Efficient Robot Skill Learning: Grounded Simulation Learning and Imitation Learning from Observation

Peter Stone

Learning Agents Research Group (LARG)
Department of Computer Science
The University of Texas at Austin

(Also, Cogitai Inc.)

Research Question

To what degree can autonomous intelligent **agents learn** in the presence of **teammates** and/or **adversaries** in **real-time, dynamic** domains?

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- Multiagent systems
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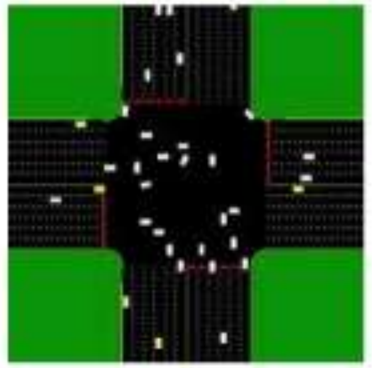

Learning to interpret natural-language commands through human-robot dialog

Jesse Thomason, Shiqi Zhang, Raymond Mooney, and Peter Stone

Department of Computer Science
The University of Texas at Austin, Austin, TX 78712 USA

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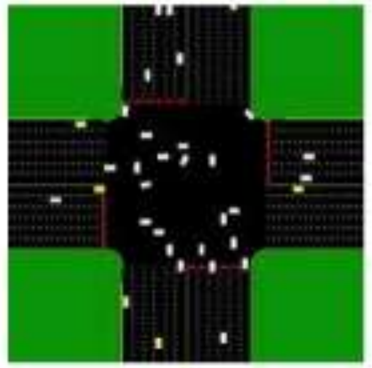

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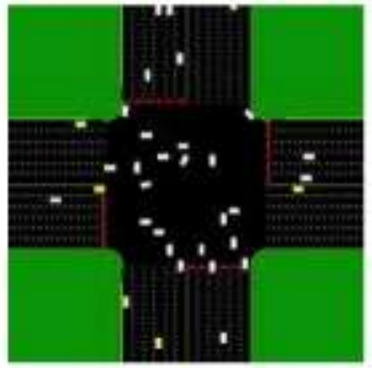


Cogitai

Self-learning Actionable AI

More than 60 Years Combined AI R&D

Leadership Team

MARK RING
CEO & Cofounder
"Continual Learning"

PETER STONE
President & COO
Cofounder

PETER WURMAN
VP Engineering

DENNIS CRESPO
VP Marketing &
Business Dev

"Brain Trust" Technical Advisory Board —The people who created Reinforcement Learning

SUTTON
U of Alberta

LITTMAN
Brown
University

ISBELL
Georgia Tech

ZHANG
U of Hamberg

VAN ROY
Stanford

SATINDER SINGH
Co-founder

BARTO
U. of Mass.

PRECUP
McGill

BOWLING
U of Alberta

PARKES
Harvard

DAYAN
Gatsby, UCL

Full Time Team

15
PHDs

20
Total

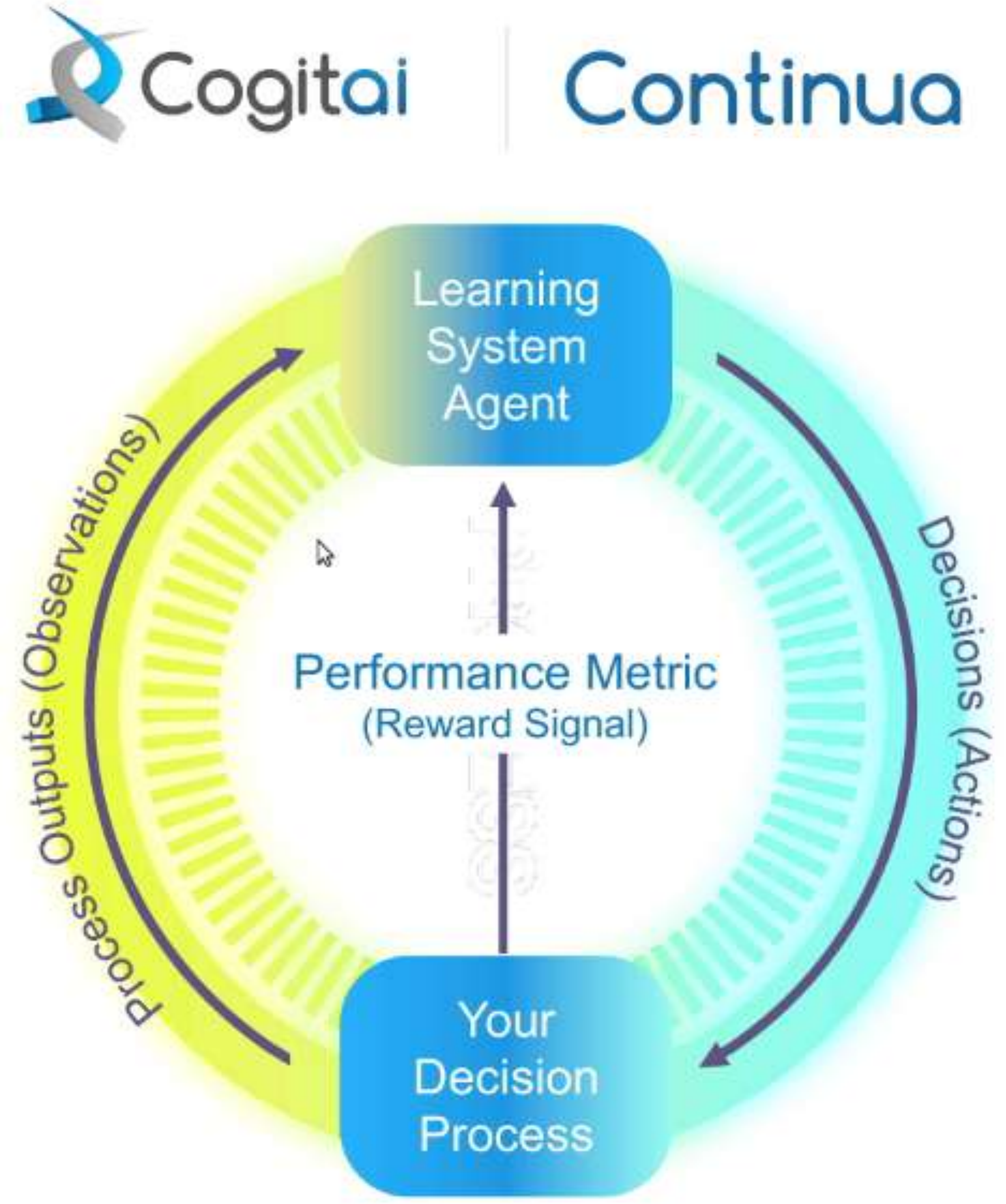
Continua™ SaaS Platform improves any process, software bot, system

<u>First Markets:</u>

Automotive Engine Control

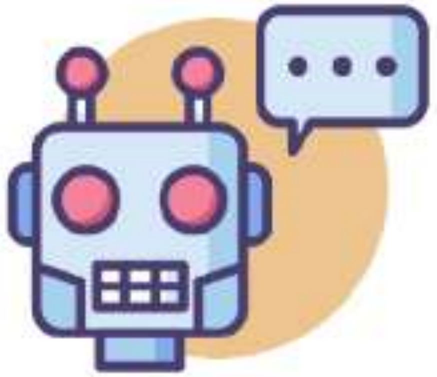
Robotics Control

Semiconductor Control



Use Cases are Endless

Easy to Replicate Across Industries



Decision Making
Customer service bots

Web marketing

Fitness coaches

Video game agents

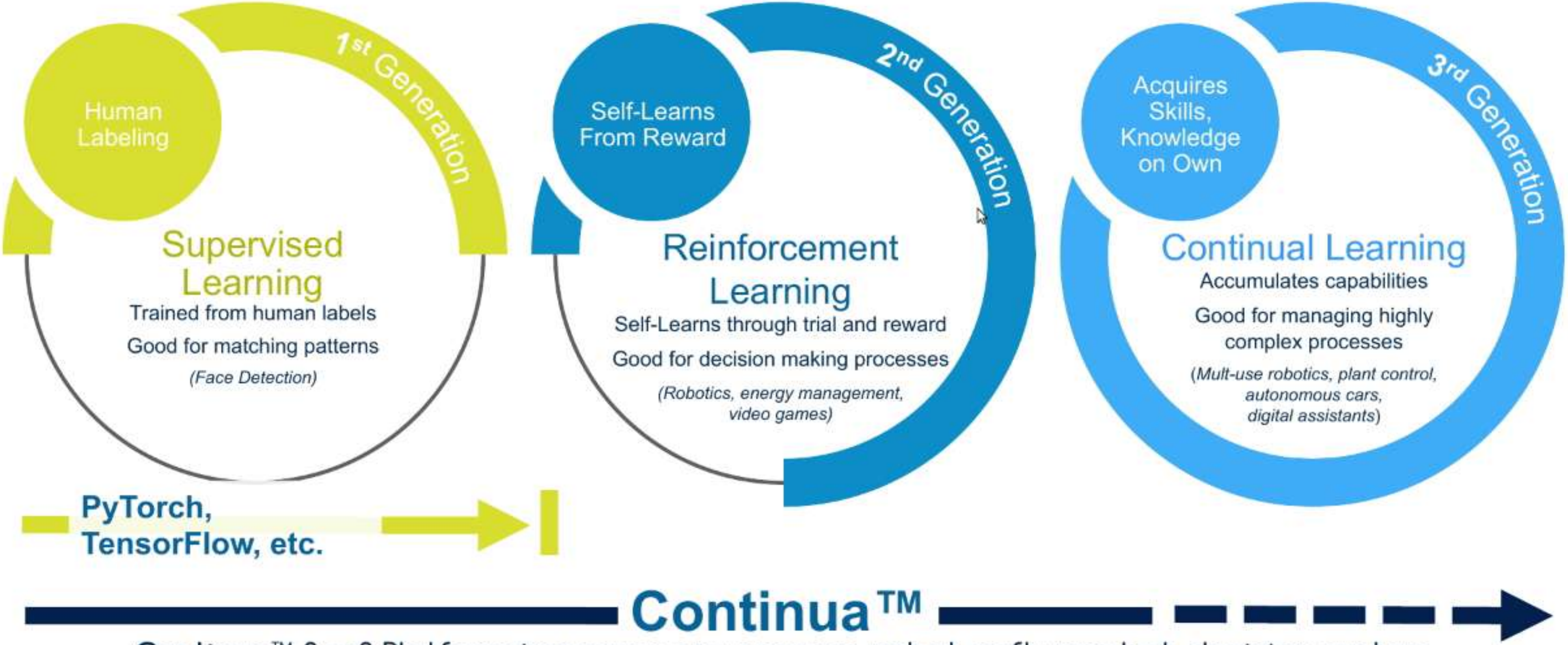
Manufacturing
Processes

Robotic process
automation

Building
management

Self-learning
vehicle

CogitAI's Aggressive Roadmap to Continual Learning



Continua™ SaaS Platform improves any process, robot, software bot, decision system

Cogitai

Self-learning Actionable AI

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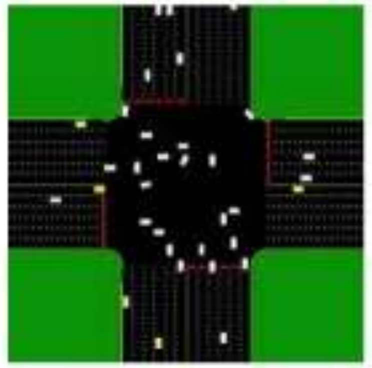

Efficient Robot Skill Learning

- **Motivation:**

Efficient Robot Skill Learning

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- **Sim2Real:**

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Efficient Robot Skill Learning

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RoboCup Soccer

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- Grand challenge: beat World Cup champions by 2050

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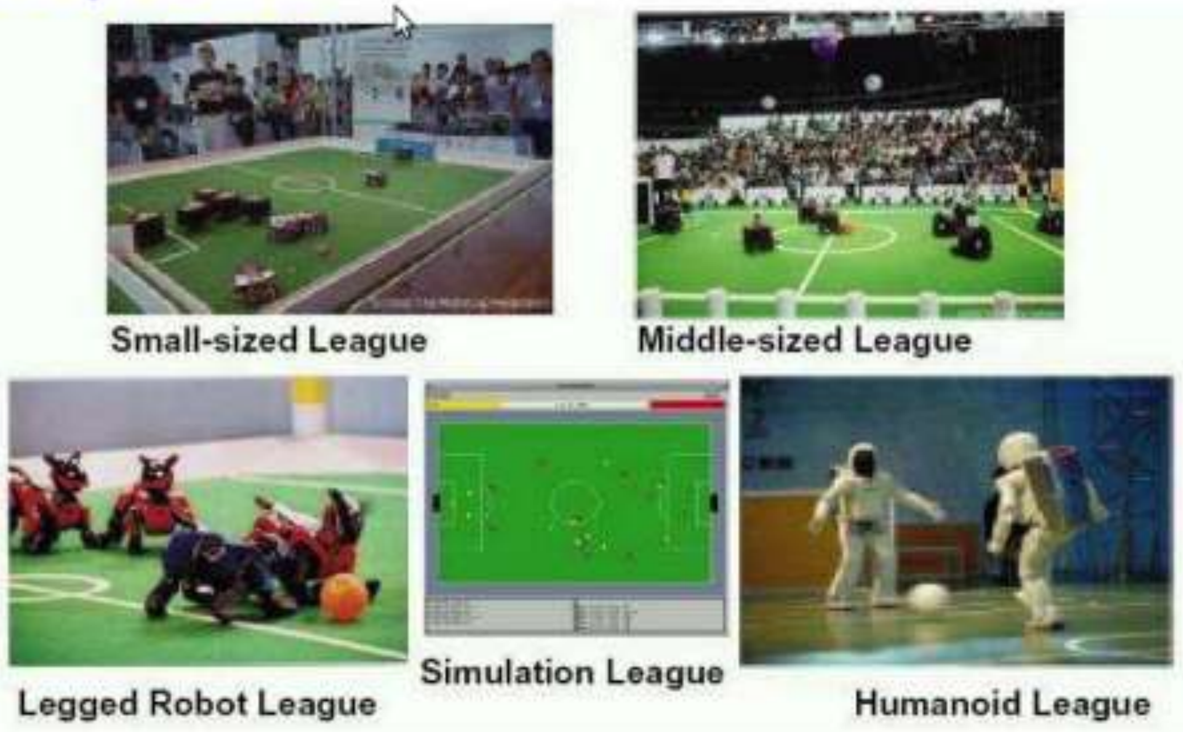

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Small-sized League
Middle-sized League
Legged Robot League
Simulation League
Humanoid League

RoboCup 1997–1998

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UT Austin Villa
3D Simulation Team
RoboCup 2017 Highlights

