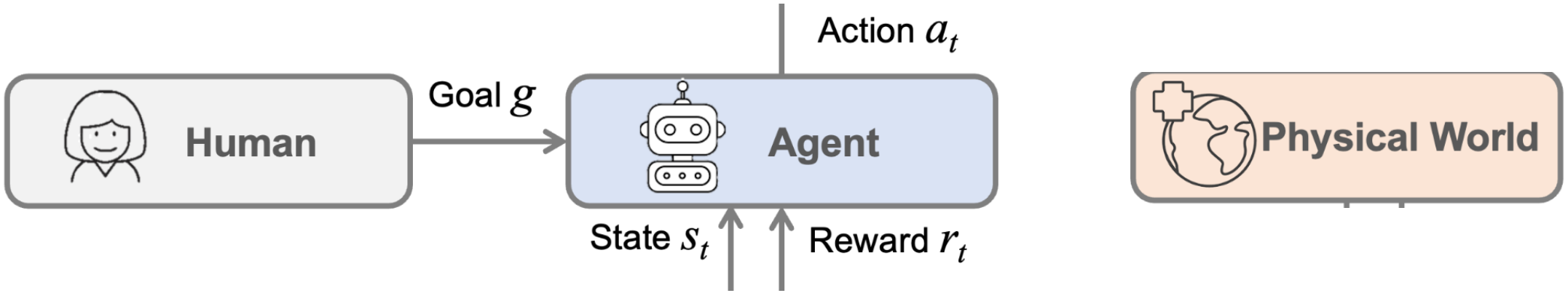

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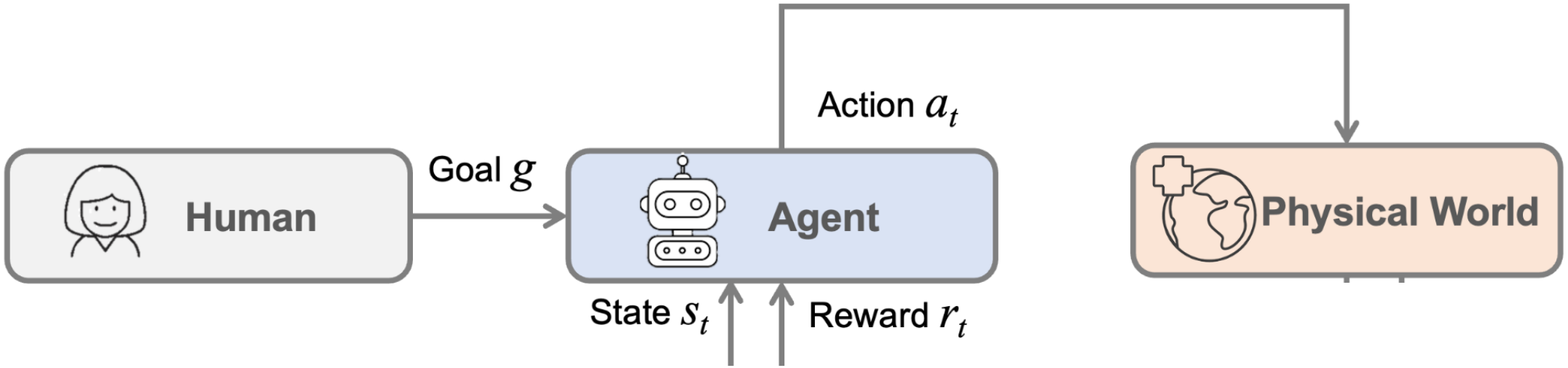

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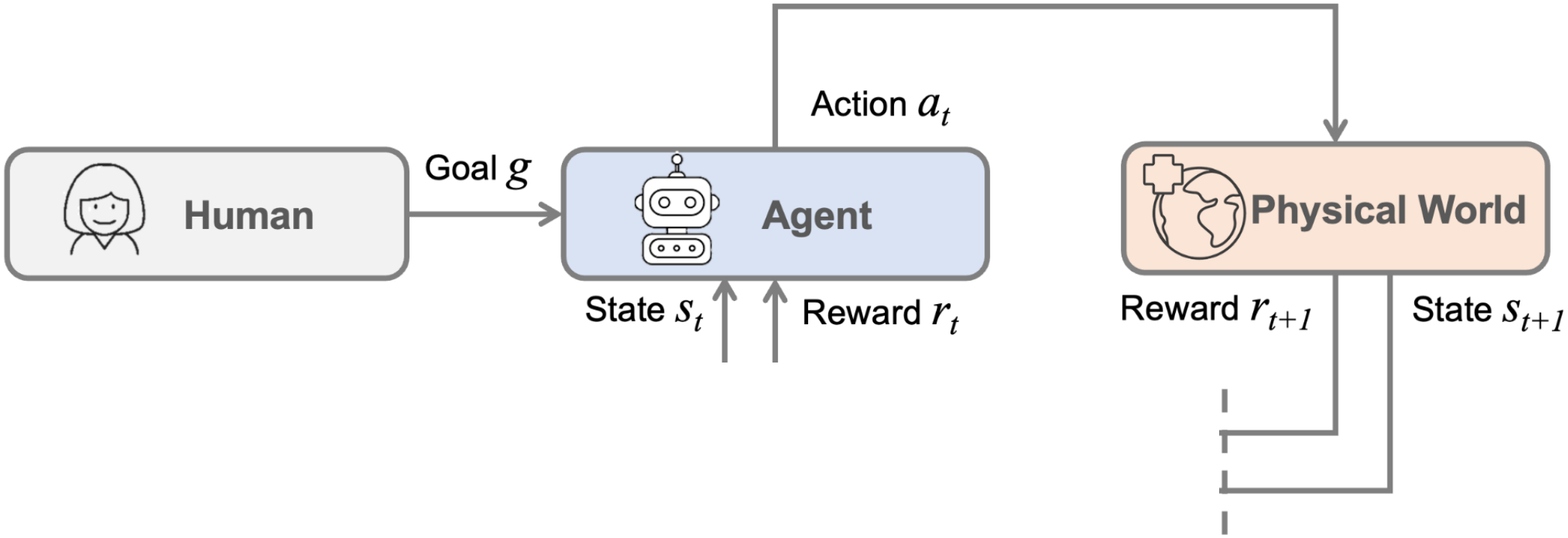

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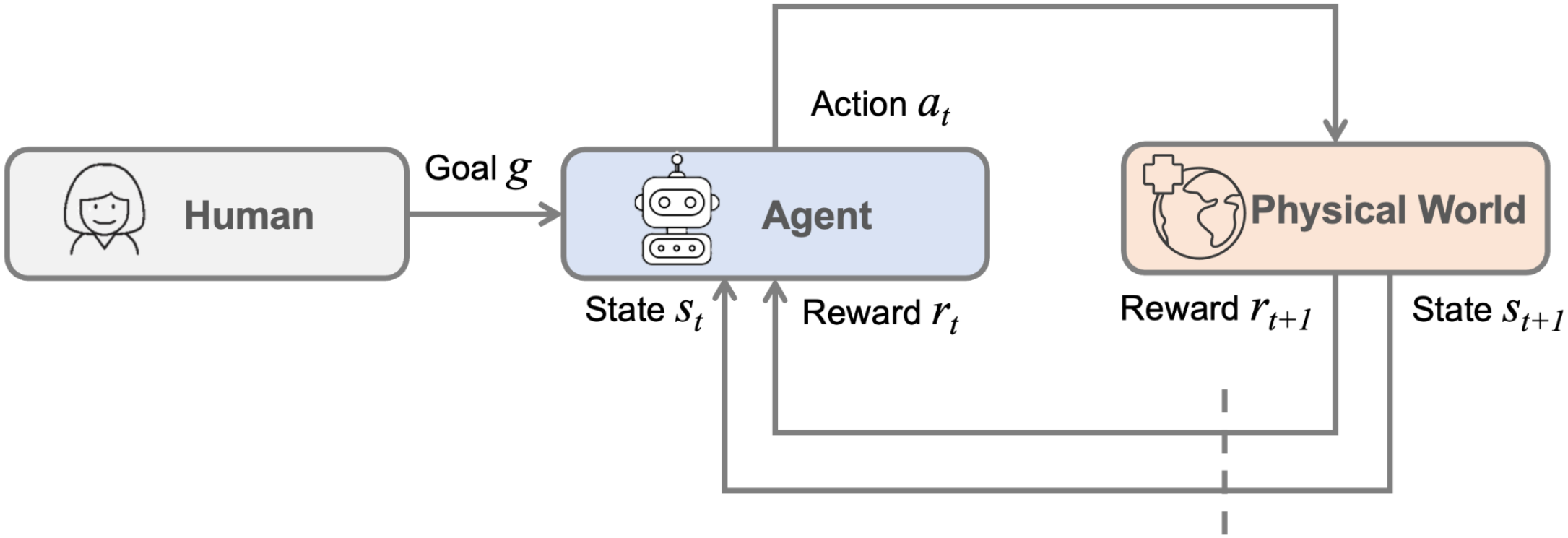