World Champions
Record: 23-0
Goals For: 171, Goals Against: 0

AUSTIN VILLA
ROBOT SOCCER TEAM
THE UNIVERSITY OF TEXAS AT AUSTIN

RoboCup Soccer

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RoboCup@Home

RoboCup@Home

Open-world Reasoning for Service Robots

Yuqian Jiang*, Nick Walker*, Justin Hart, Peter Stone

RoboCup@Home

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Reinforcement Learning for Physical Robots

Patrick
MacAlpine

Josiah
Hanna

Reinforcement Learning for Physical Robots

Patrick MacAlpine

Josiah Hanna

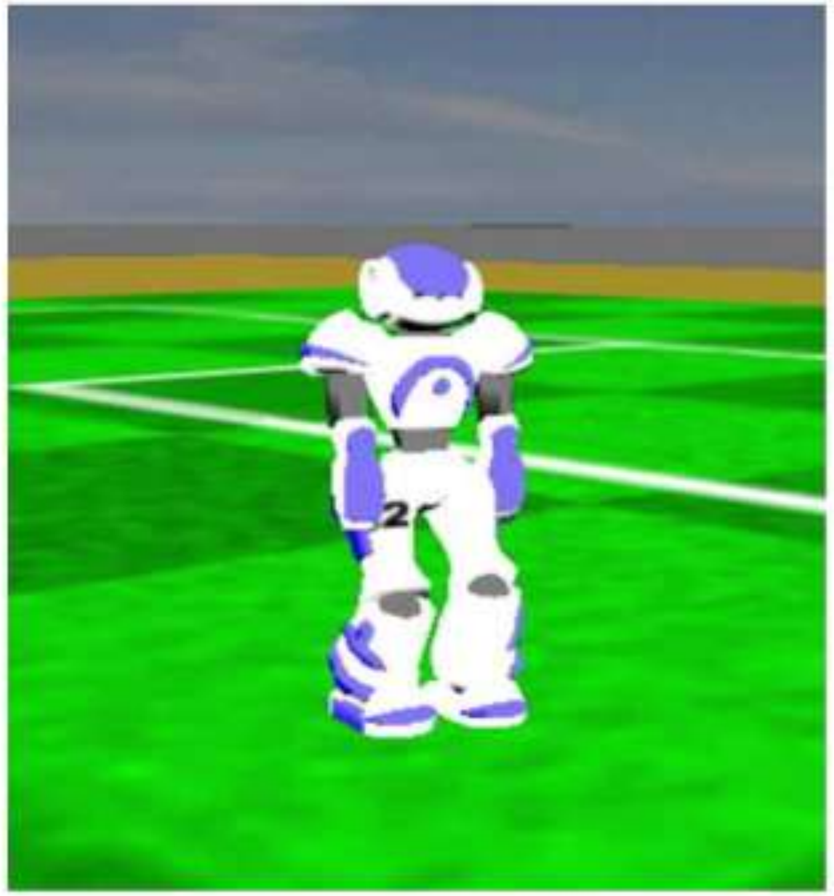
Learning on physical robots:

- Not data-efficient
- Requires supervision
- Manual resets
- Robots break
- Wear and tear make learning non-stationary

Reinforcement Learning in Simulation

Learning in simulation:

- Thousands of trials in parallel
- No supervision needed
- Automatic resets
- Robots don't break



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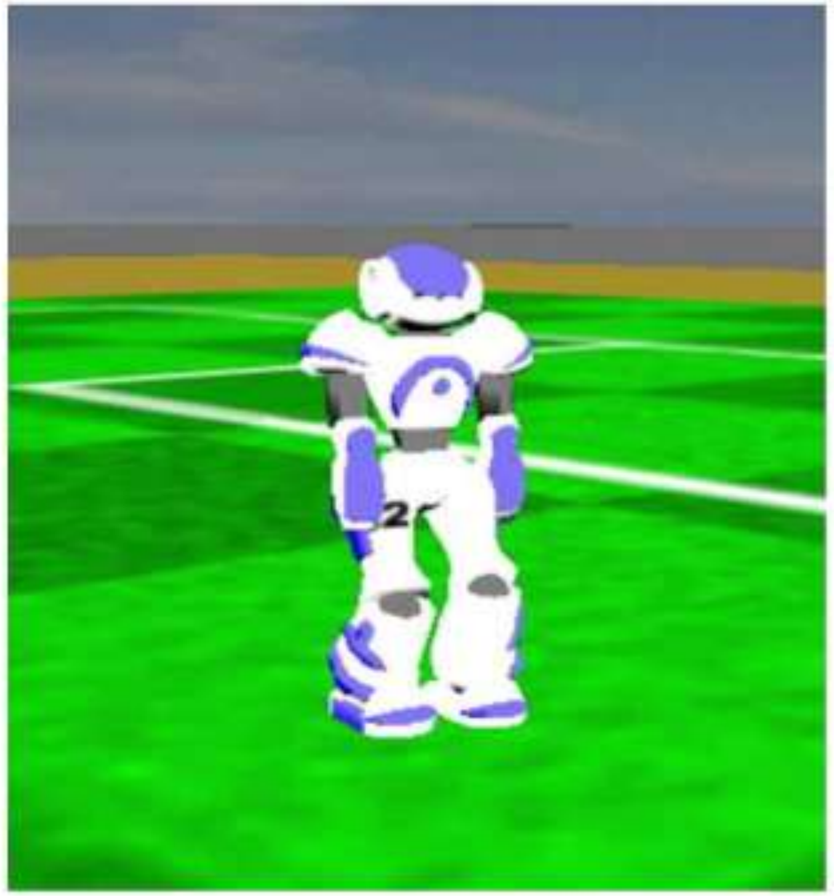

But, policies **learned in simulation** often **fail in the real world**.


UTAustinVilla
0:0
<Right>
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Playmode: BeforeKickOff

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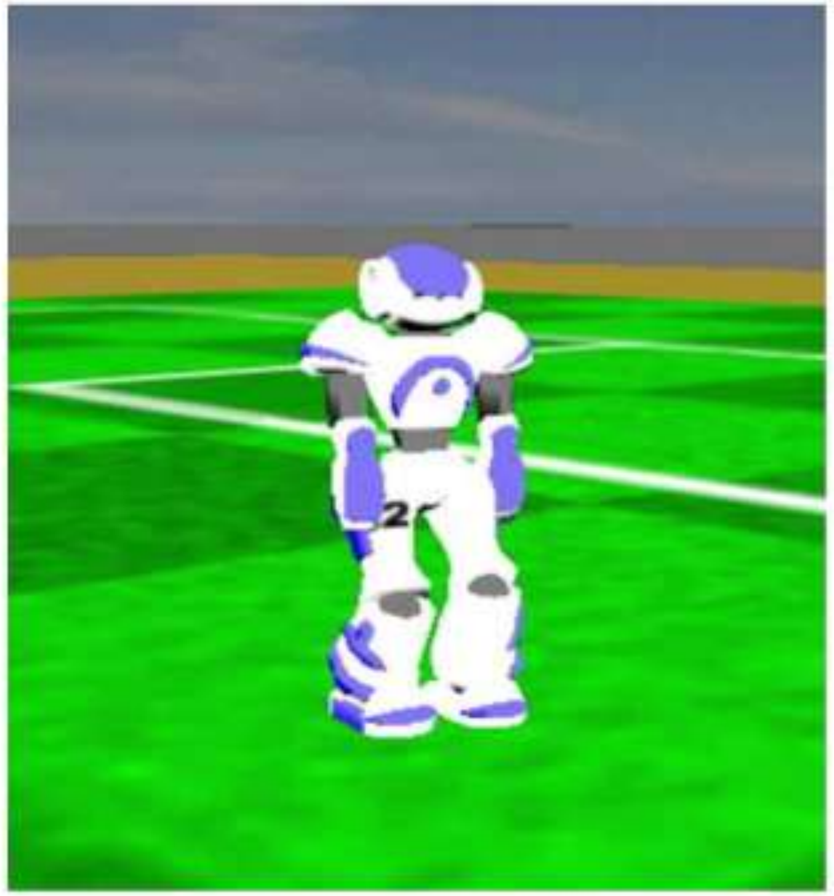

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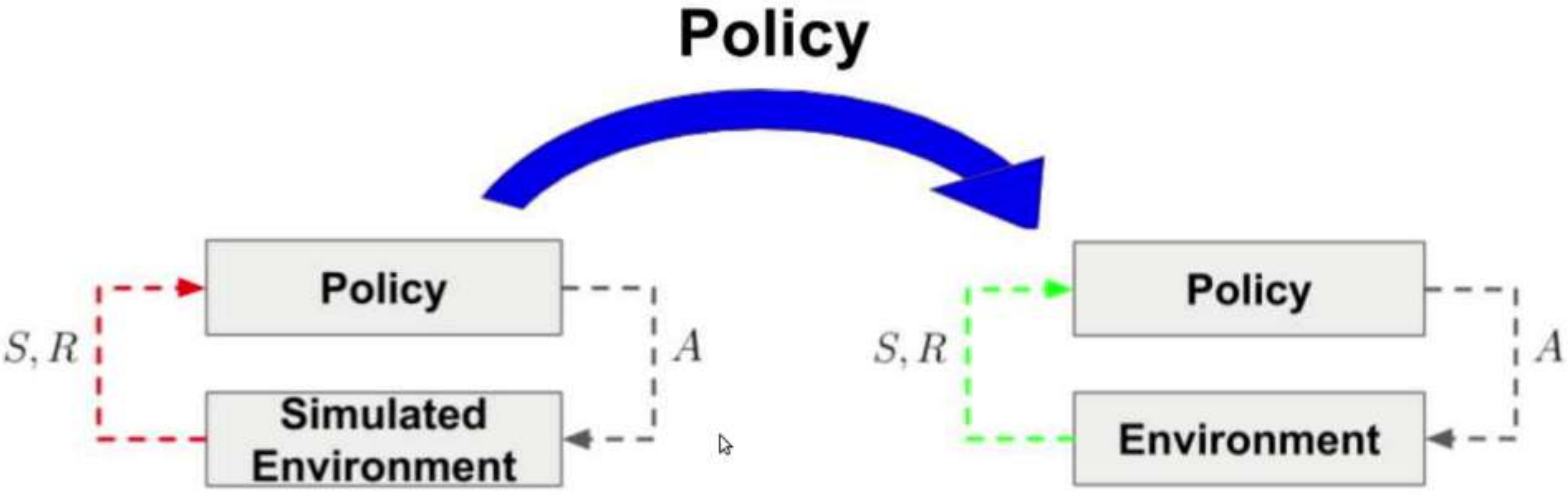

(Cutler and How, "Efficient Reinforcement Learnng for Robots using Informative Simulated Priors");
(Cully et al., "Robots that can adapt like animals");
(Rusu et al., "Sim-to-real robot learning from pixels with progressive nets")

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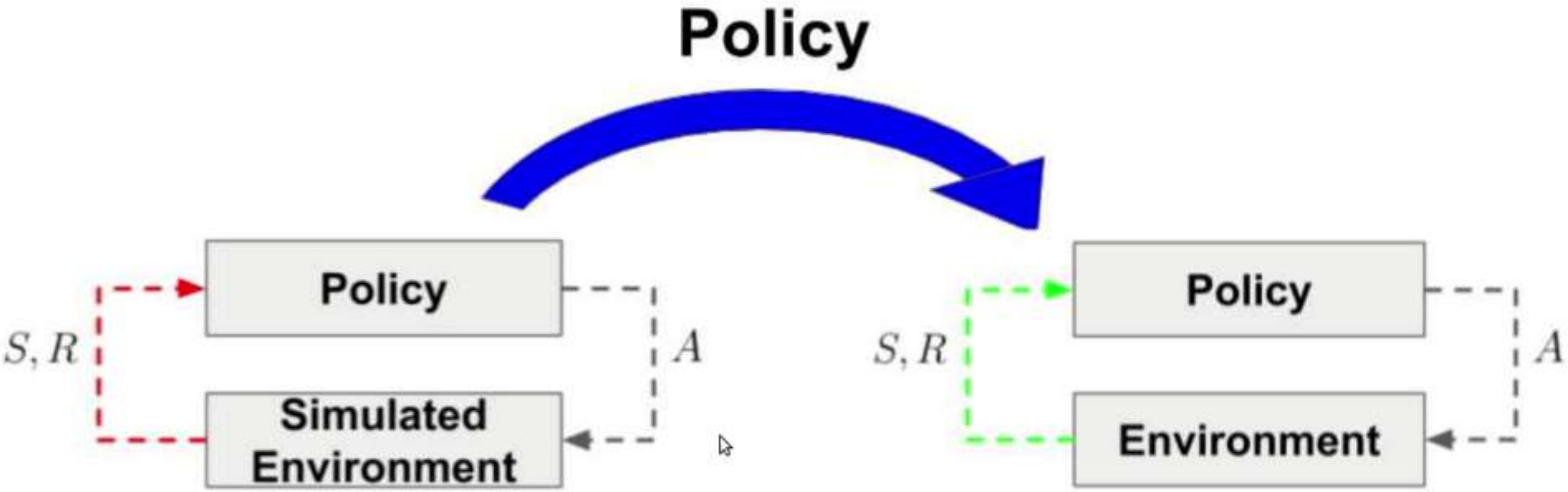

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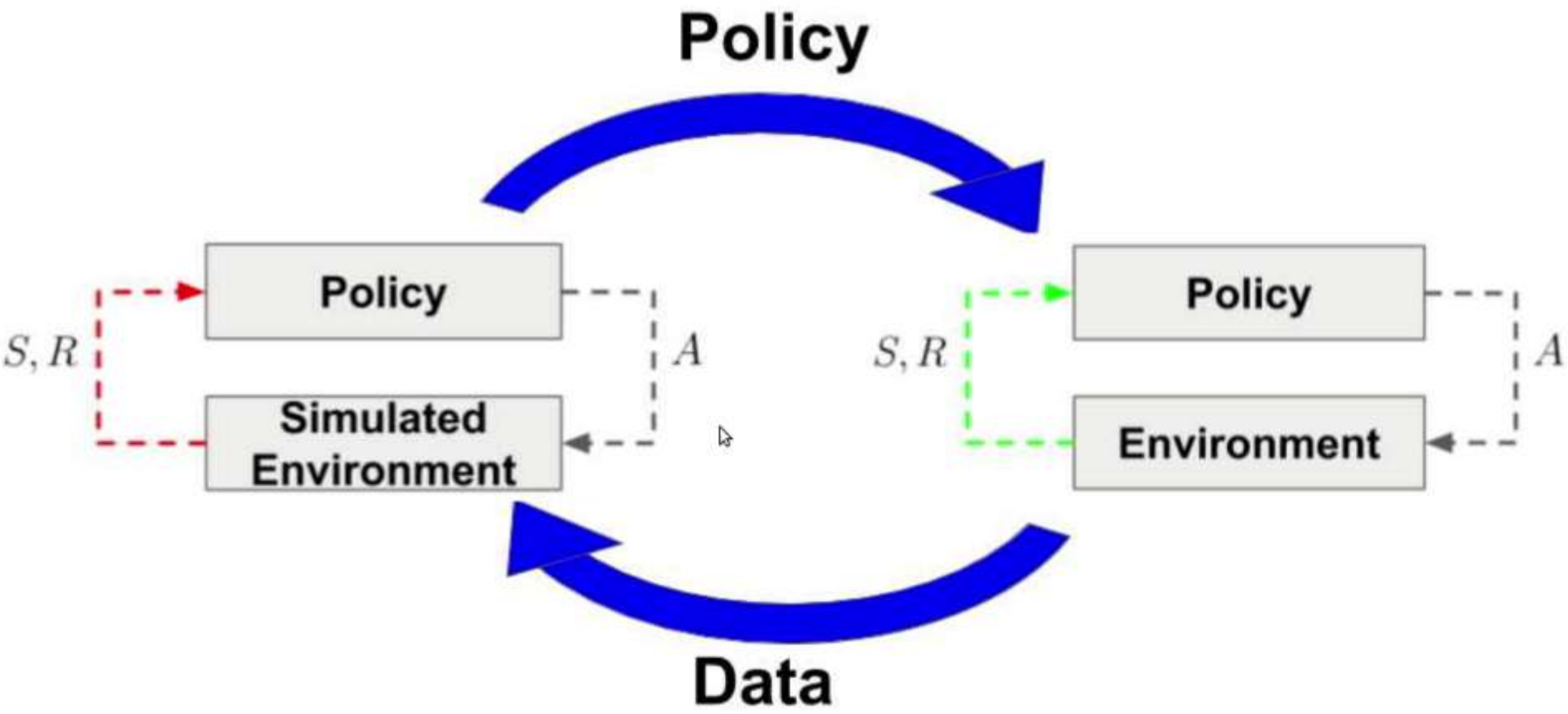