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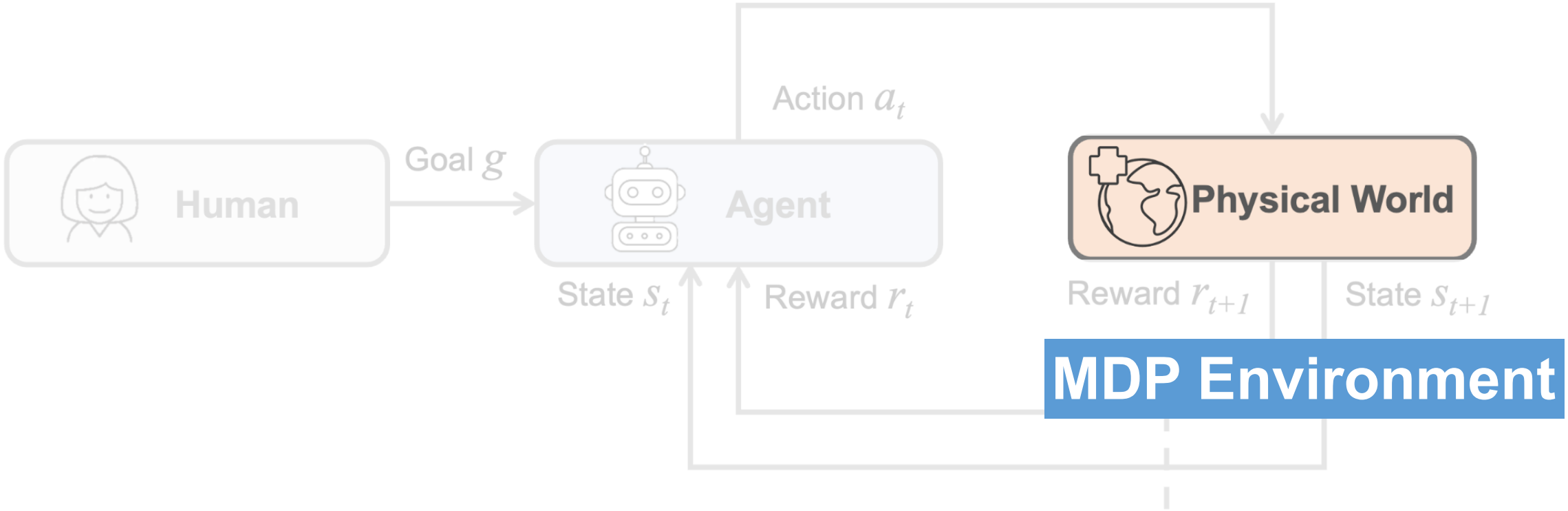
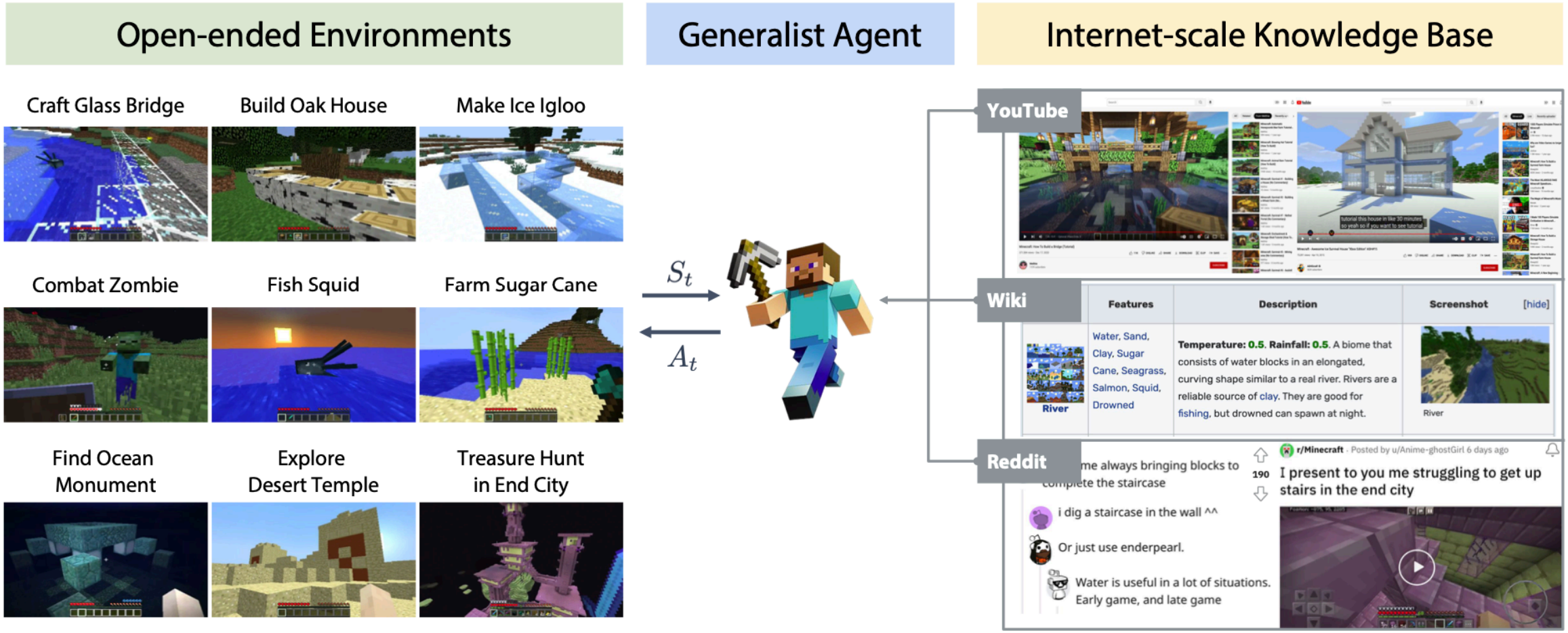


MDP Environment: MineCraft

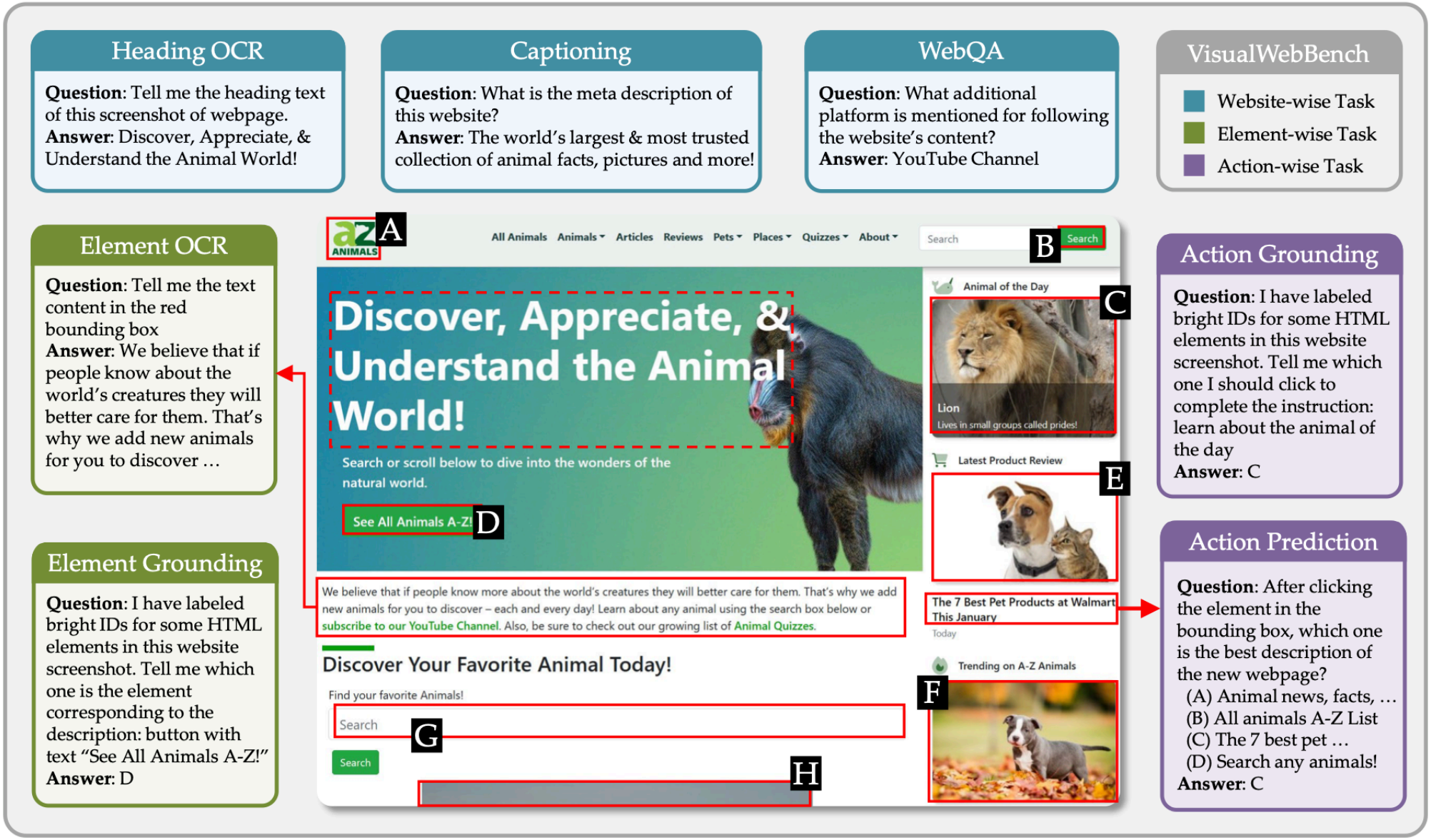


MineDojo

MineDojo: Building Open-Ended Embodied Agents with Internet-Scale Knowledge https://arxiv.org/abs/2206.08853

MDP Environment: GTA

MDP Environment: Web Agent Env



VisualWebBench: How Far Have Multimodal LLMs Evolved in Web Page Understanding and Grounding? https://arxiv.org/pdf/2404.05955

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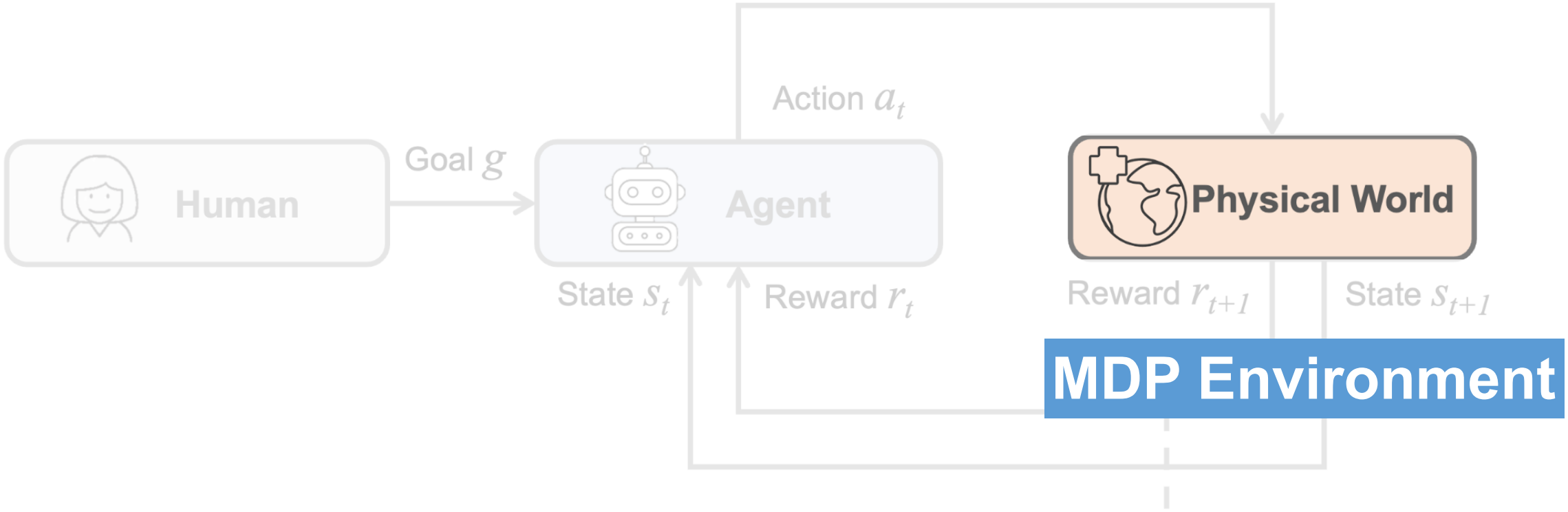

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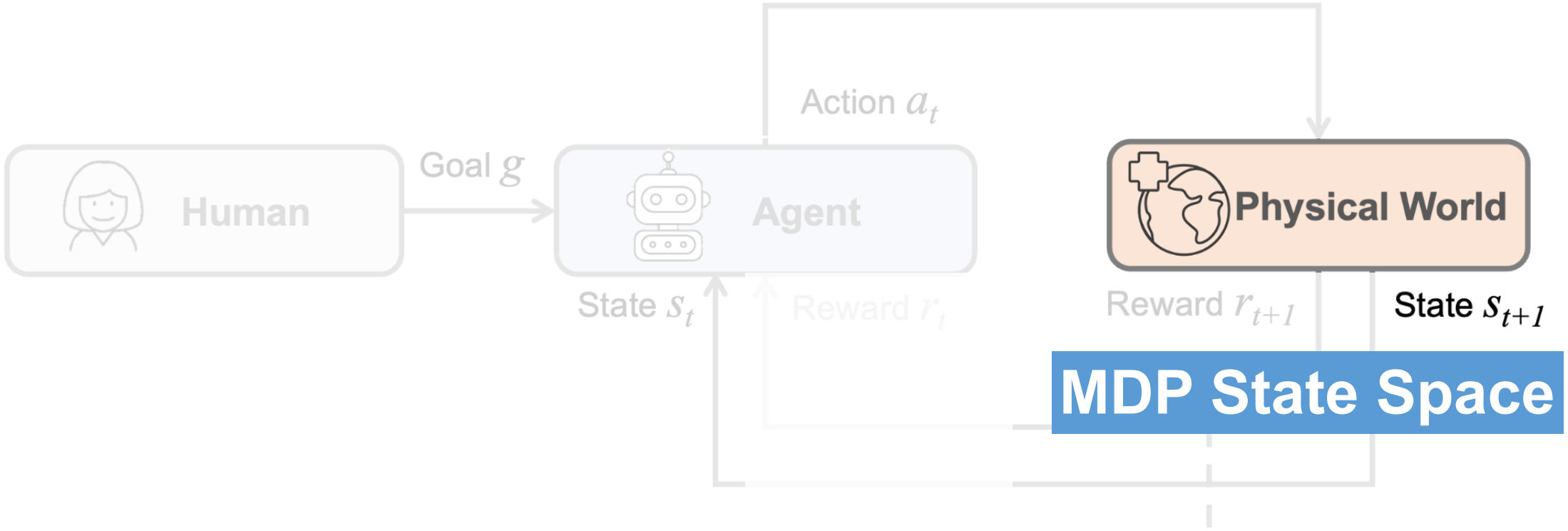

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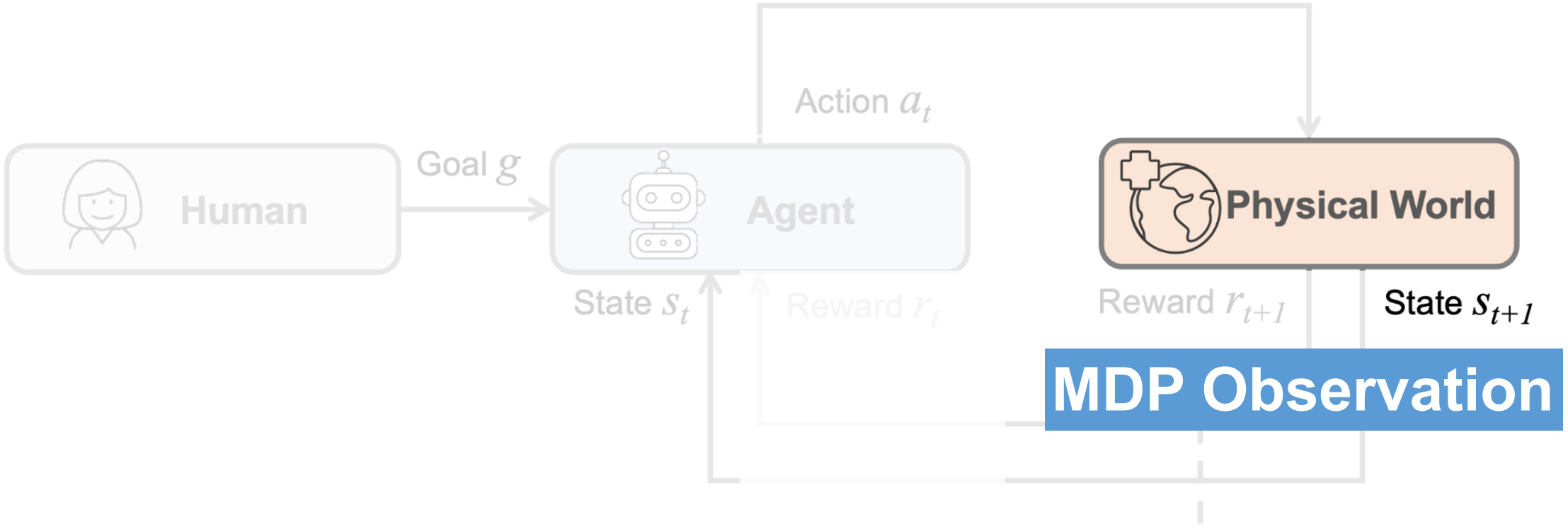


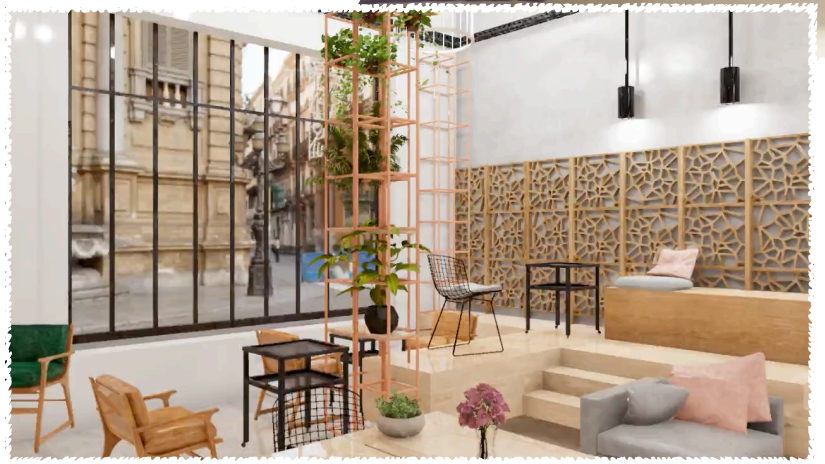
Environment：Observation

Environment：Observation (Rendered 2D Images)

Environment：Observation (Rendered 2D Images)

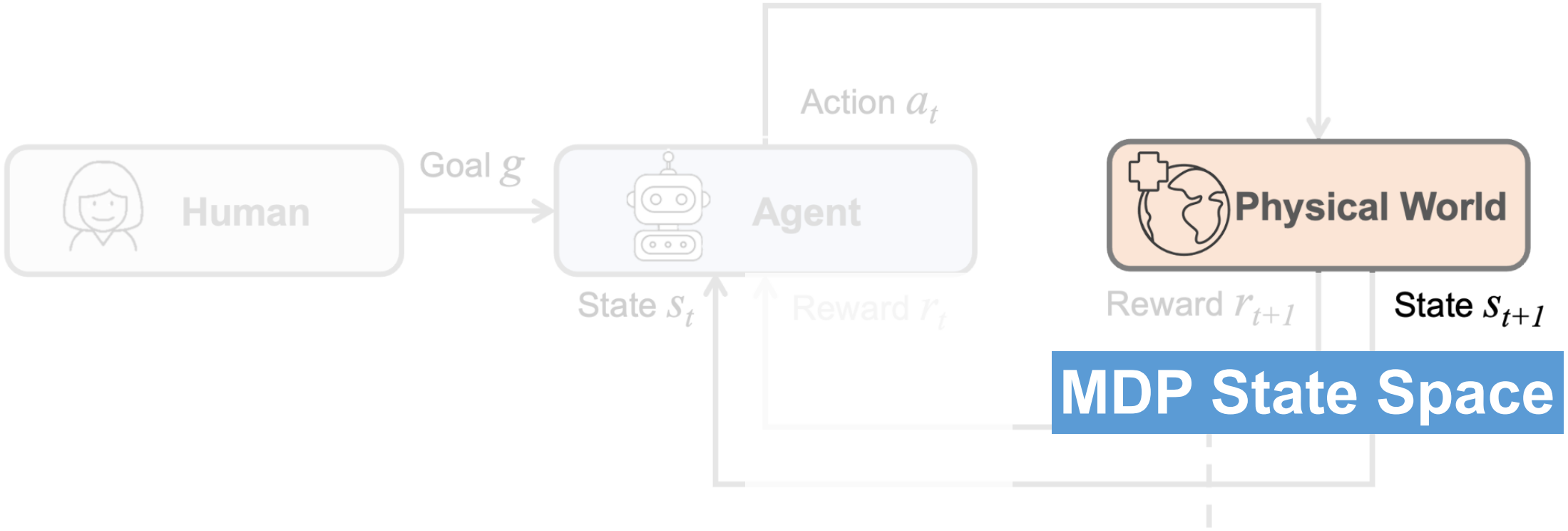
Enabled by large dataset of realistic interactive scenes and objects

50 Scenes



https://behavior.stanford.edu/

Let us go back to MDPs (Markov Decision Processes)



Environment : Observation → State (3D Assets & States)

Environment : Observation → State (3D Assets & States)

50 Scenes

Enabled by large dataset of realistic interactive scenes and objects



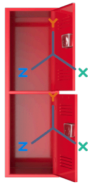



10000 Objects

Semantic

Properties: cookable, sliceable, freezable, burnable, deformable
…
Cooking temperature: 58°C
…

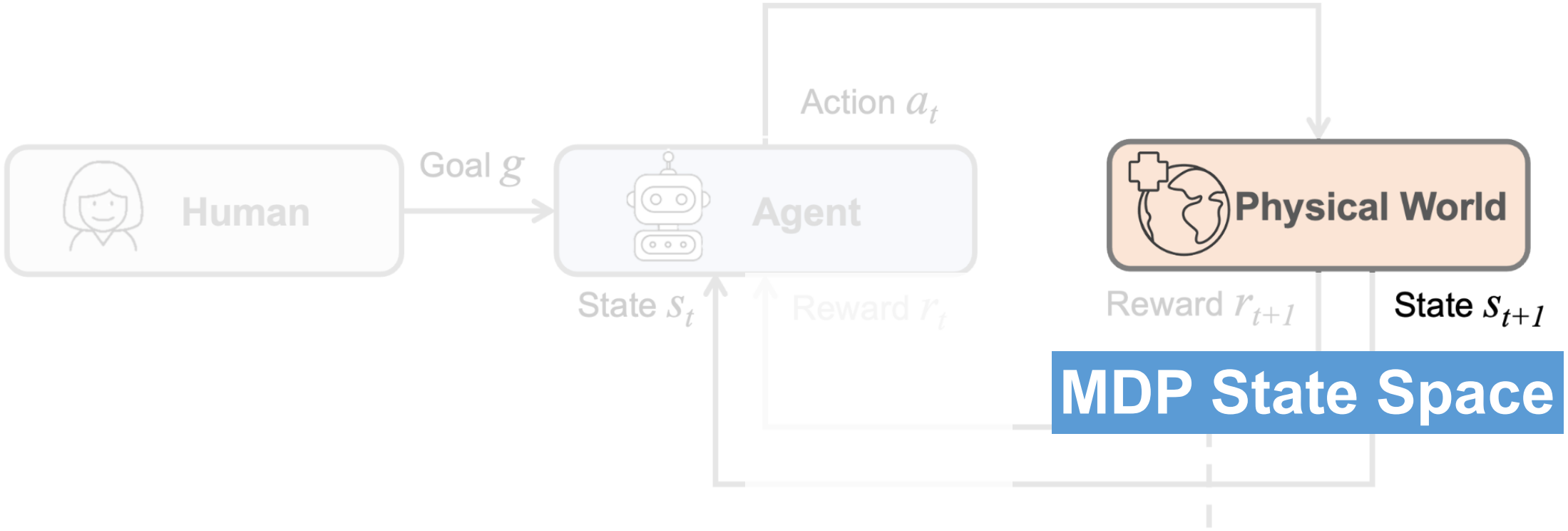
Physical



Articulation annotation (joint type, origin, axis, limit)
Mass, friction, CoM, …
Canonical size and orientation

https://behavior.stanford.edu/

Let us go back to MDPs (Markov Decision Processes)