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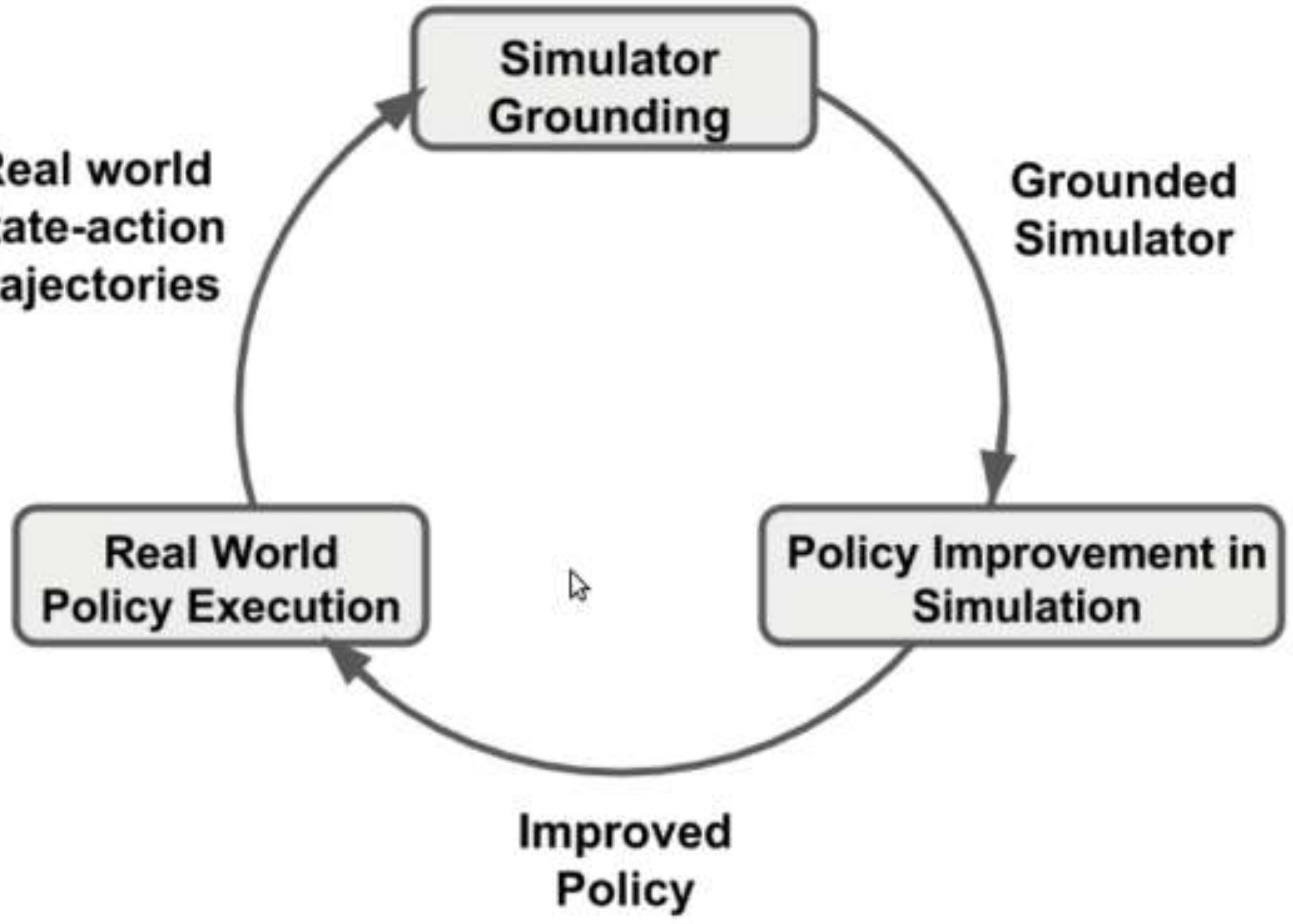

Farchy, Barrett, MacAlpine, and Stone, AAMAS 2013

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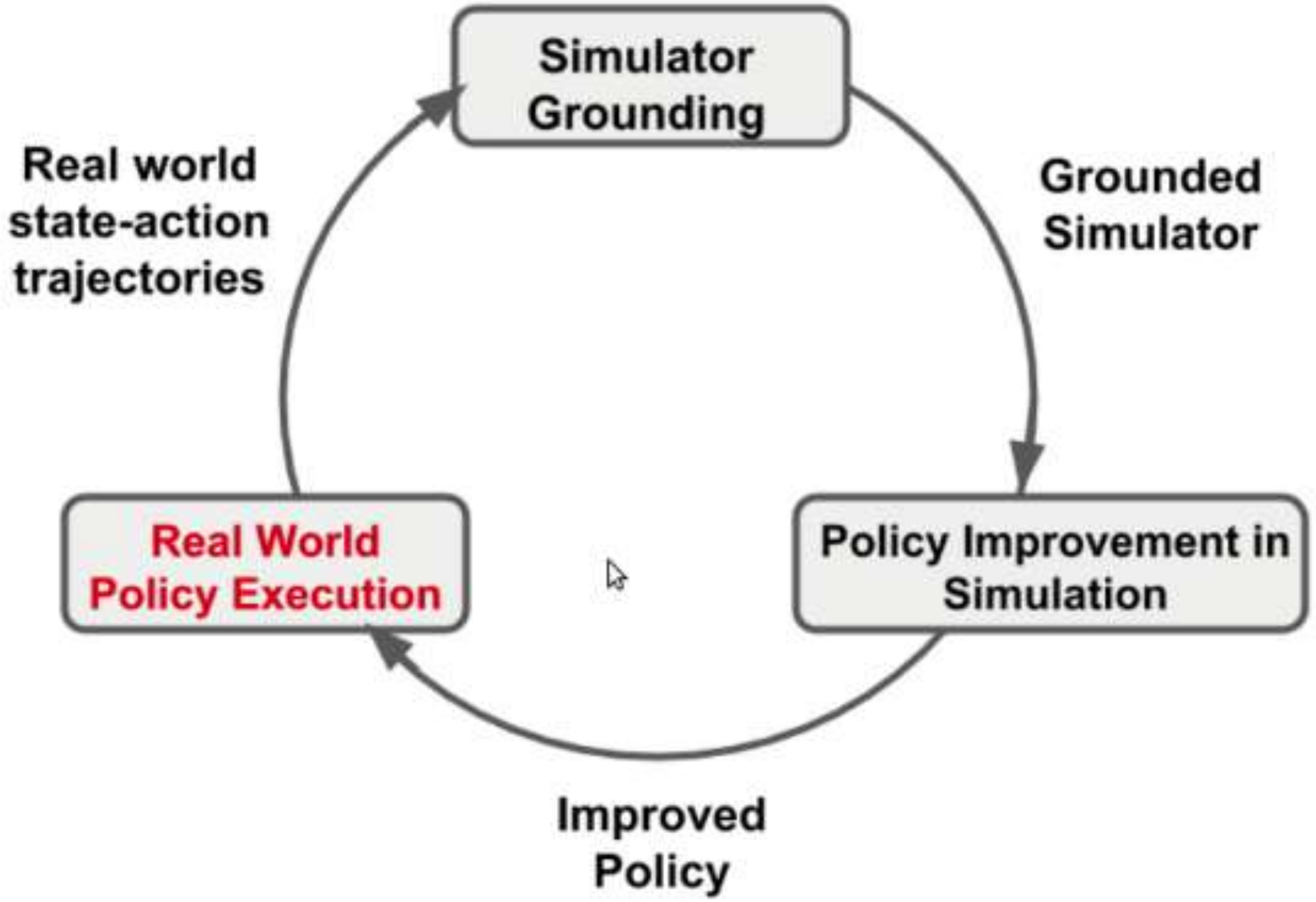

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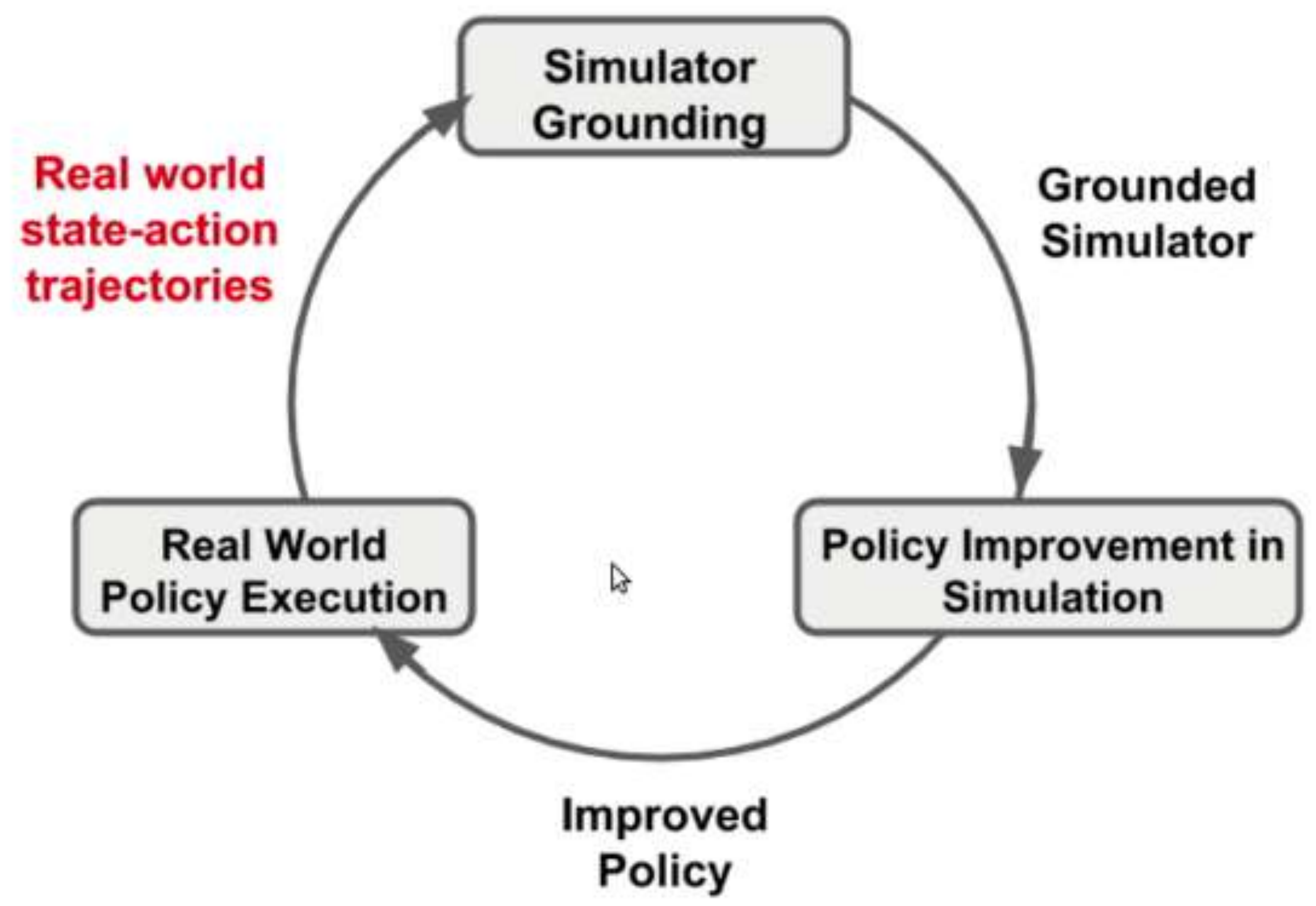

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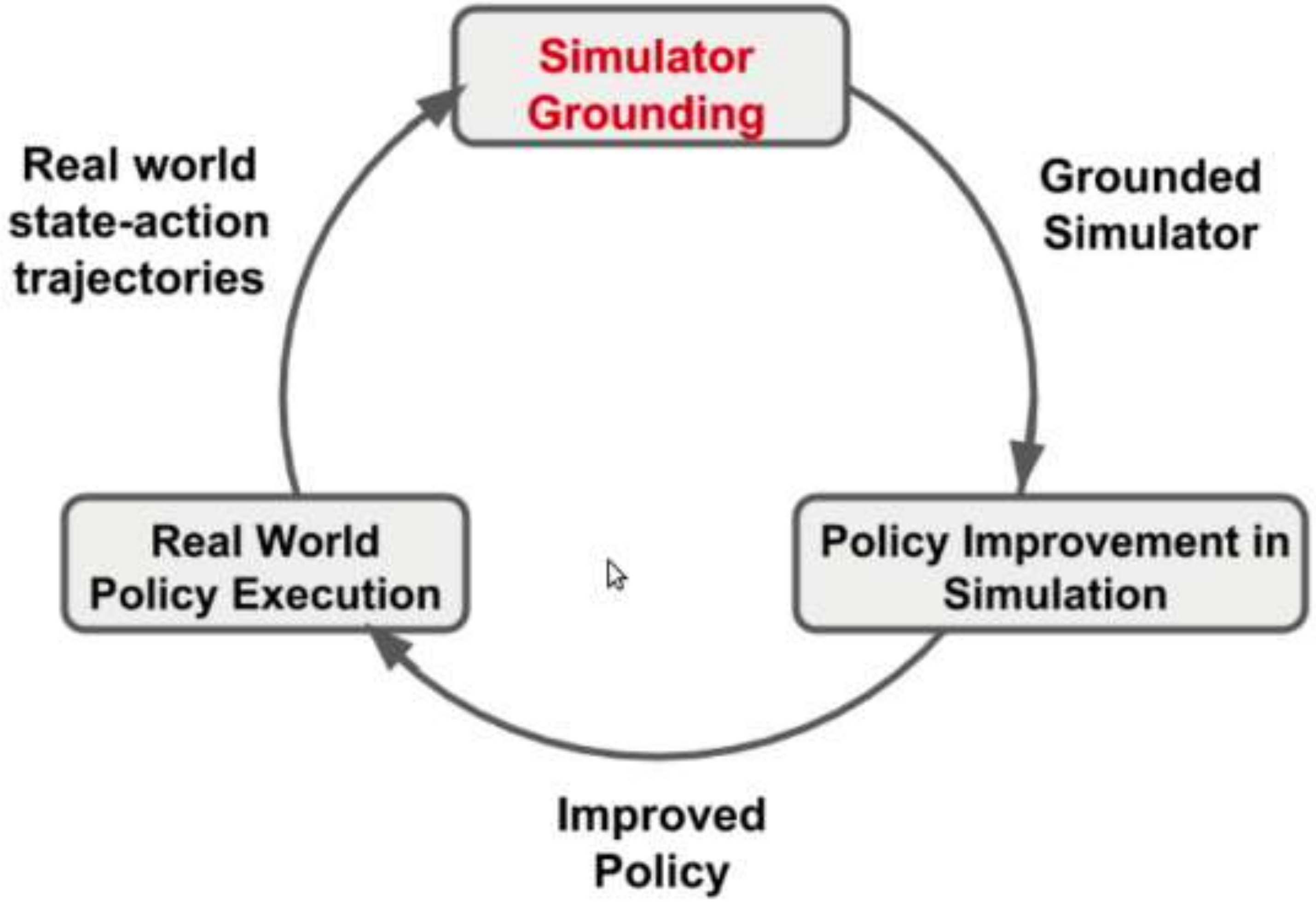