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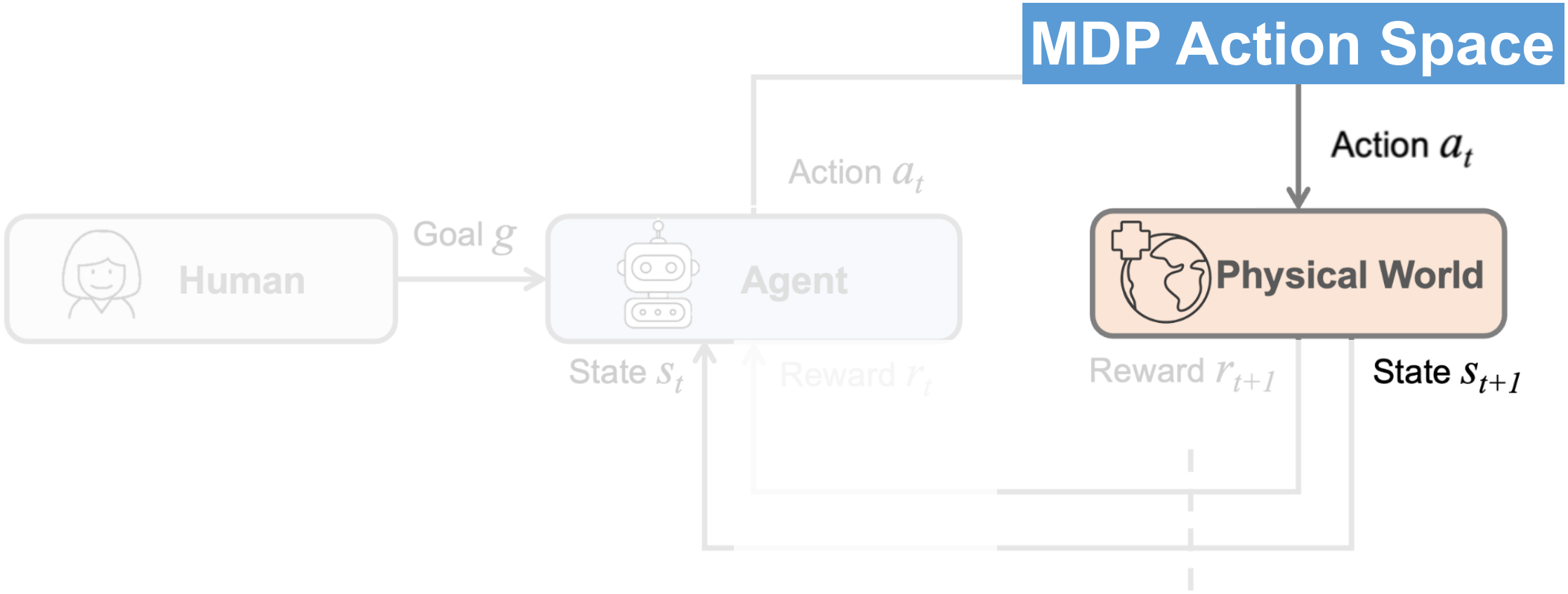
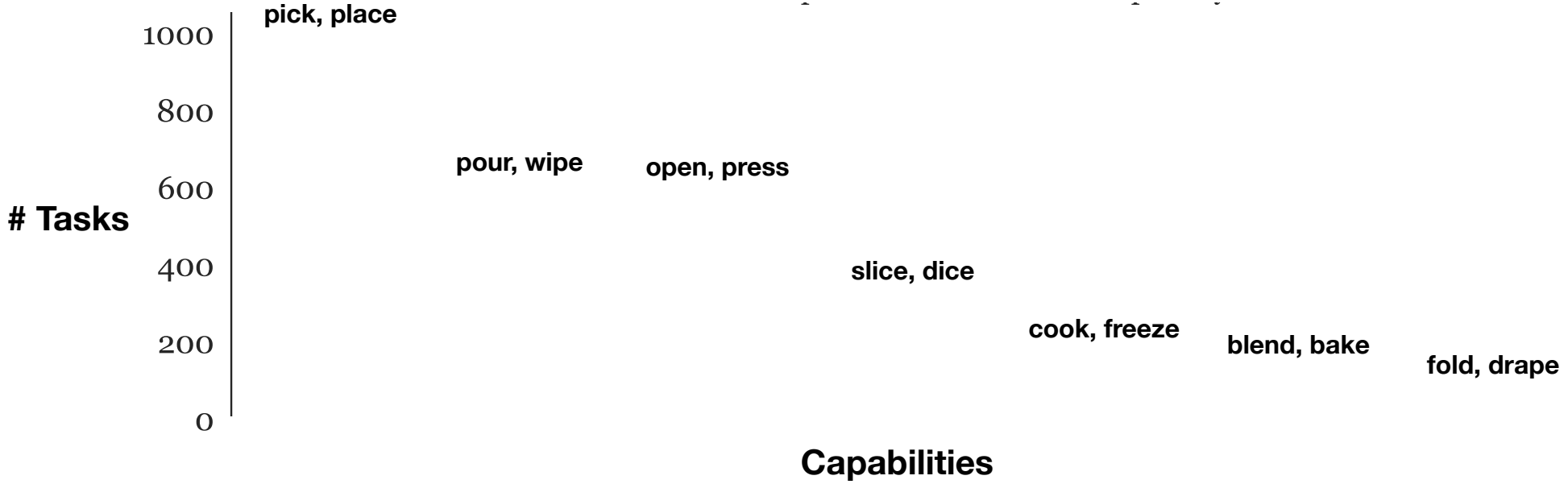


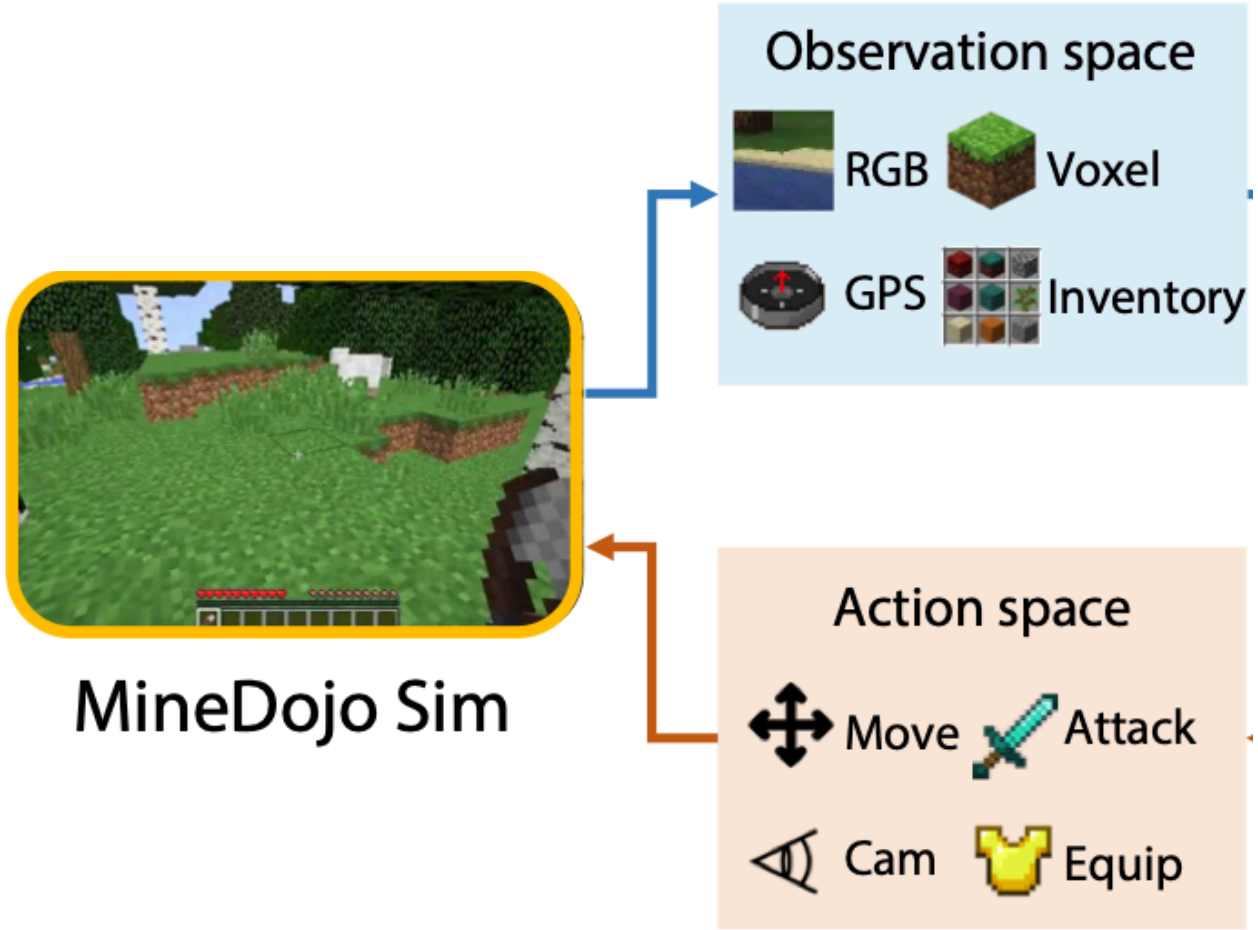
Action : can robots learn to solve these tasks?

→ What capabilities are needed?



https://behavior.stanford.edu/

MDP Action Space: Skills



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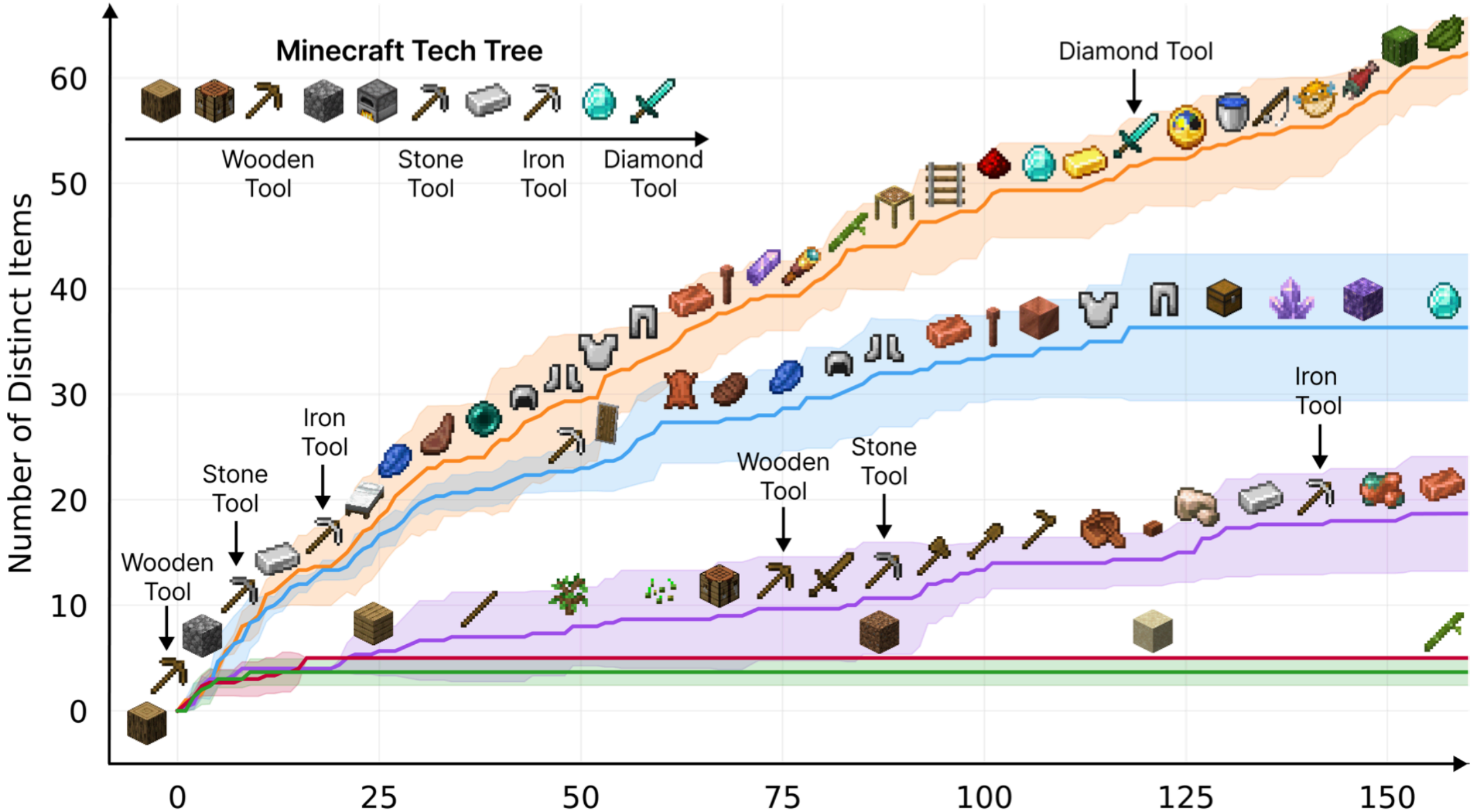

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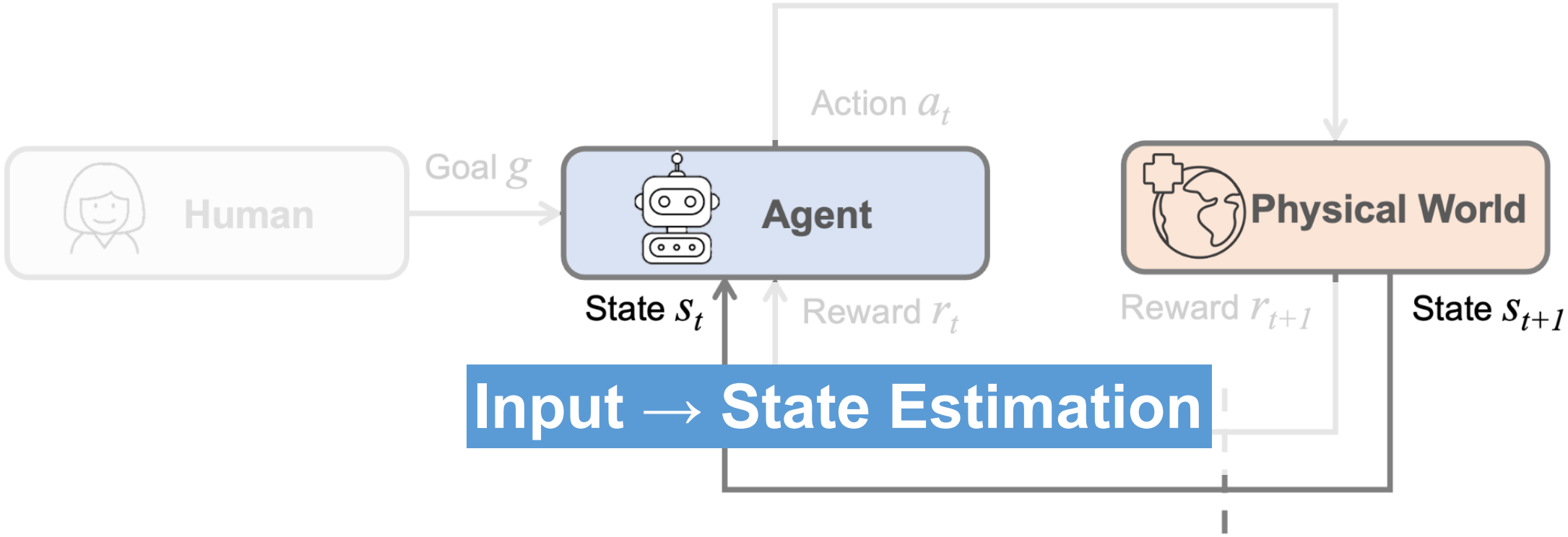


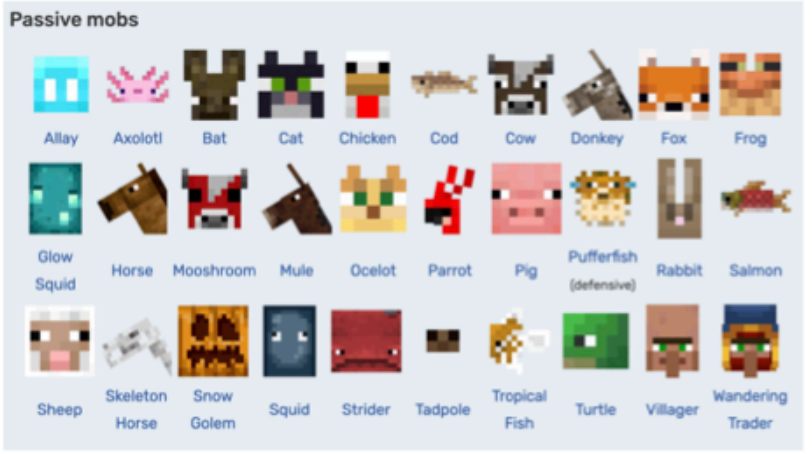
Perception / State Estimation

$o \rightarrow s$

Observation → State Estimation (Assets & States)

Observation (2D rendered scenes)

State (3D assets)



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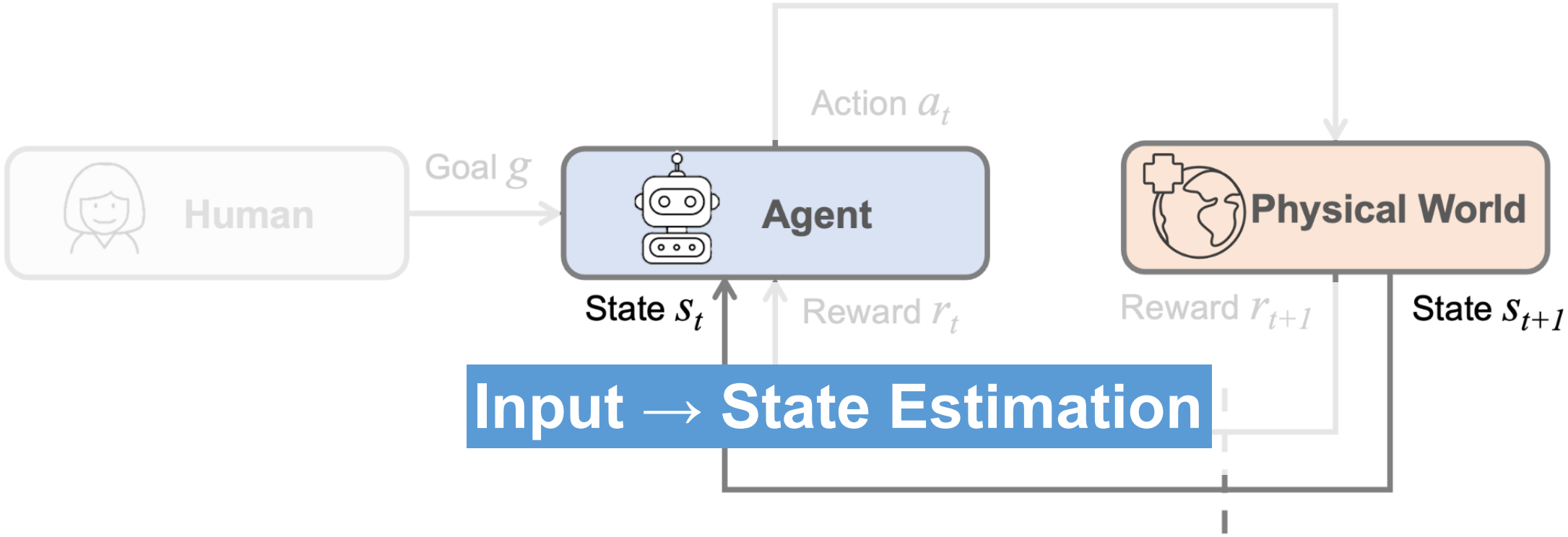