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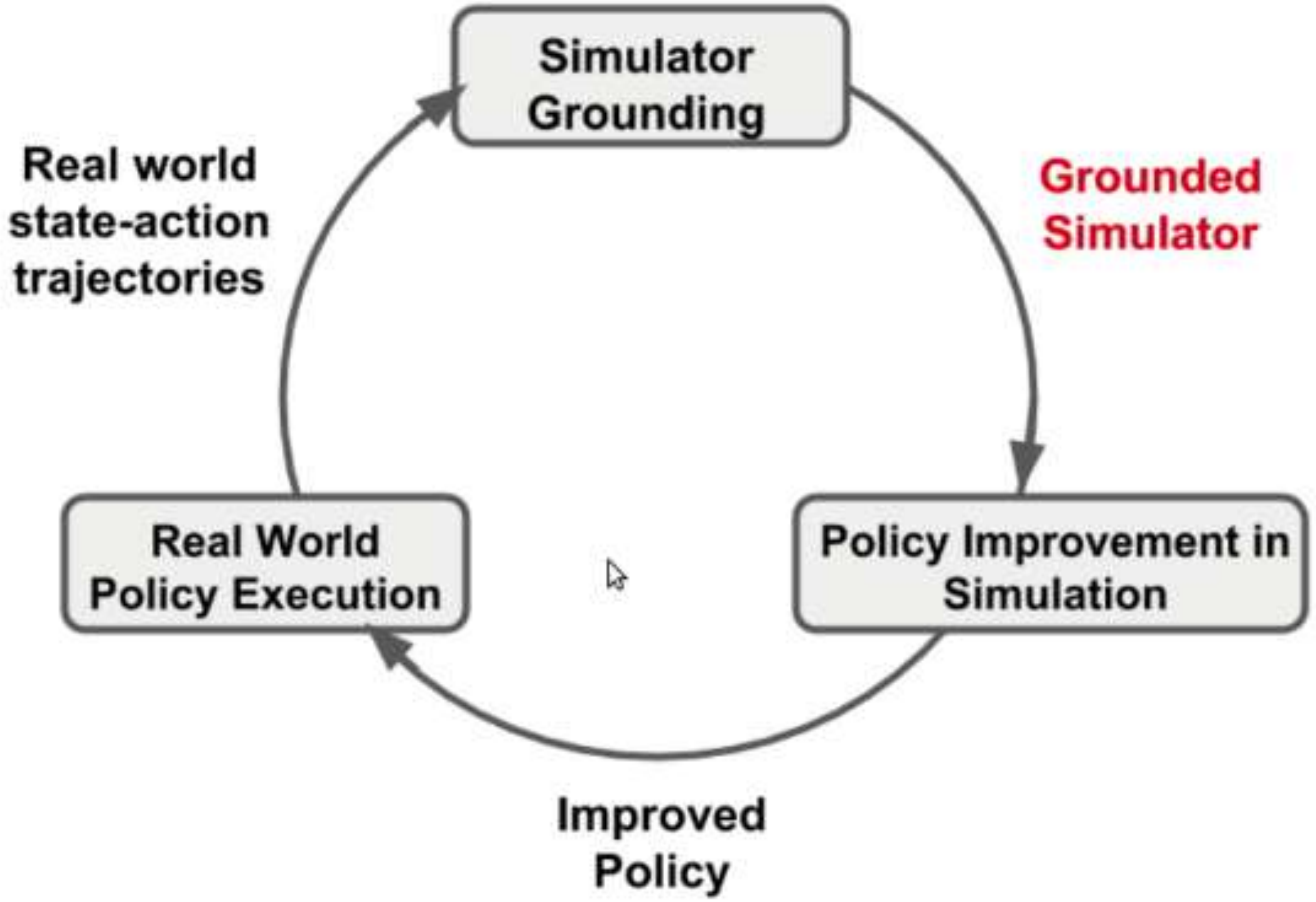

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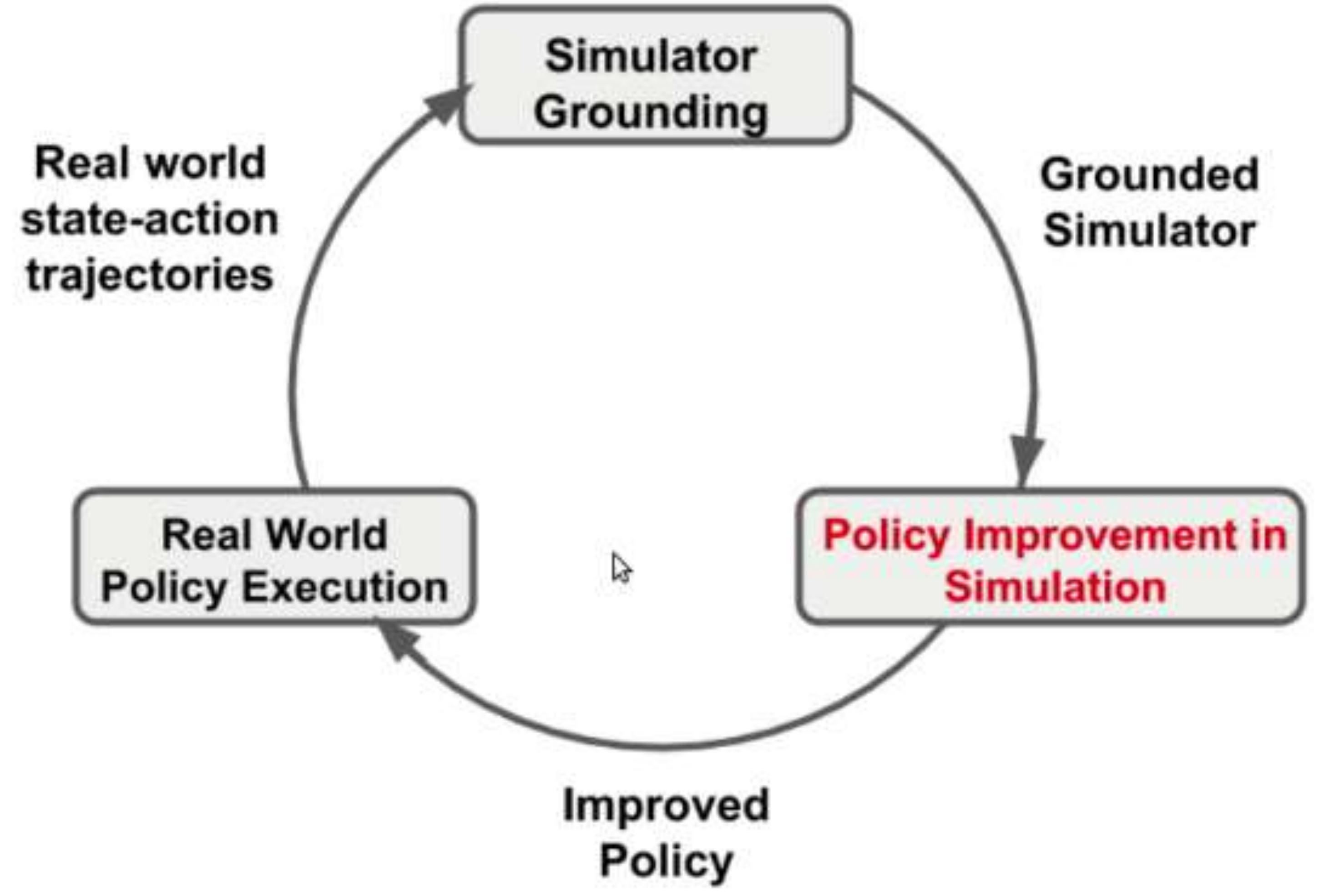

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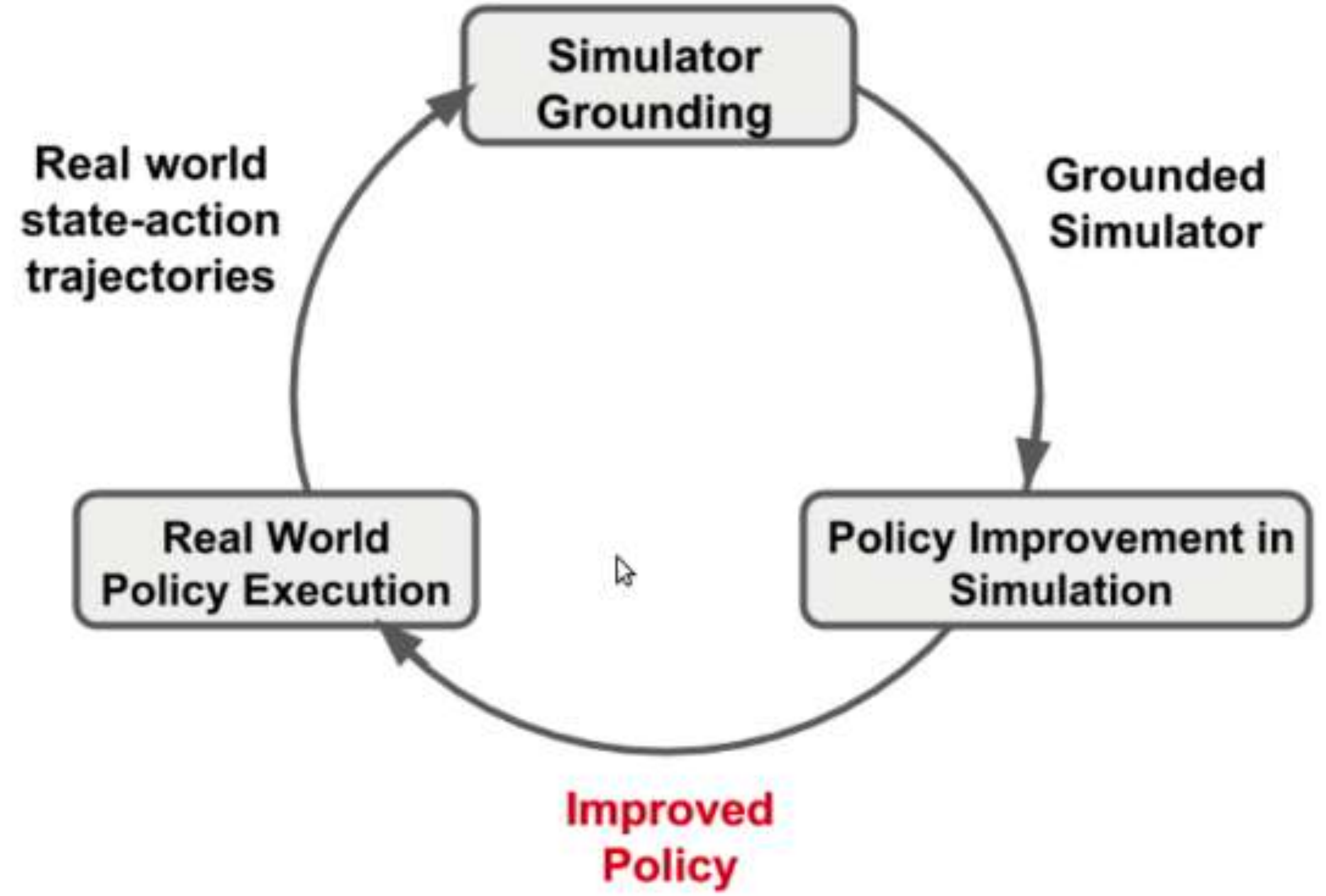

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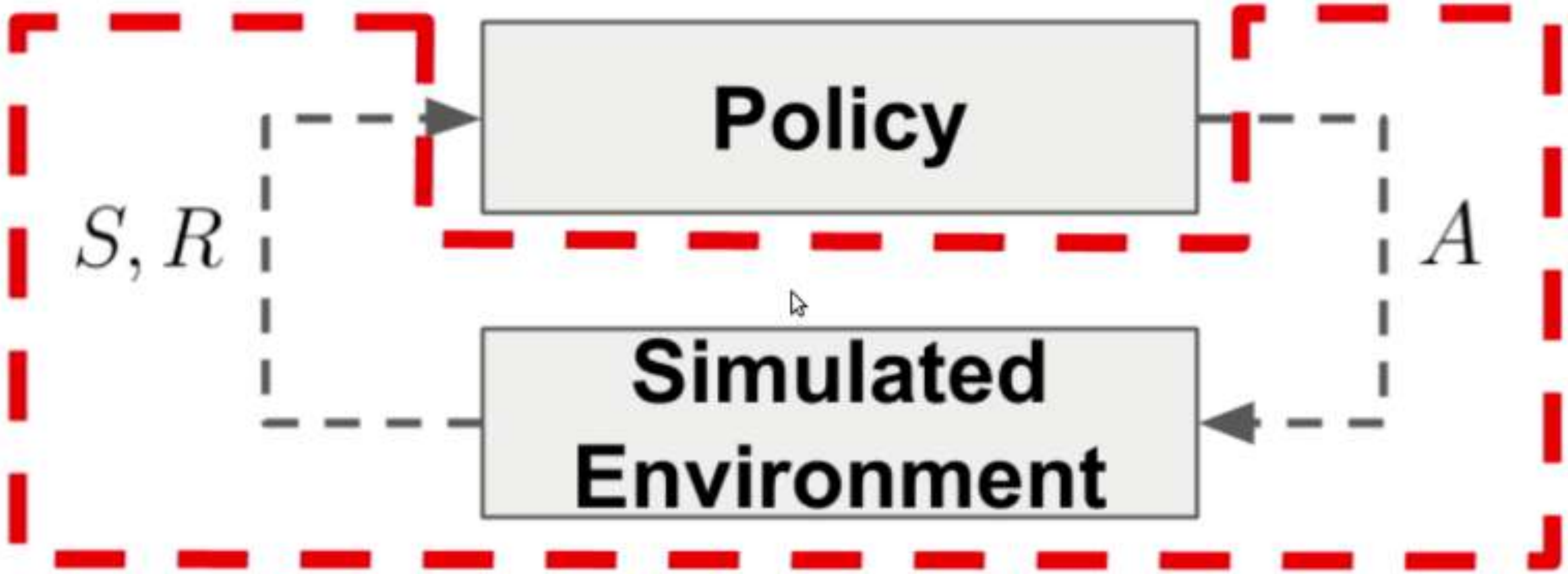

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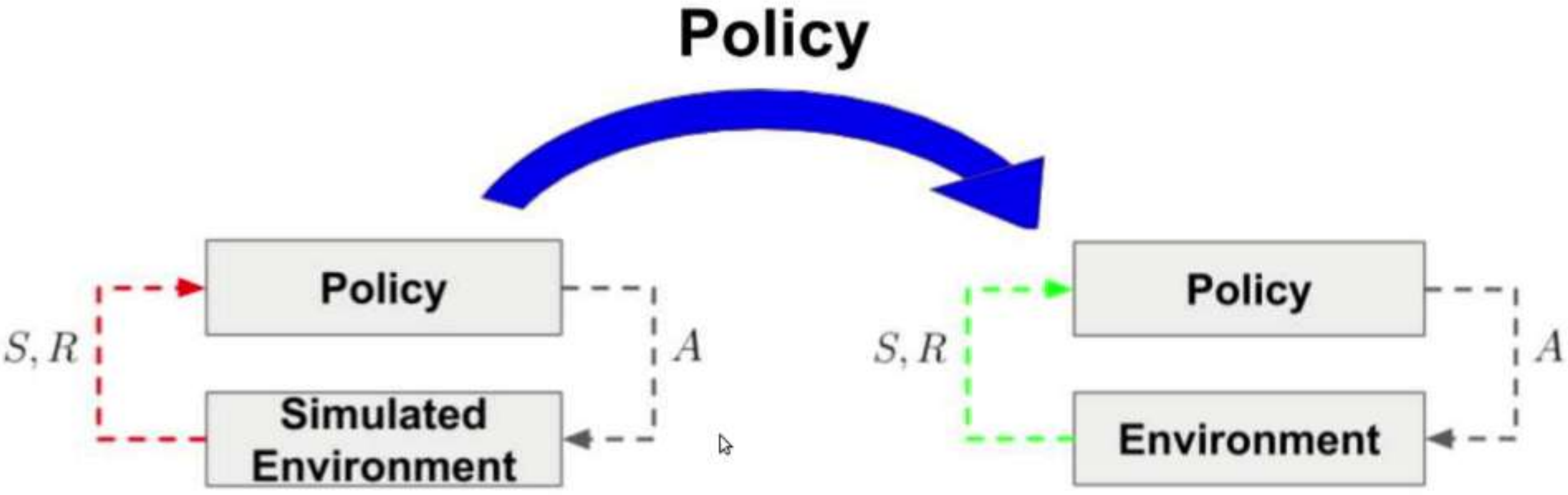

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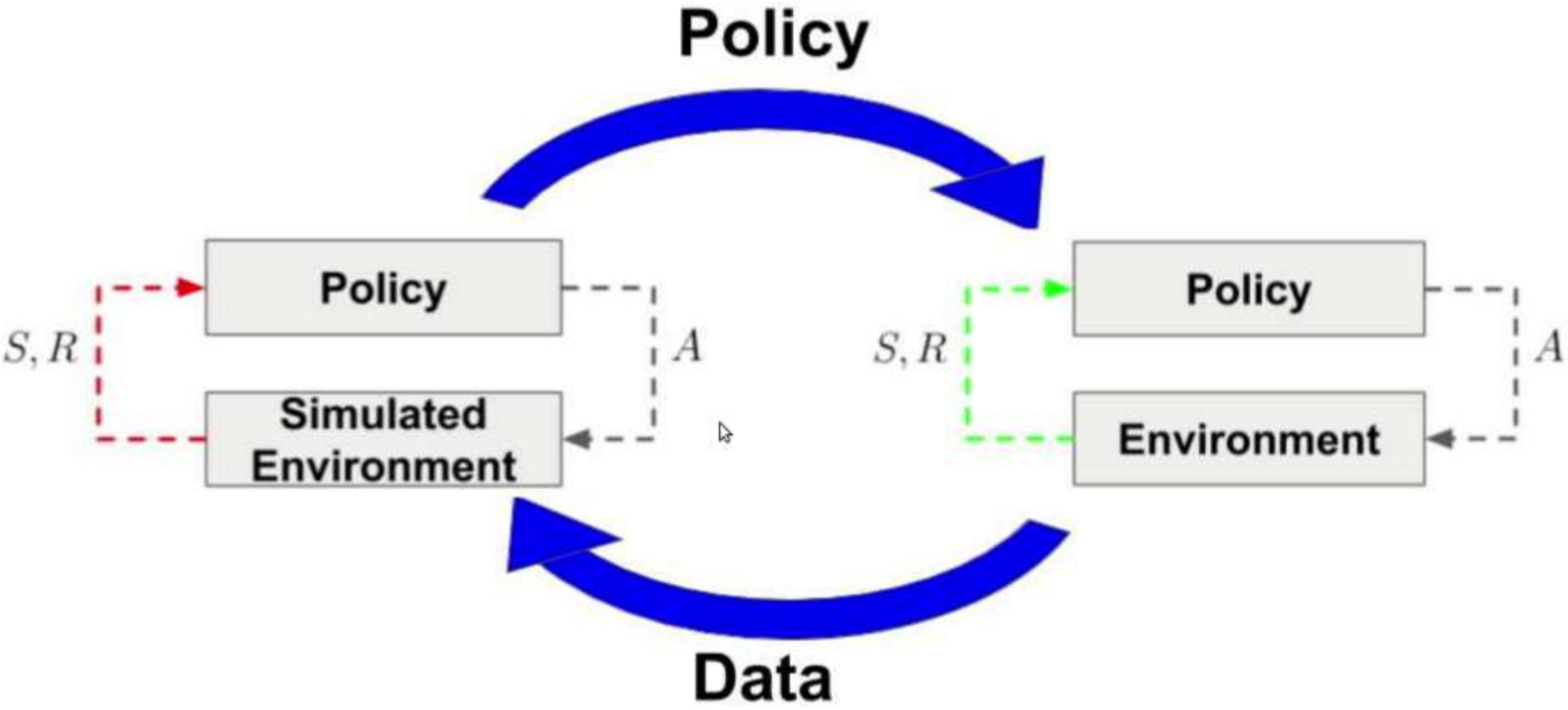

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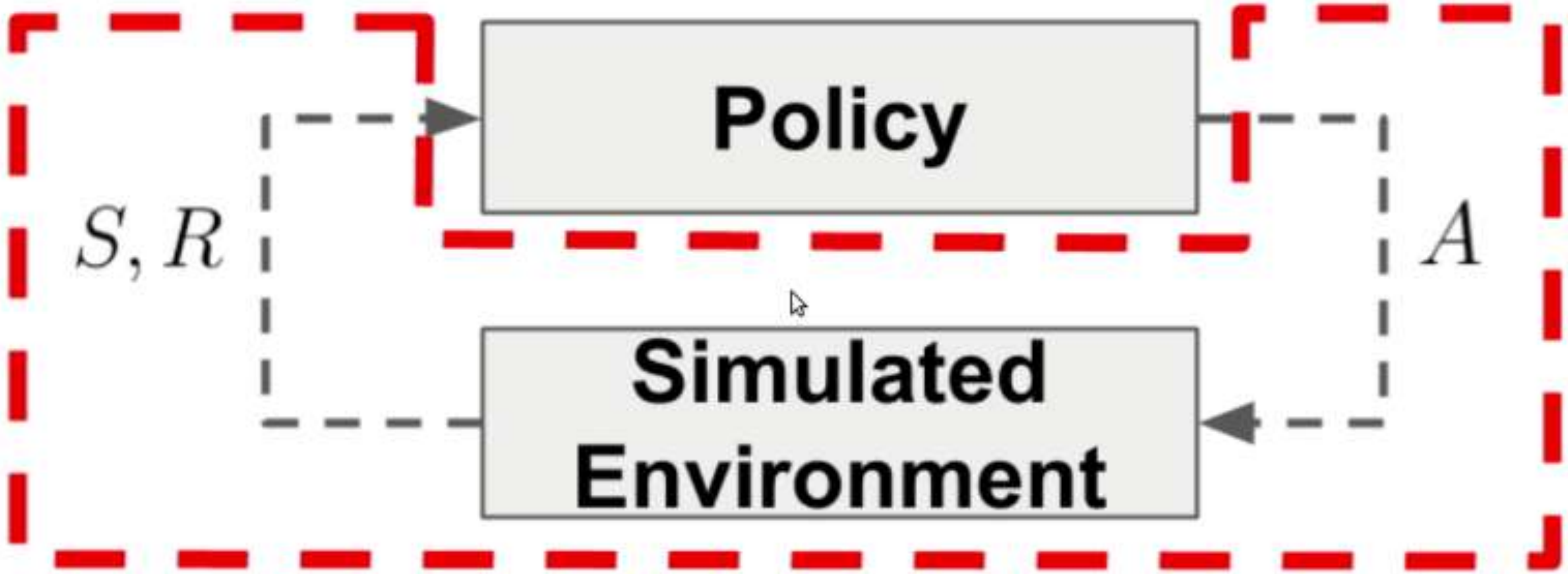

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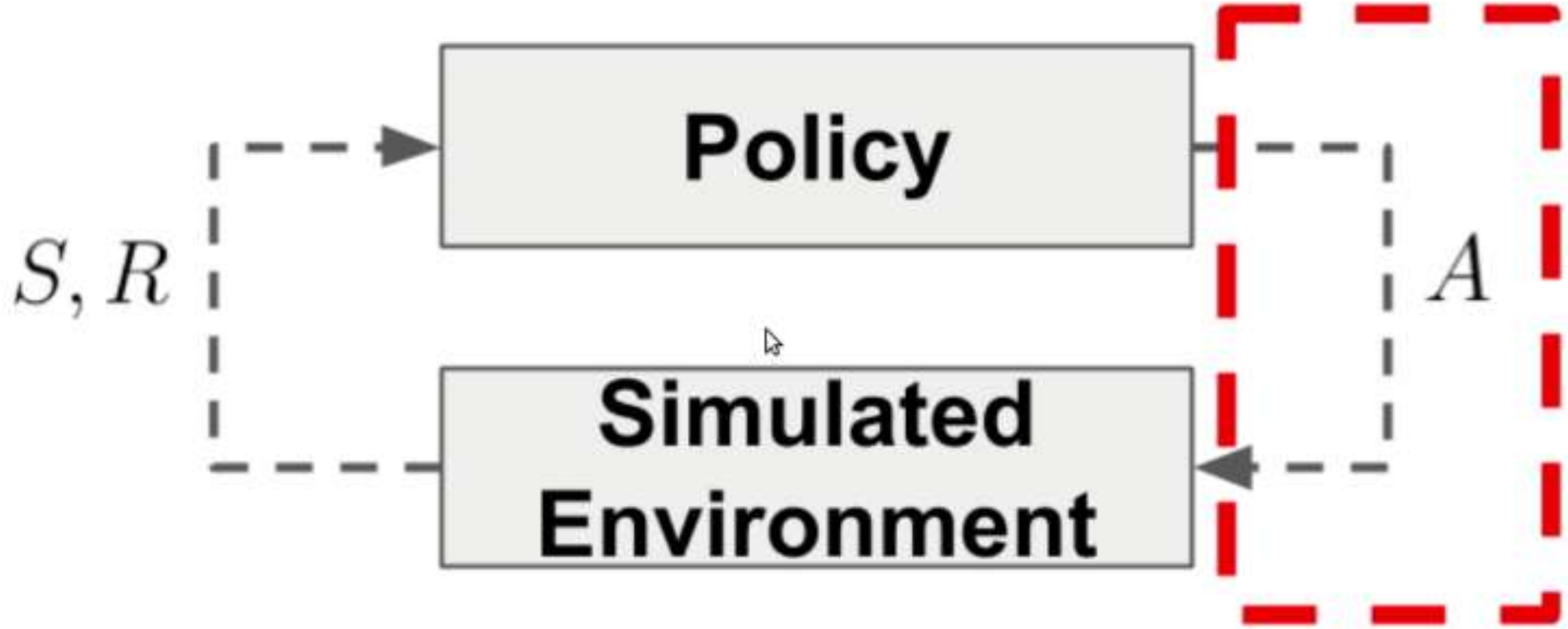
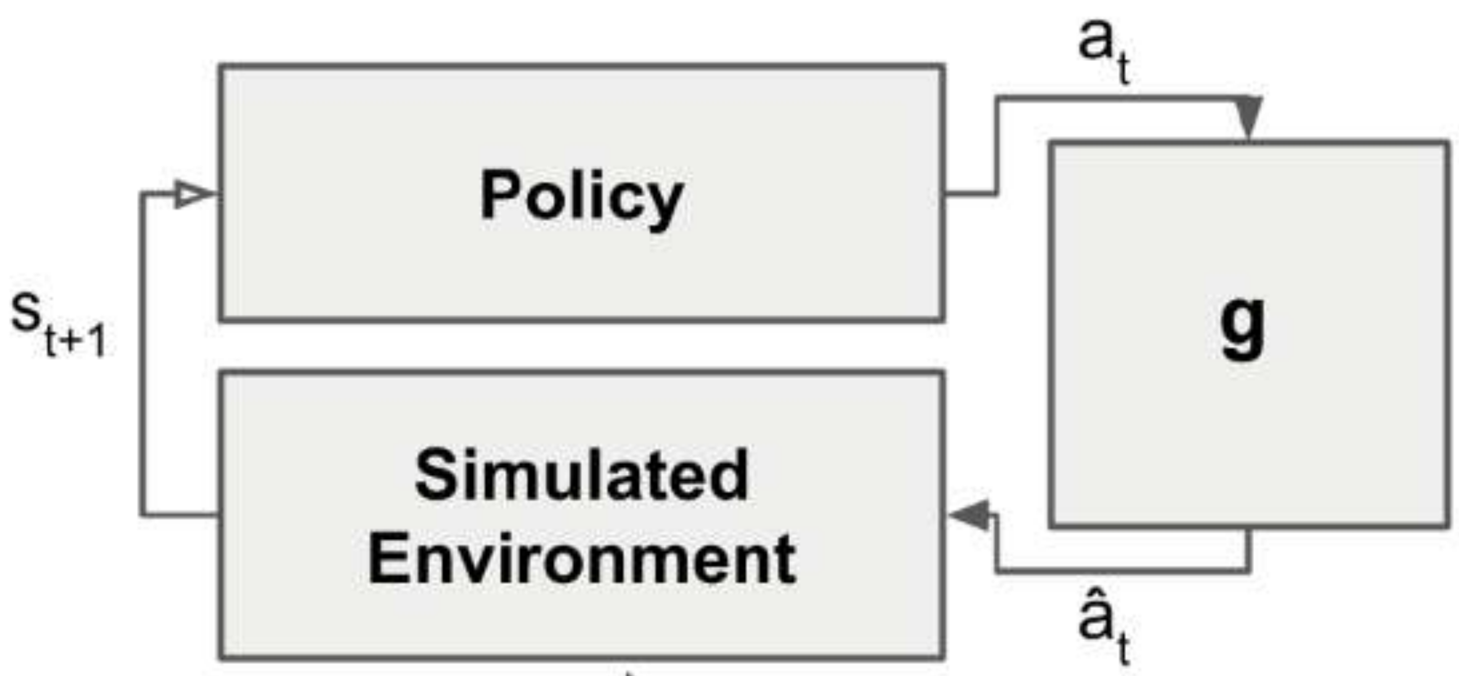


Grounded Action Transformation



Replace robot's action $\mathbf{a}_t$ with an action that produces a more "realistic" transition.