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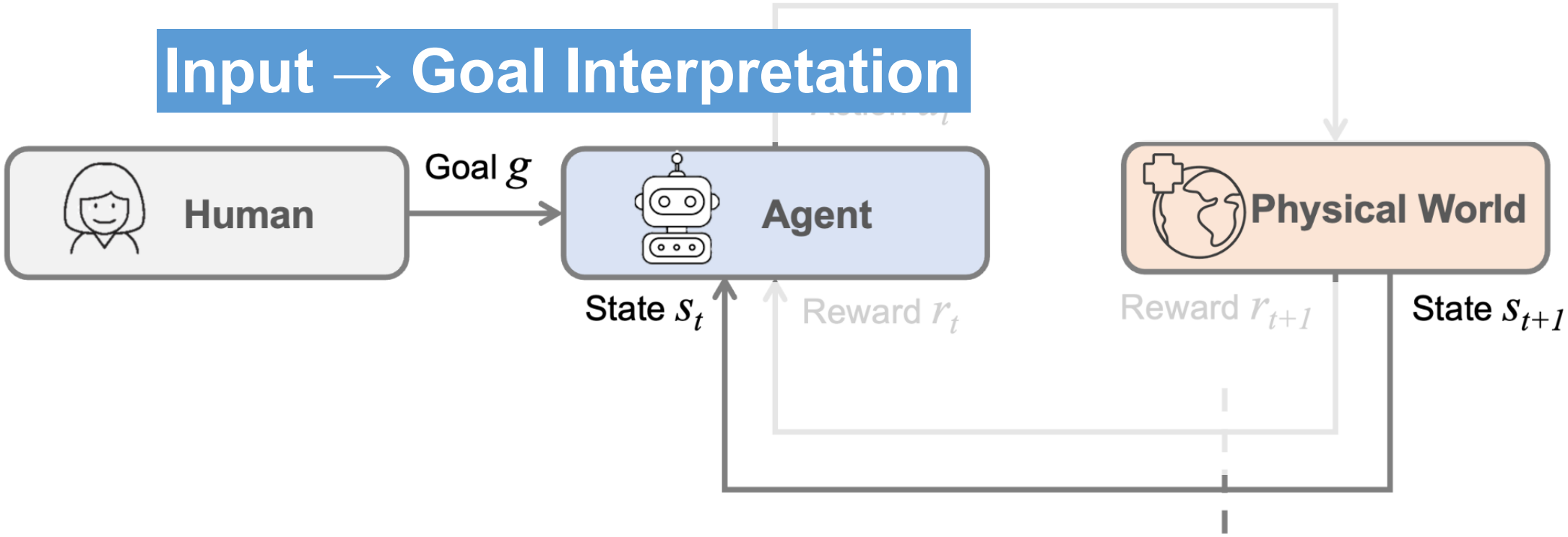


Goal Interpretation

g

Set up the table.

...

on_top_of (turkey, table)

...

LLM

Set up the table.

...

on_top_of (turkey, table)

...

LLM

Use the plates.

...

on_top_of (plate, table)

on_top_of (turkey, plate)

...

LLM

Goal : defines a task?

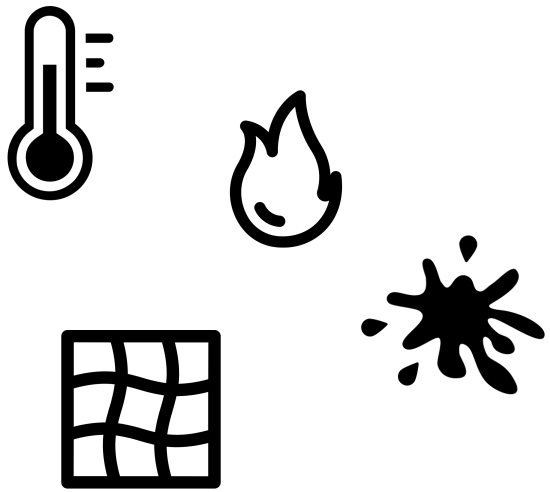
wikiHow to do anything

YouTube

“Pack lunch”

What objects?

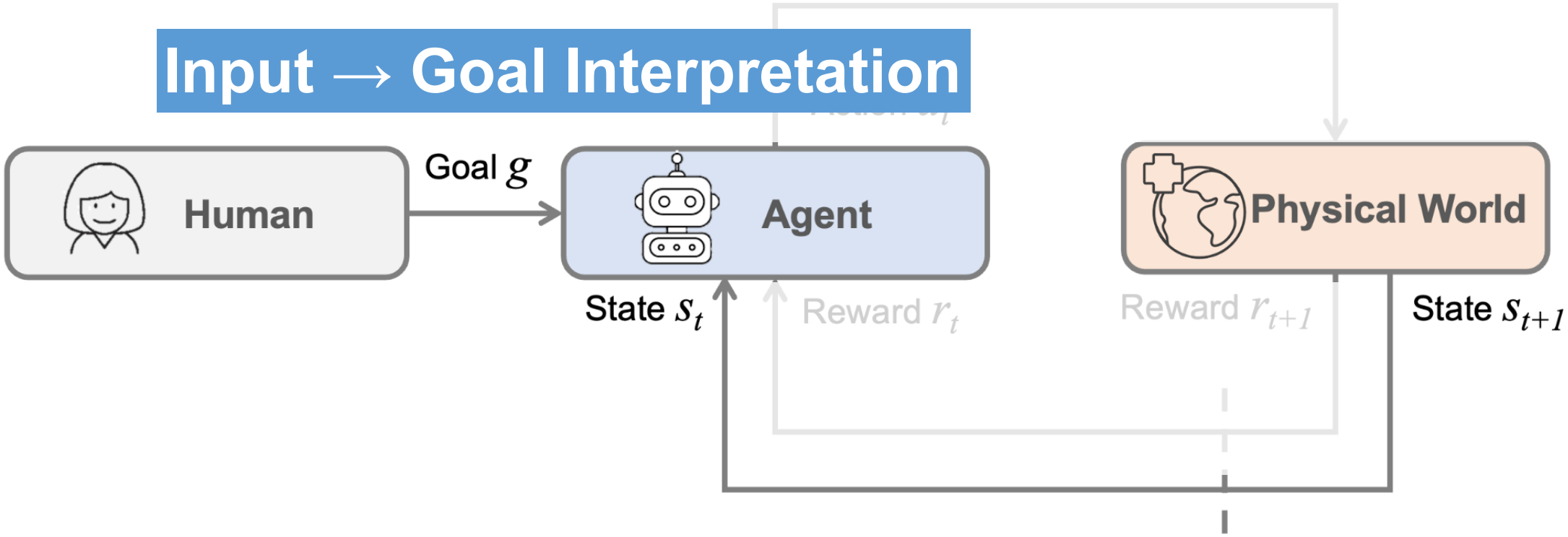
What properties?



Start & Goal?

- **apple** in **fridge**
- **burger** in **fridge**
- **water bottle** in **fridge**
- **paper bag** on **counter**

Let us go back to MDPs (Markov Decision Processes)



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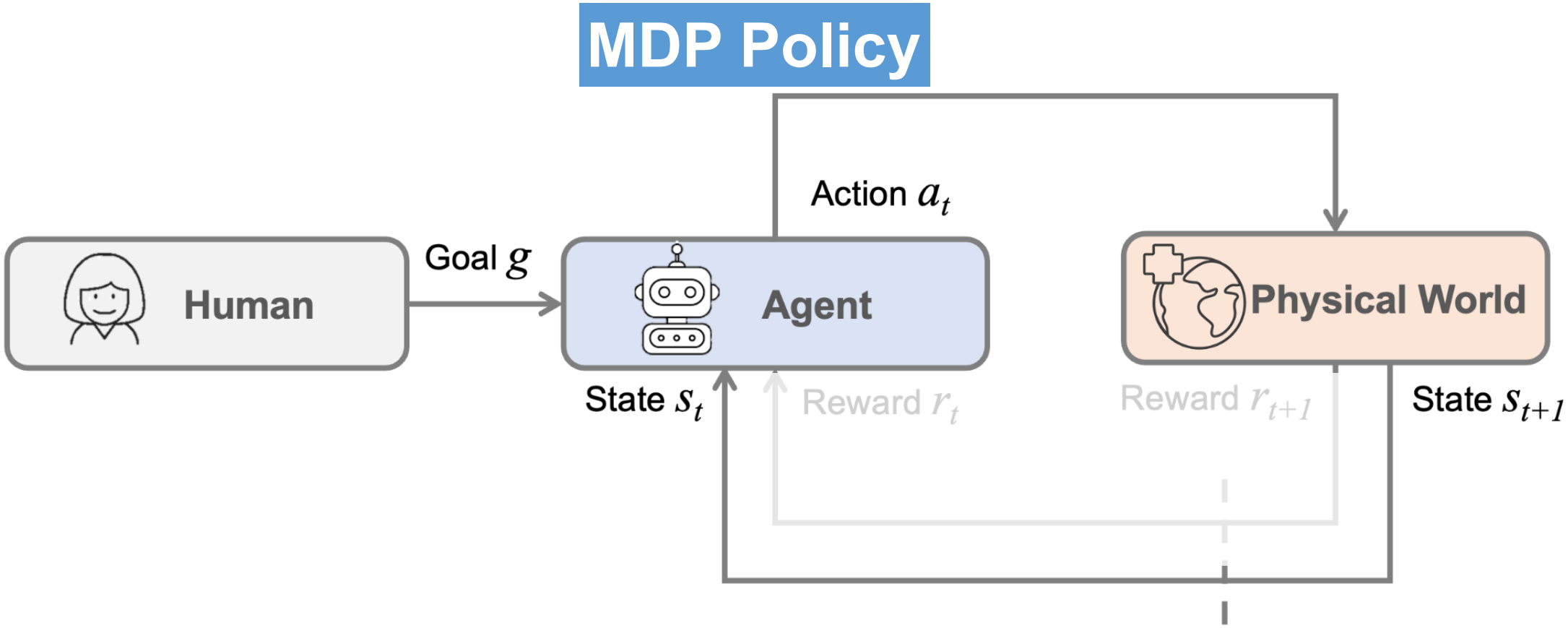

Policy

$$\pi(o, g) \rightarrow a$$

Input: Preserving food

Environment

… inside (strawberry, pan) …

Goal

… cooked (strawberry) …

Operator

BEHAVIOR

Action Trajectory

… ✓

A7 OPEN (oven) ✓

A8 RIGHT_GRASP(pan) ✓

A9 RIGHT_PLACE_INSIDE (oven)

A10 CLOSE(oven)

A11 COOK(strawberry)

…

LLM Output

This video is for demonstration only. There're no actual controller-level actions. For action execution examples, visit our repository: https://github.com/embodied-agent-interface/embodied-agent-interface.