Hanna and Stone, AAAI 2017

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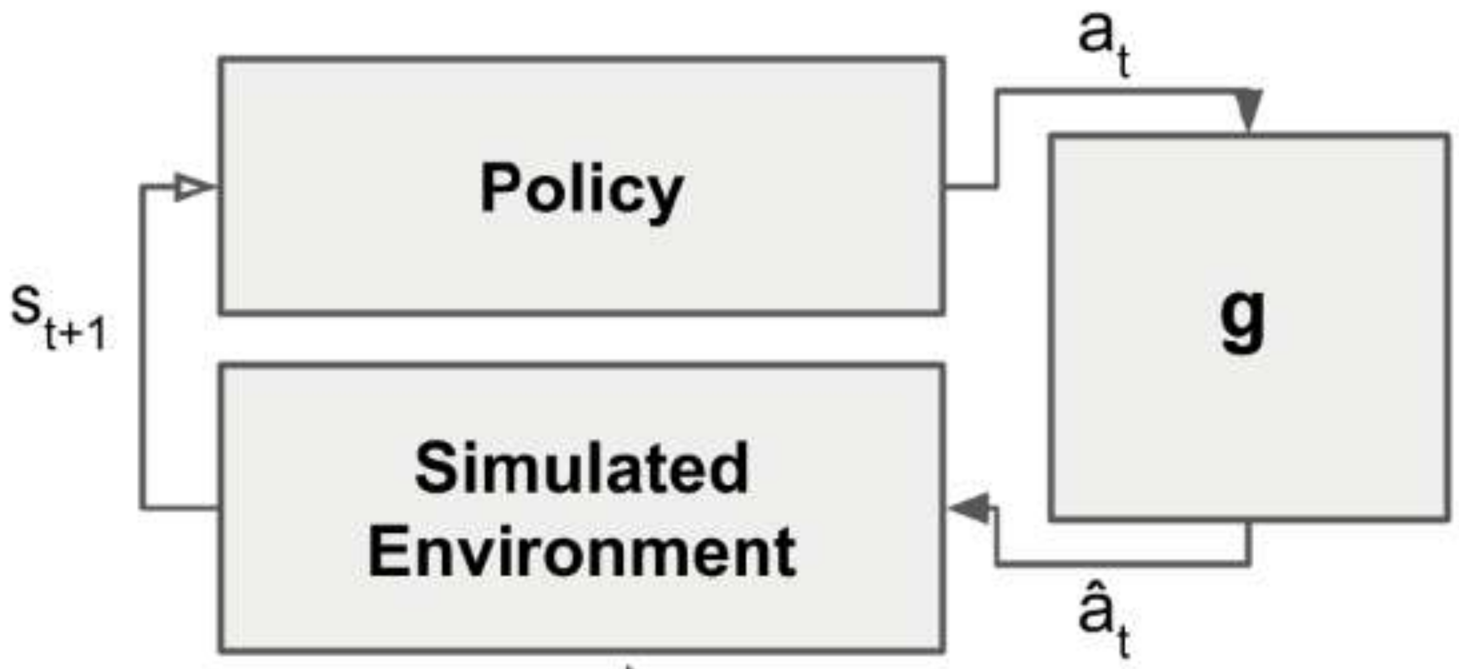

Replace robot's action $\mathbf{a}_t$ with an action that produces a more "realistic" transition.

Learn this action as a function $g(\mathbf{s}_t, \mathbf{a}_t)$.

Hanna and Stone, AAAI 2017

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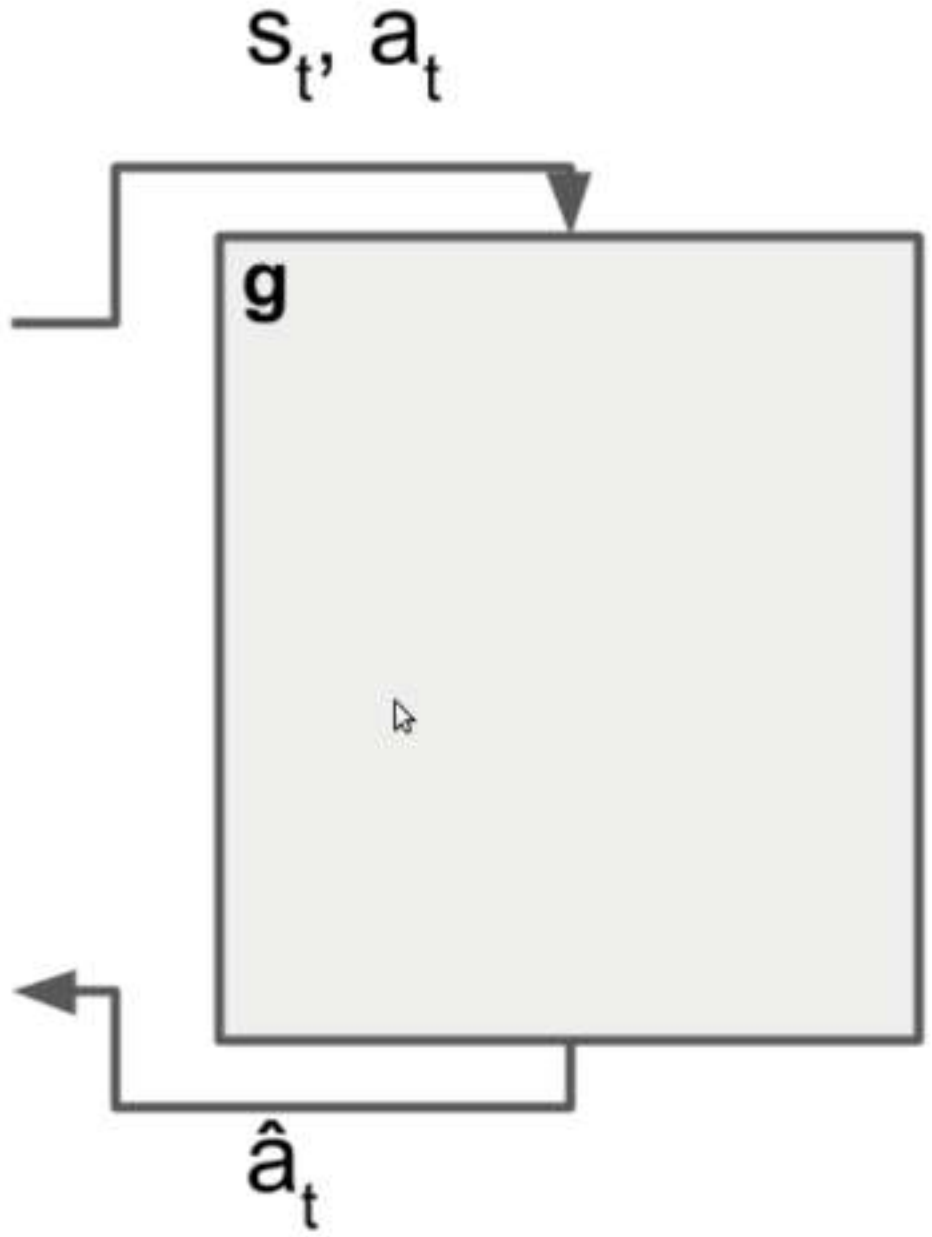

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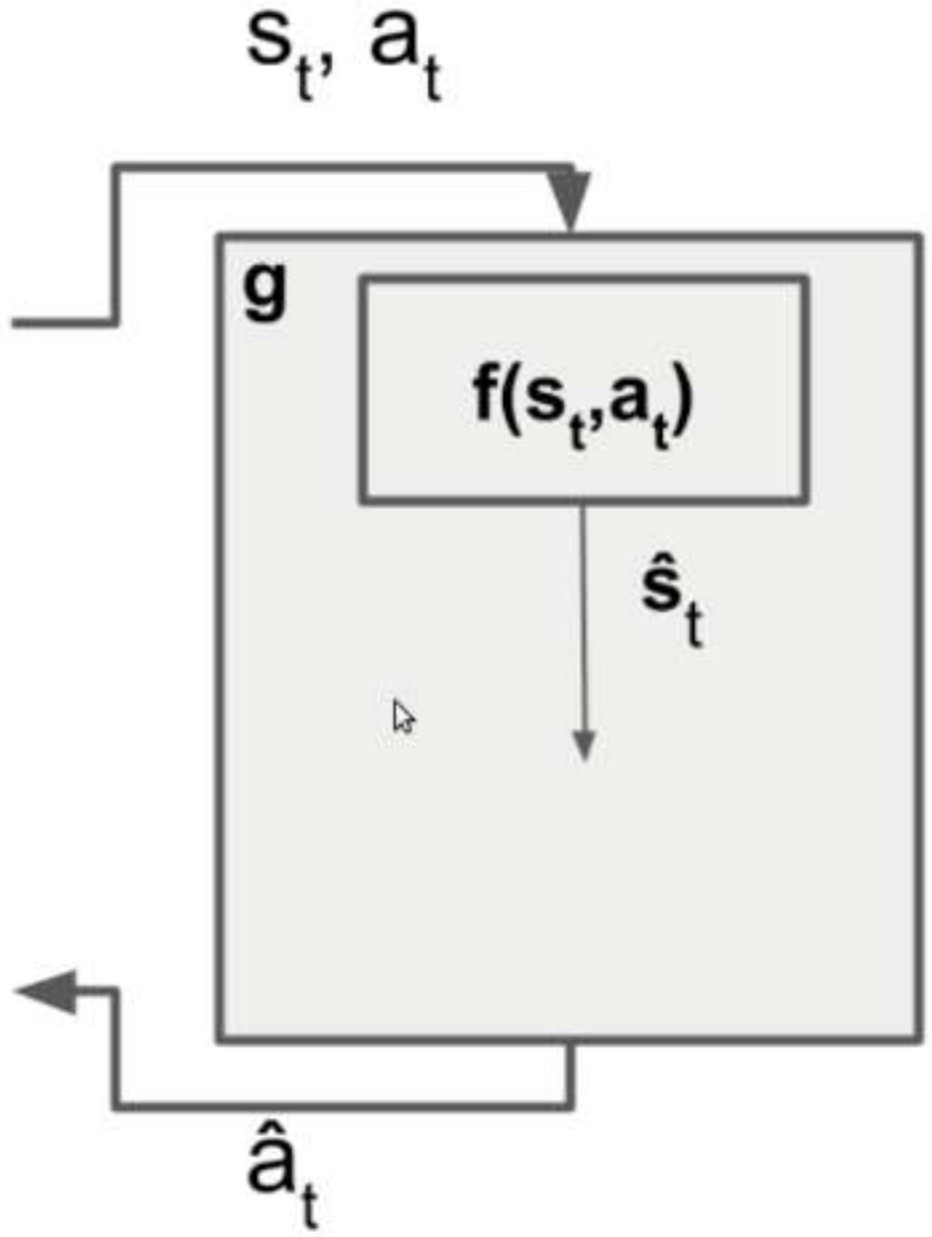

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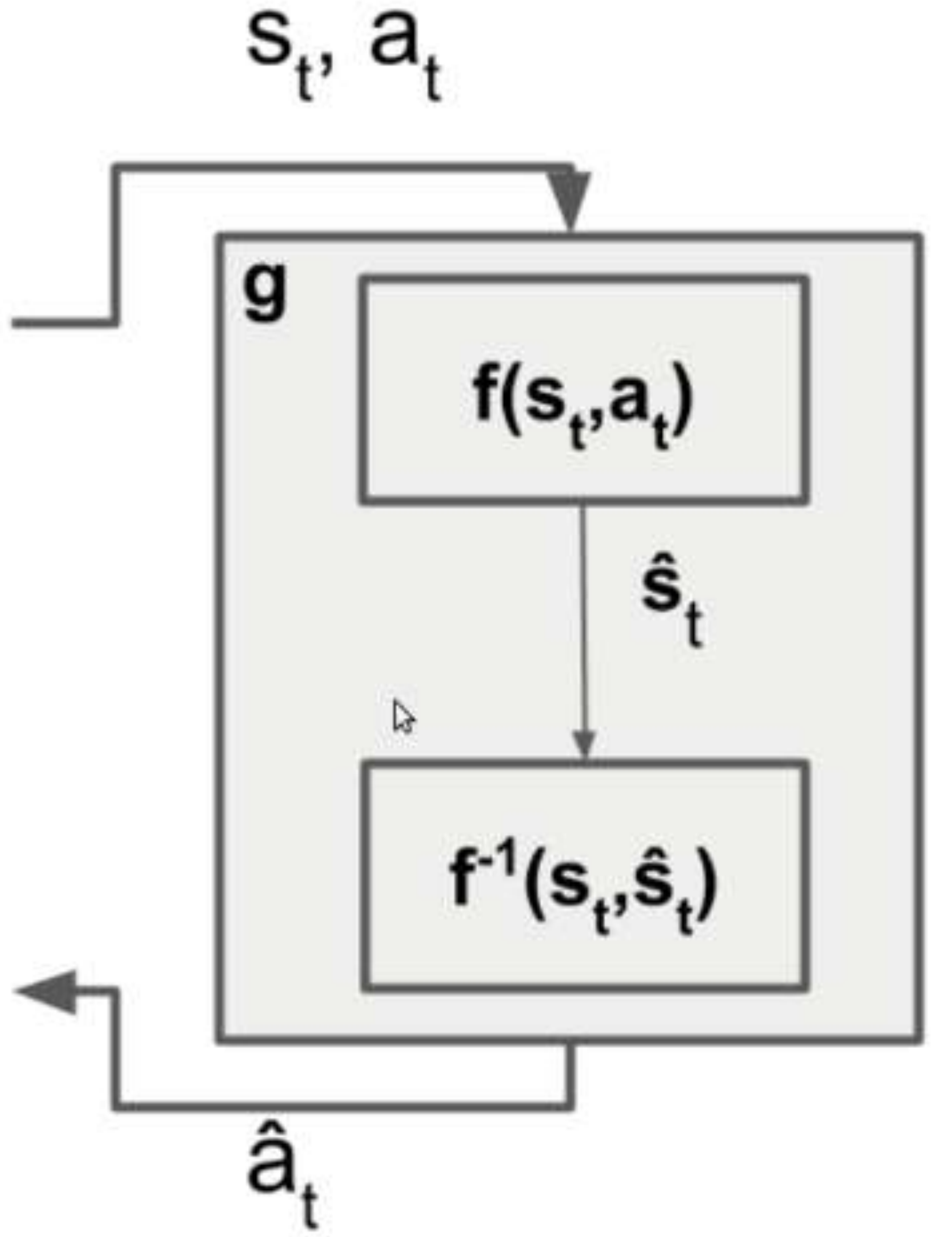