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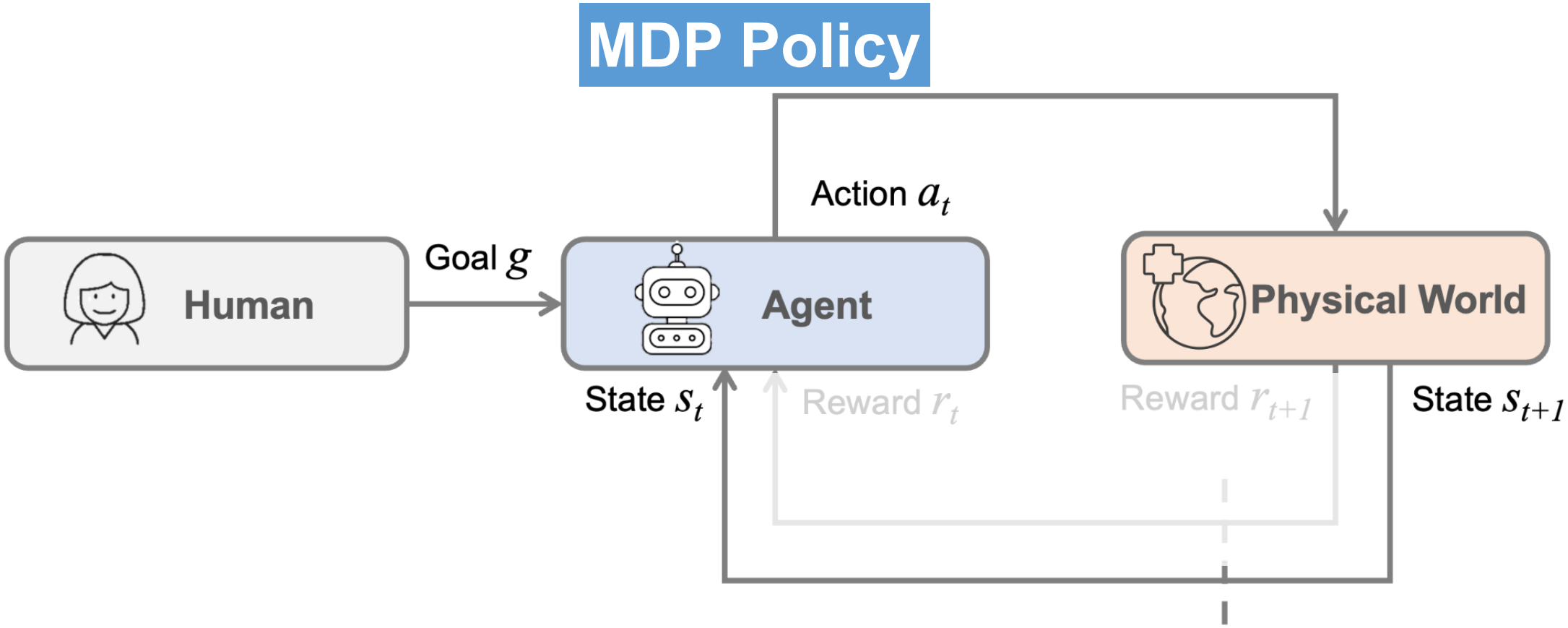

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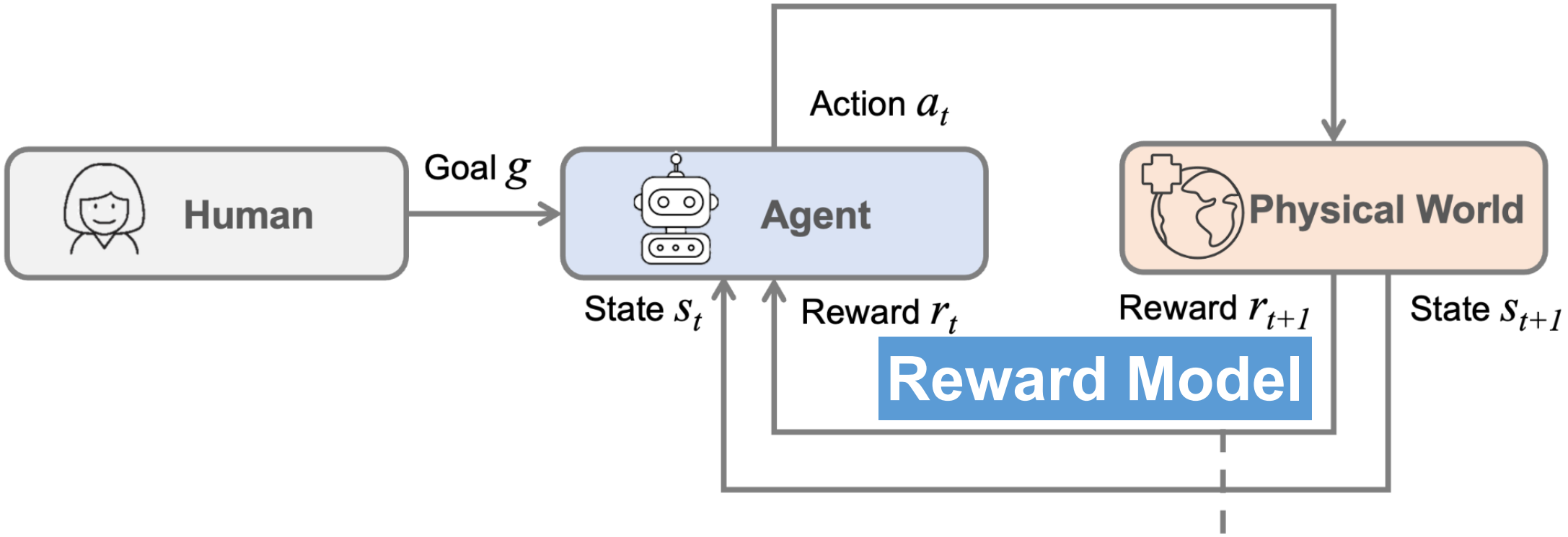
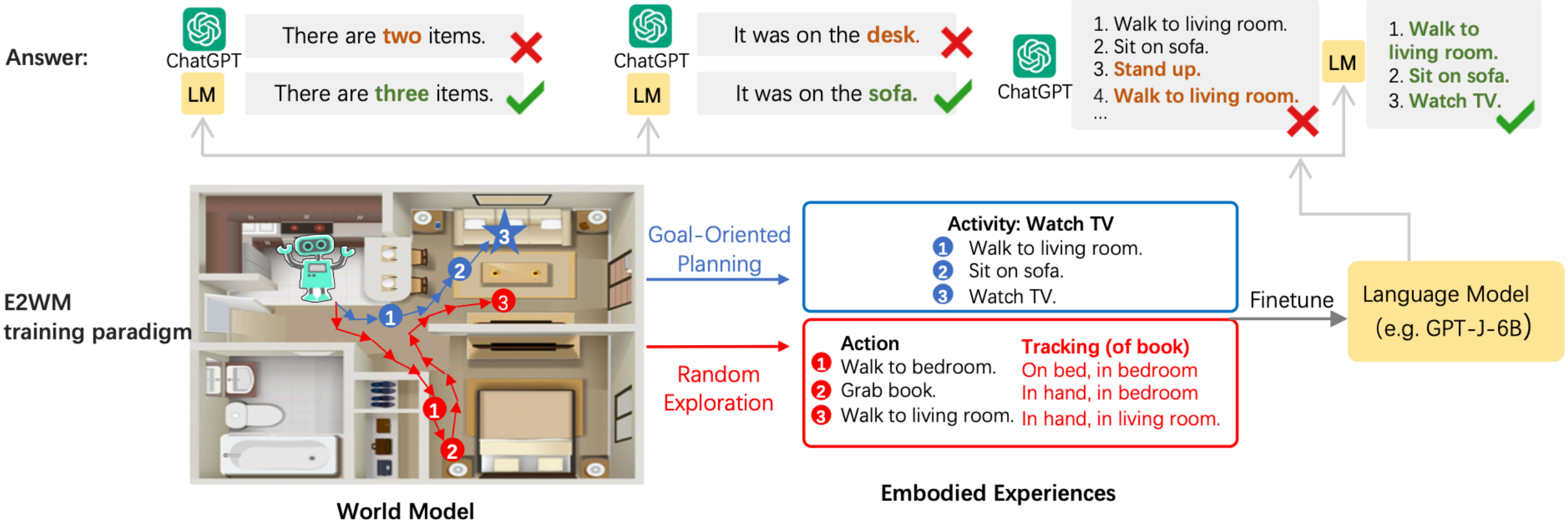


Reward Model

$o, a \rightarrow r$

Reward Model



https://arxiv.org/pdf/2305.10626

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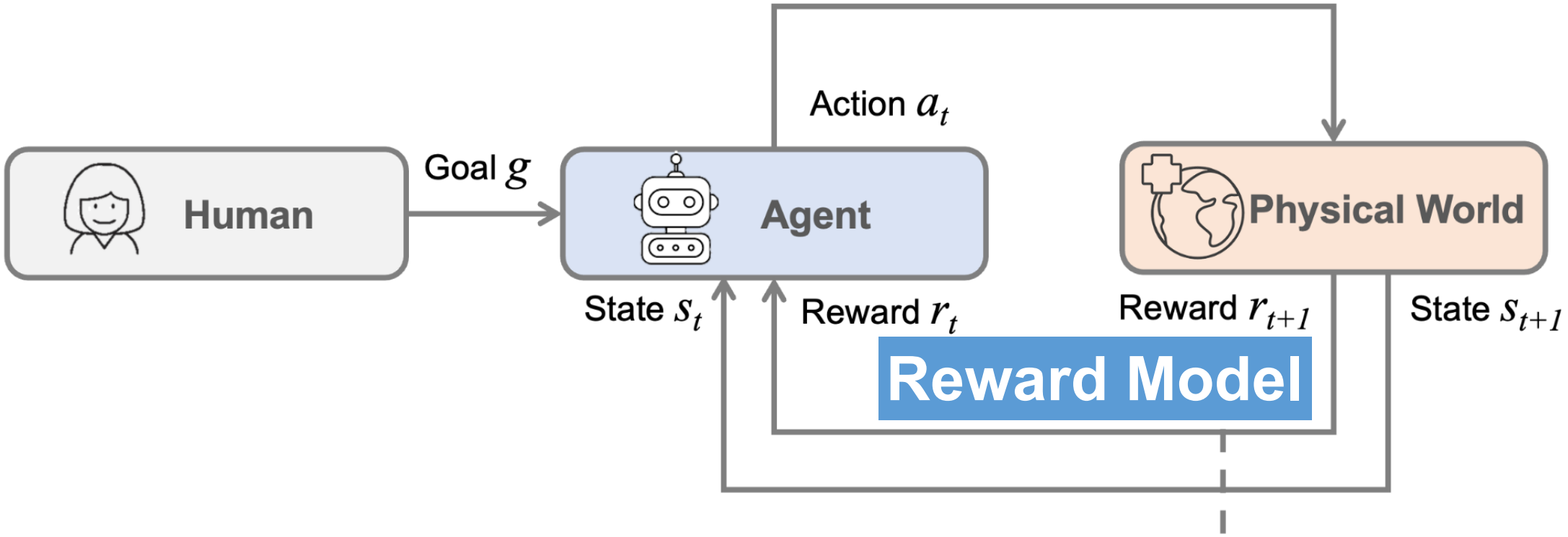