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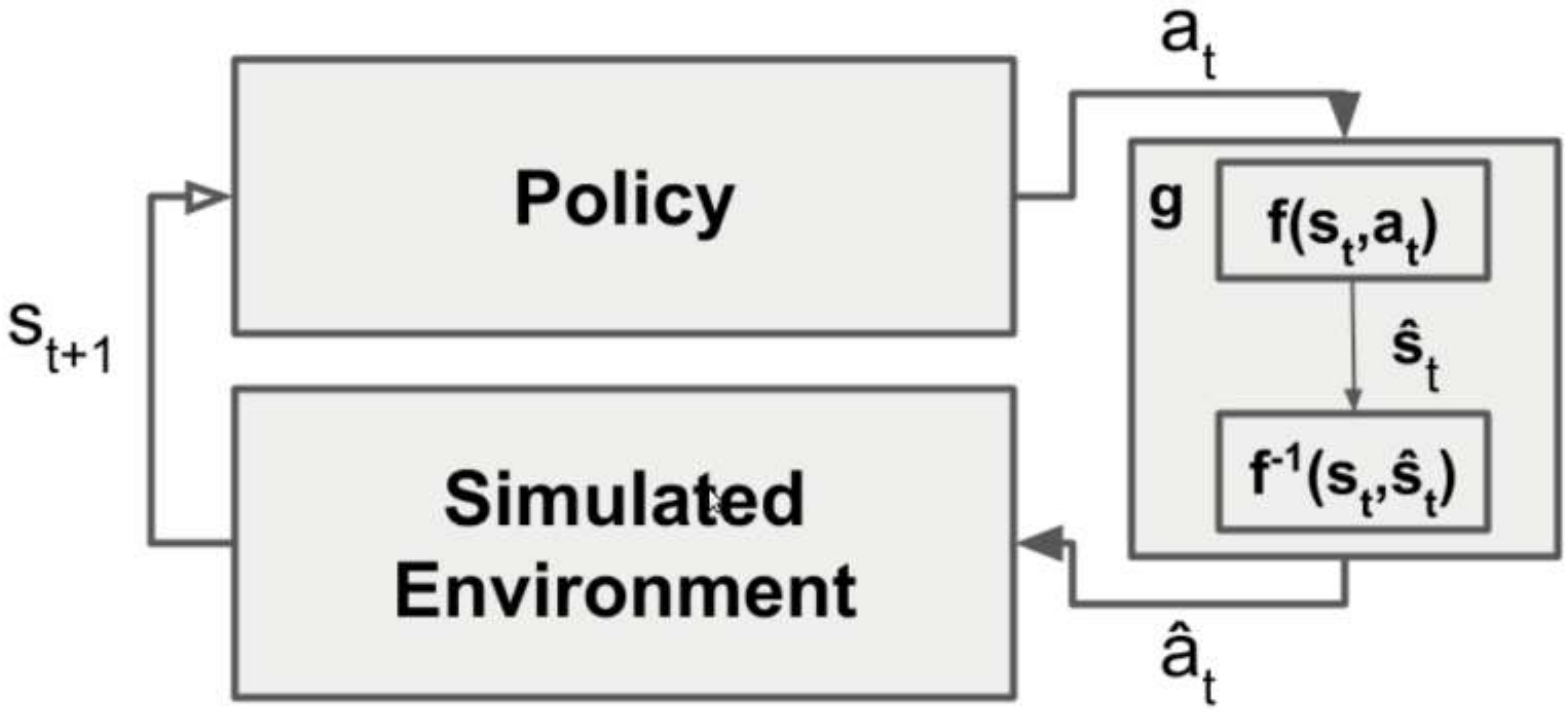
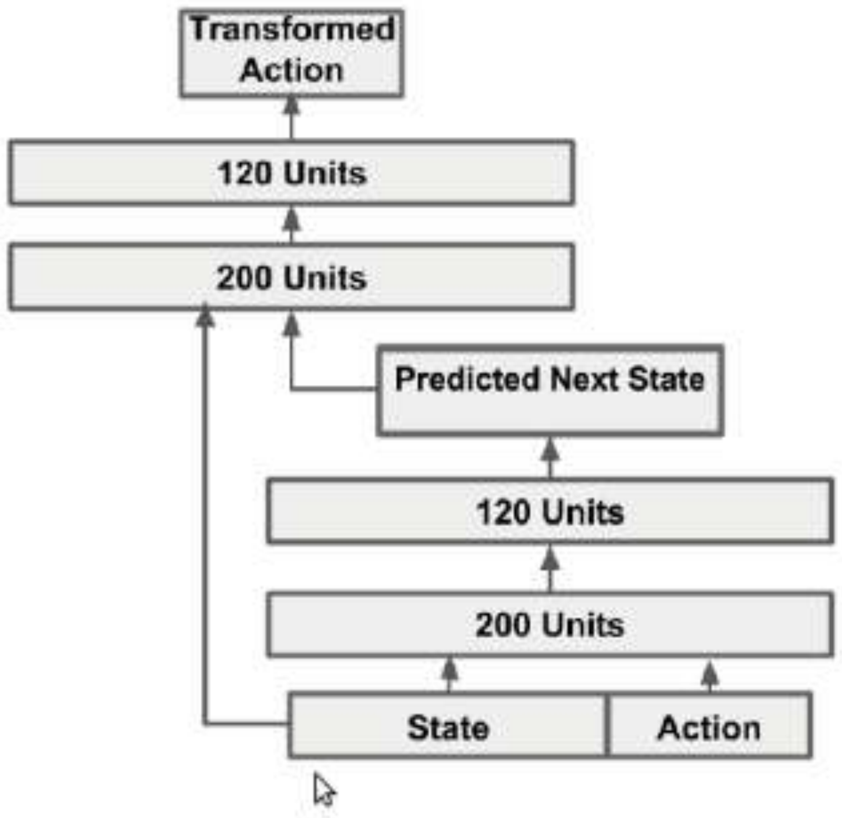


Supervised Implementation



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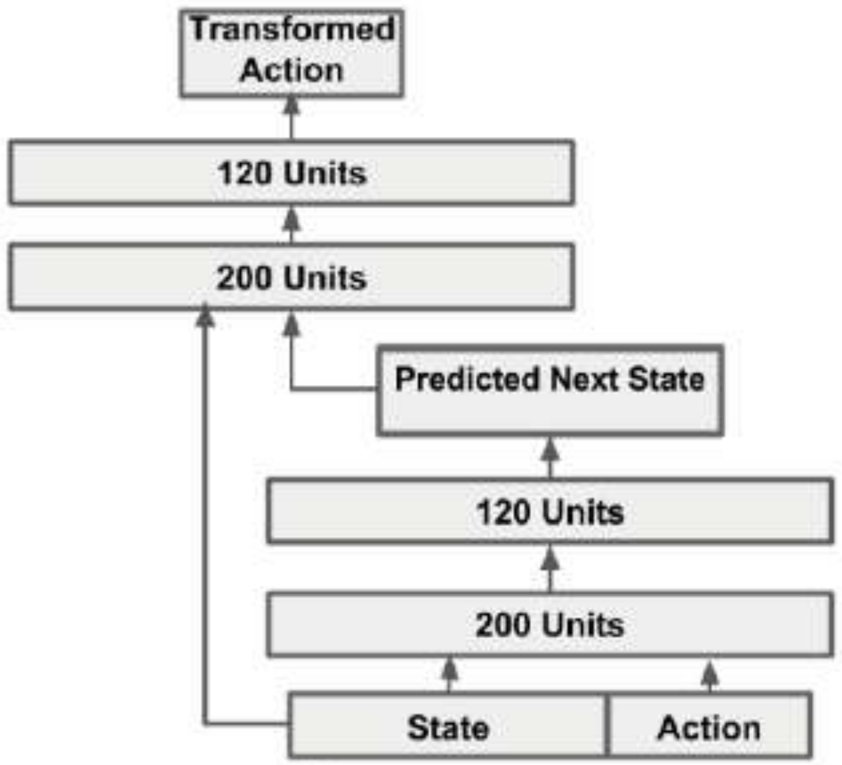

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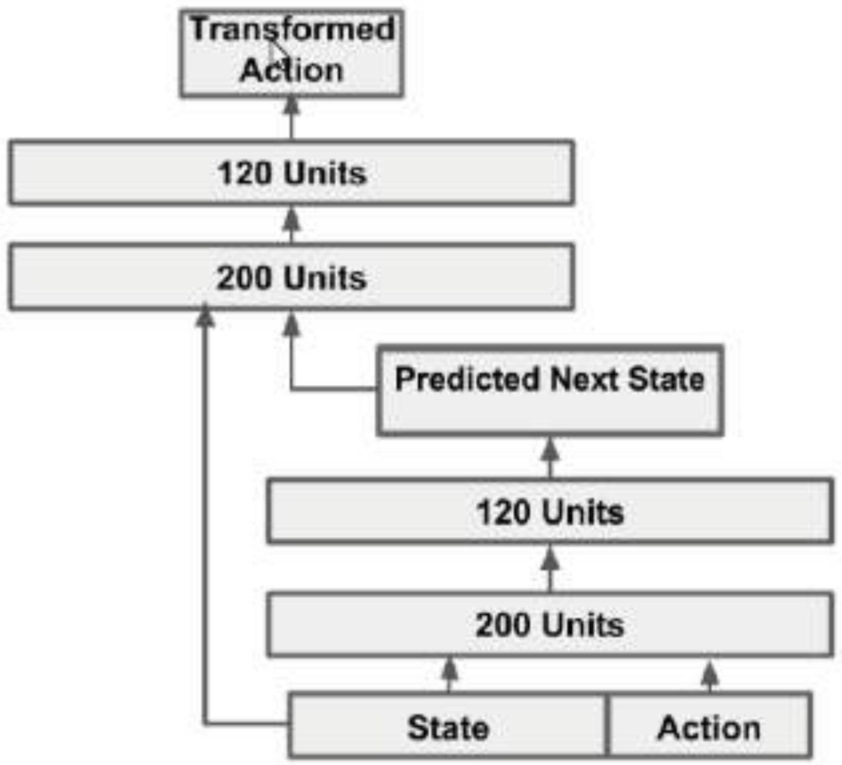

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- Initial policy in Initial vs. grounded simulator

Empirical Results

(a) Softbank NAO

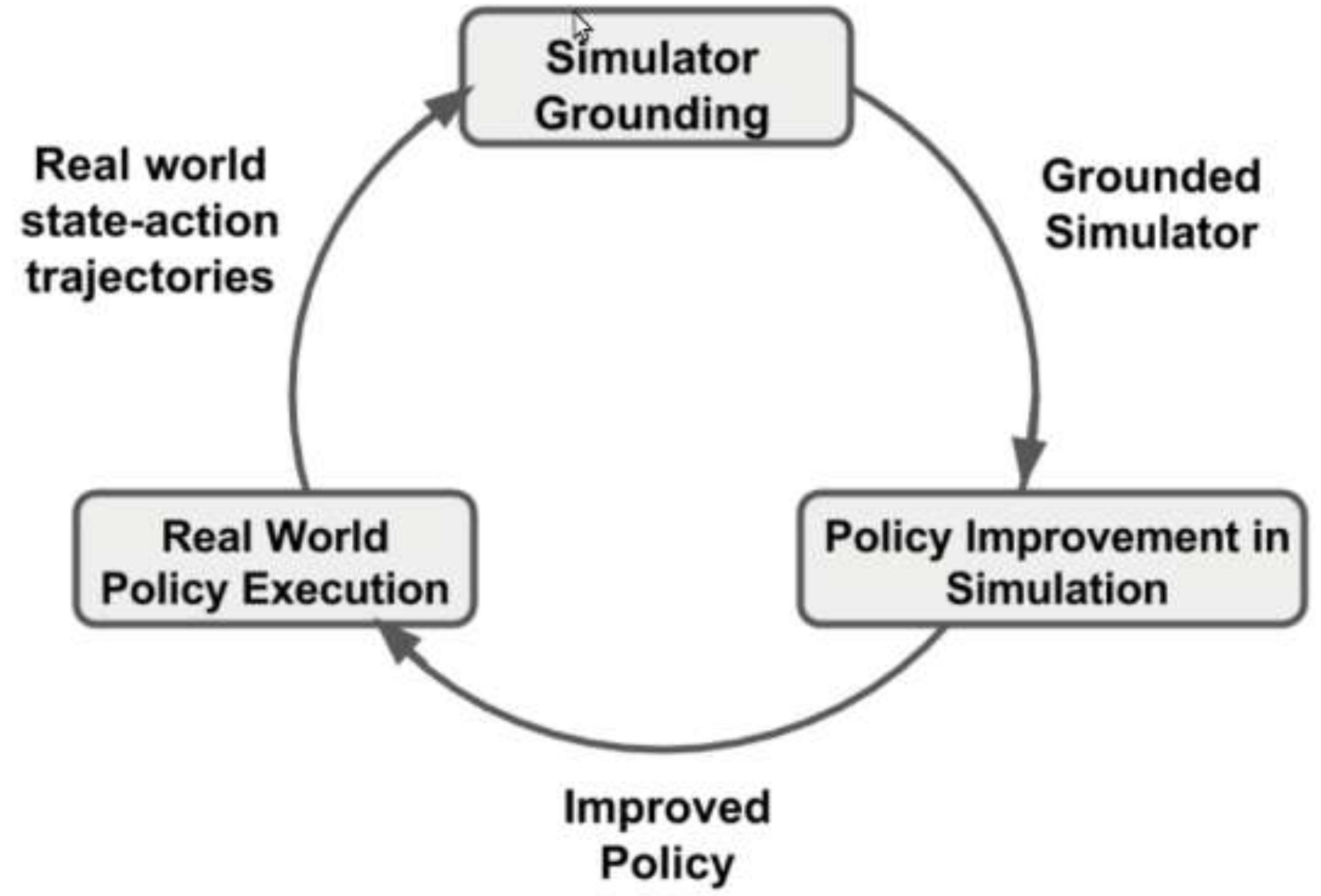
(b) Gazebo NAO

(c) SimSpark NAO

Applied GAT to learning fast bipedal walks for the Nao robot.