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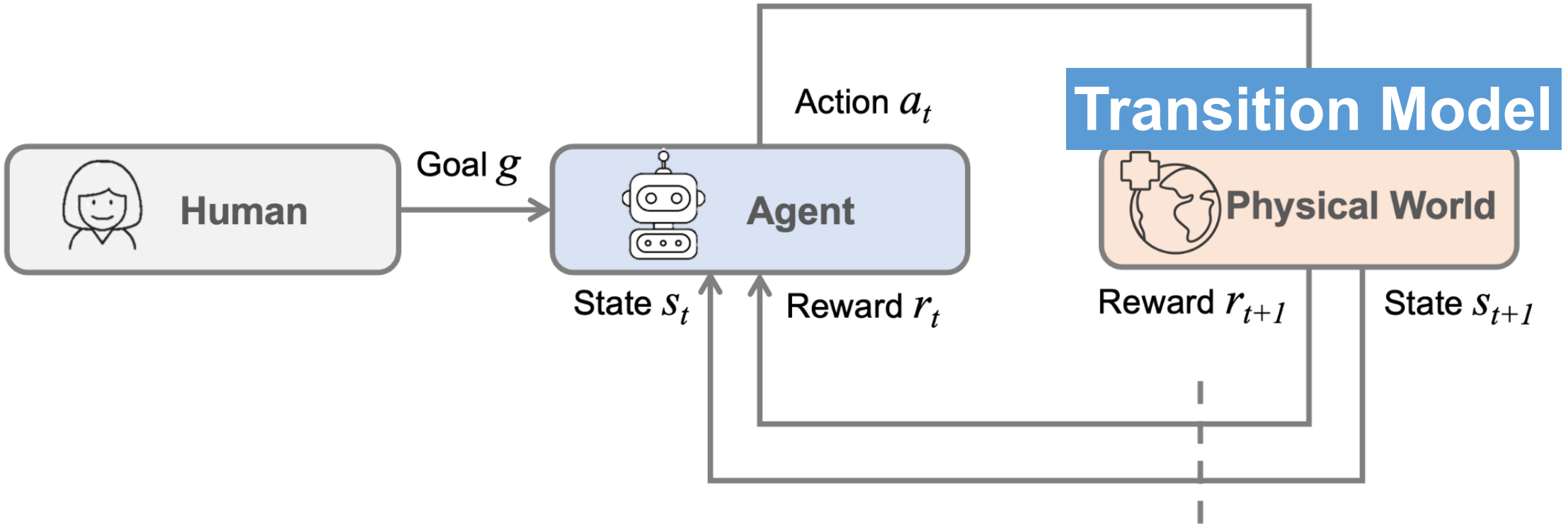


Transition Model

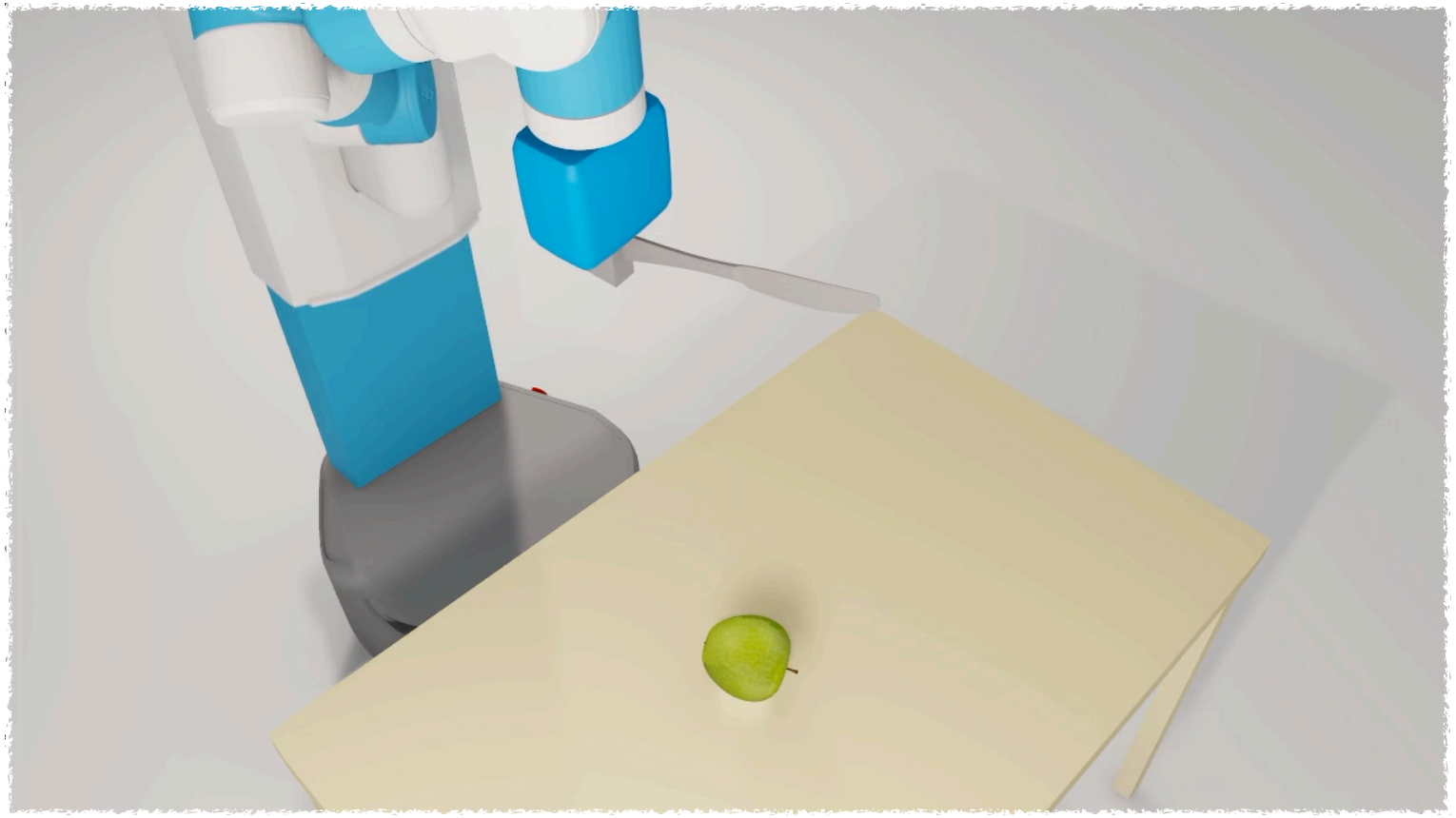
$$o_t, a \rightarrow o_{t+1}$$

"World Modeling"

OmniGibson

Physics Transition Examples

```
class SlicingRule:
```



https://behavior.stanford.edu/

OmniGibson

Physics Transition Interface

```
class TransitionRule:

def condition(self, *args) -> bool

def transition(self, *args)
```

Determines whether a transition should occur

What should happen when a transition is triggered

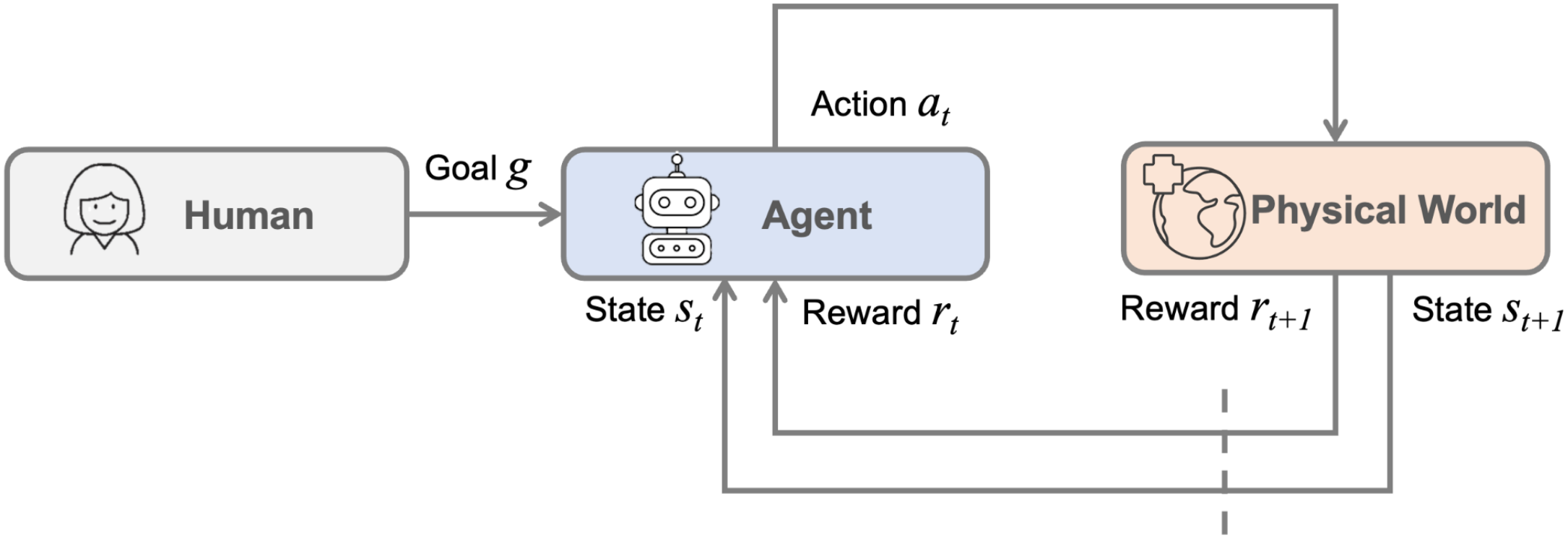
Allows us to capture arbitrarily complex **physical phenomena**!

OmniGibson

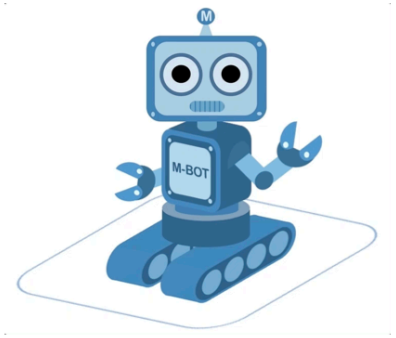
Physics Transition Examples

```
class SlicingRule:

def condition(self, *args) -> bool

    # Return True if a slicer object is touching
    a sliceable object with sufficient force


def transition(self, *args)

    # Remove the sliceable object and
    import its sliced component objects
```

Let us go back to MDPs (Markov Decision Processes)



Virtual Agents vs Physical Agents



Different Instantiations of MDP

Perfect actuations

Perfect odometry

RGB only perception

●
●
●

Noisy actuations

Noisy odometry

Multiple perceptual modalities

●
●
●

https://embodiedqa.org/slides/eqa_matterport_slides.pdf

Outline

Content	Time	Presenter
1. Motivation and Overview	15min	Manling Li
2. Foundation Models meet Virtual Agents	45min	Manling Li
3. Foundation Models meet Physical Agents		
Overview & Perception	25min	Jiayuan Mao
High-level & Low-level Decision Making	50min	Wenlong Huang
4. Robotic Foundation Models	30min	Yunzhu Li
5. Remaining Challenges	15min	Yunzhu Li
QA	30min	

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