- Initial policy: University of New South Wales Walk Engine.
- Policy Search Algorithm: CMA-ES stochastic search method.

Empirical Results



Method	Velocity (cm/s)	% Improve
Initial policy	19.3	0.0

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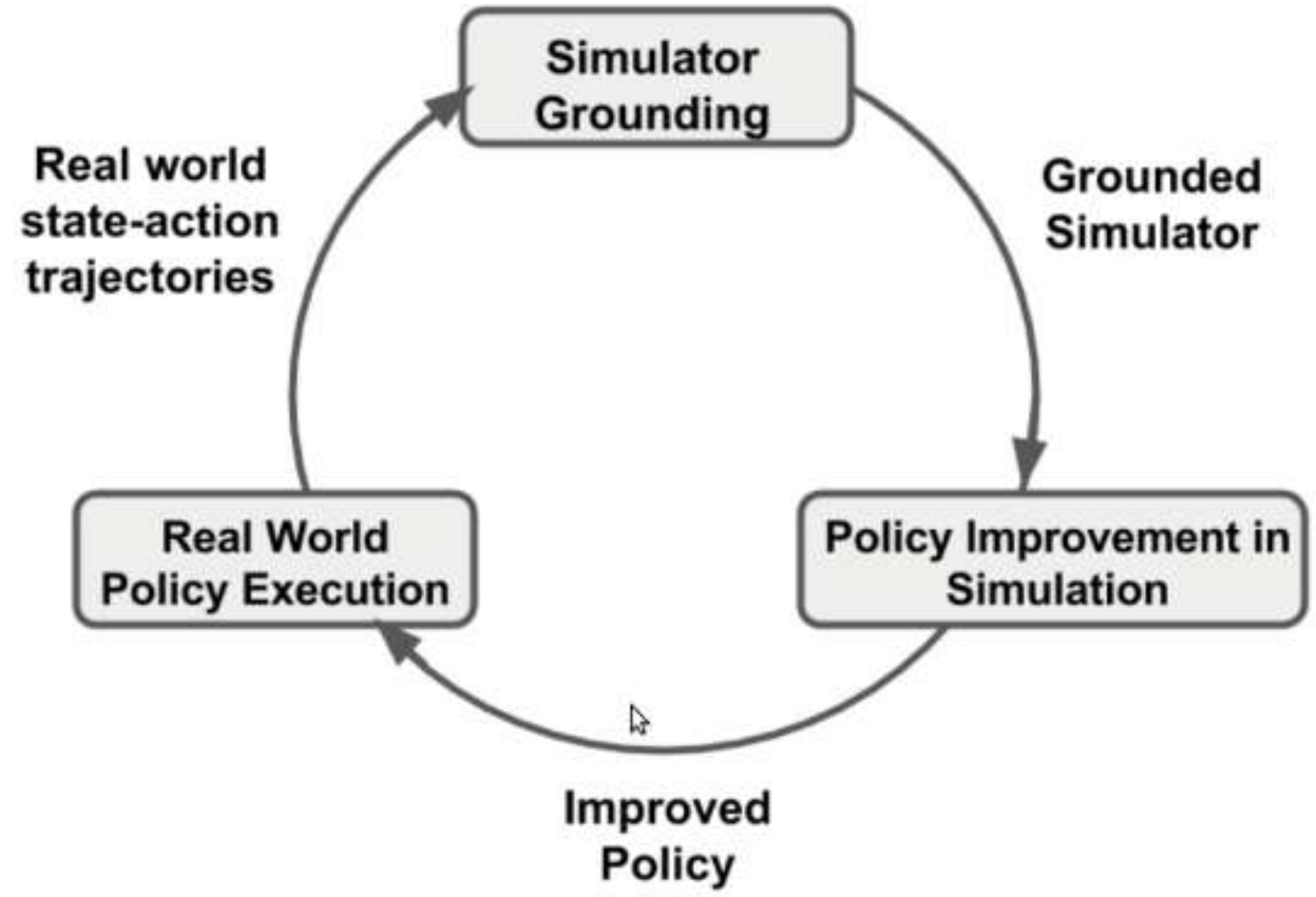

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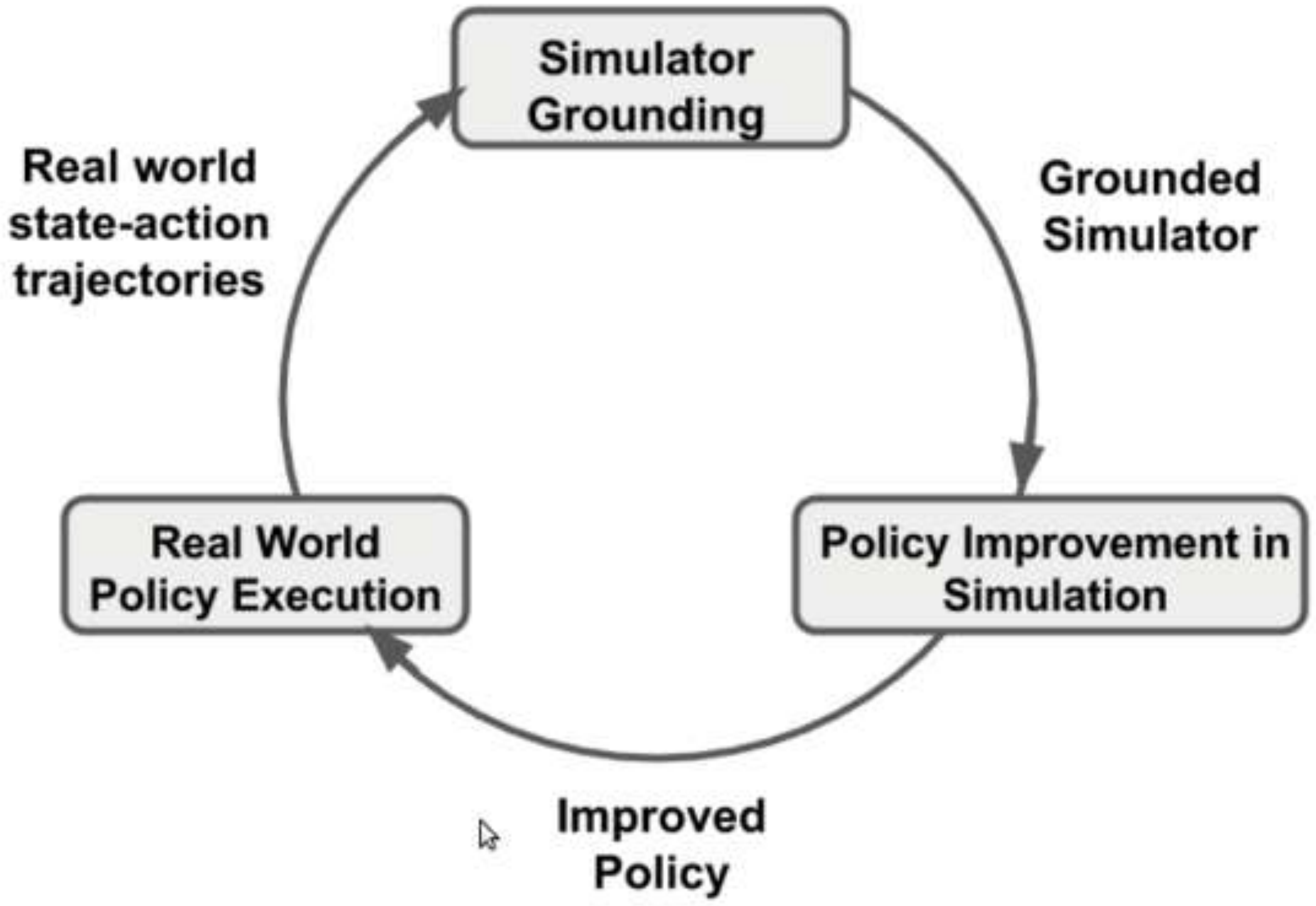

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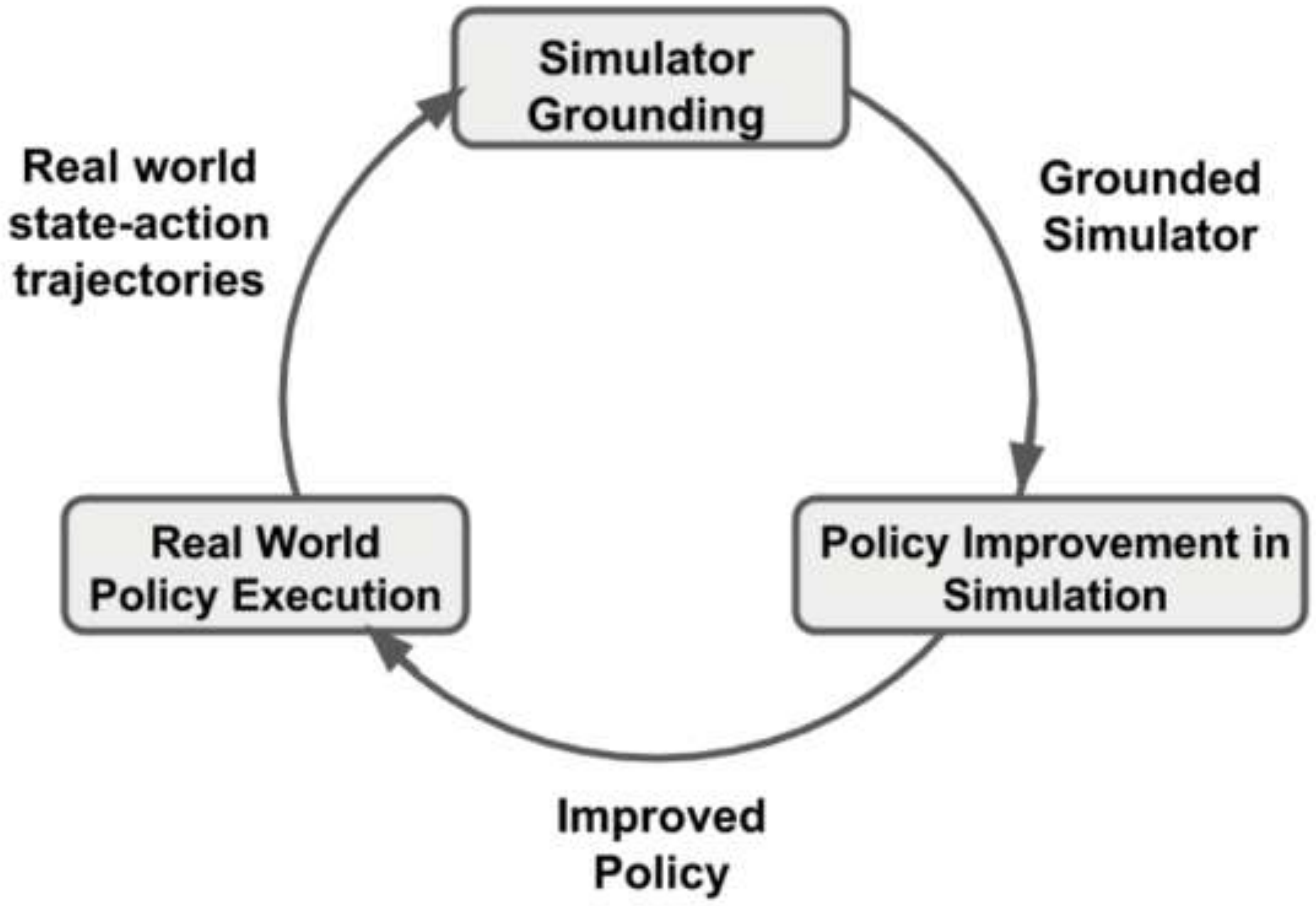

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2nd iteration	**28.0**	43.3

GSL Summary

- Introduced **Grounded Simulation Learning** for Sim2Real.

Hanna and Stone, AAAI 2017

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- Improved walk speed of Nao robot by over 40% compared to state-of-the-art walk engine.
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Patrick MacAlpine

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- When does grounding actions work and when does it not?

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Robot Skill Learning: Real World to Sim and Back

- Motivation: RoboCup
- Sim2Real: Grounded Simulation Learning
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Faraz Torabi

Garrett Warnell

Imitation Learning

Goal:

- Learn how to make decisions by trying to imitate another agent.

Imitation Learning

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Conventional Imitation Learning:

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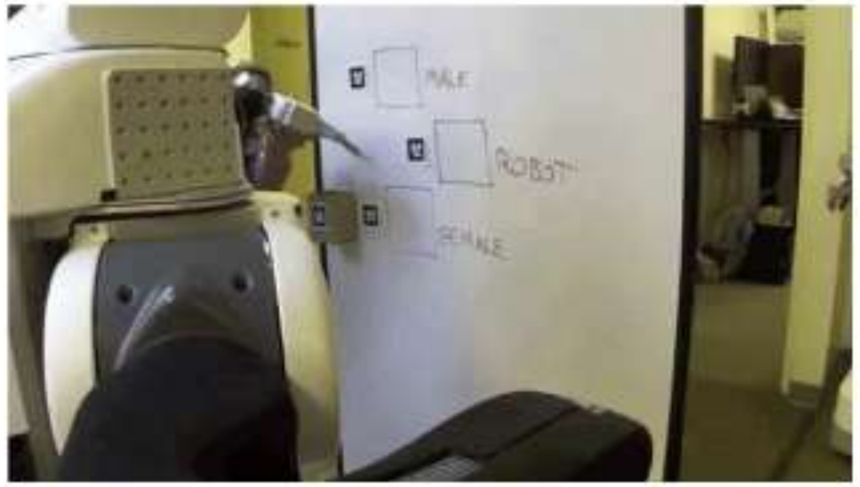

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Conventional Imitation Learning:

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Challenge:

- Precludes using a large amount of demonstration data where action sequences are not given (e.g. YouTube videos).

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Imitation Learning

Algorithms:

Imitation Learning

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- Behavioral Cloning:

Imitation Learning

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[3] Ho and Ermon, "Generative adversarial imitation learning".

[4] Finn, Levine, and Abbeel, "Guided cost learning: Deep inverse optimal control via policy optimization".

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Formulation:

- Given:
  - $D_{demo} = (s_0, s_1, ...)$
- Learn:
  - $\pi : \mathcal{S} \rightarrow \mathcal{A}$

Imitation from Observation

Previous work:

Imitation from Observation

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- Time Contrastive Networks (TCN).[5]
- Imitation from observation: Learning to imitate behaviors from raw video via context translation.[6]
- Learning invariant feature spaces to transfer skills with reinforcement learning.[7]

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Concentrate on perception; require time-aligned demonstrations.

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Efficient Robot Skill Learning

- Motivation: RoboCup
- Sim2Real: Grounded Simulation Learning
- Imitation Learning from Observation:
  - **Model-based approach:** BCO
  - Model-free approach: GAIfO

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- Imitation Learning: $D_{demo} = \{(s_0, a_0), (s_1, a_1), ...\}$

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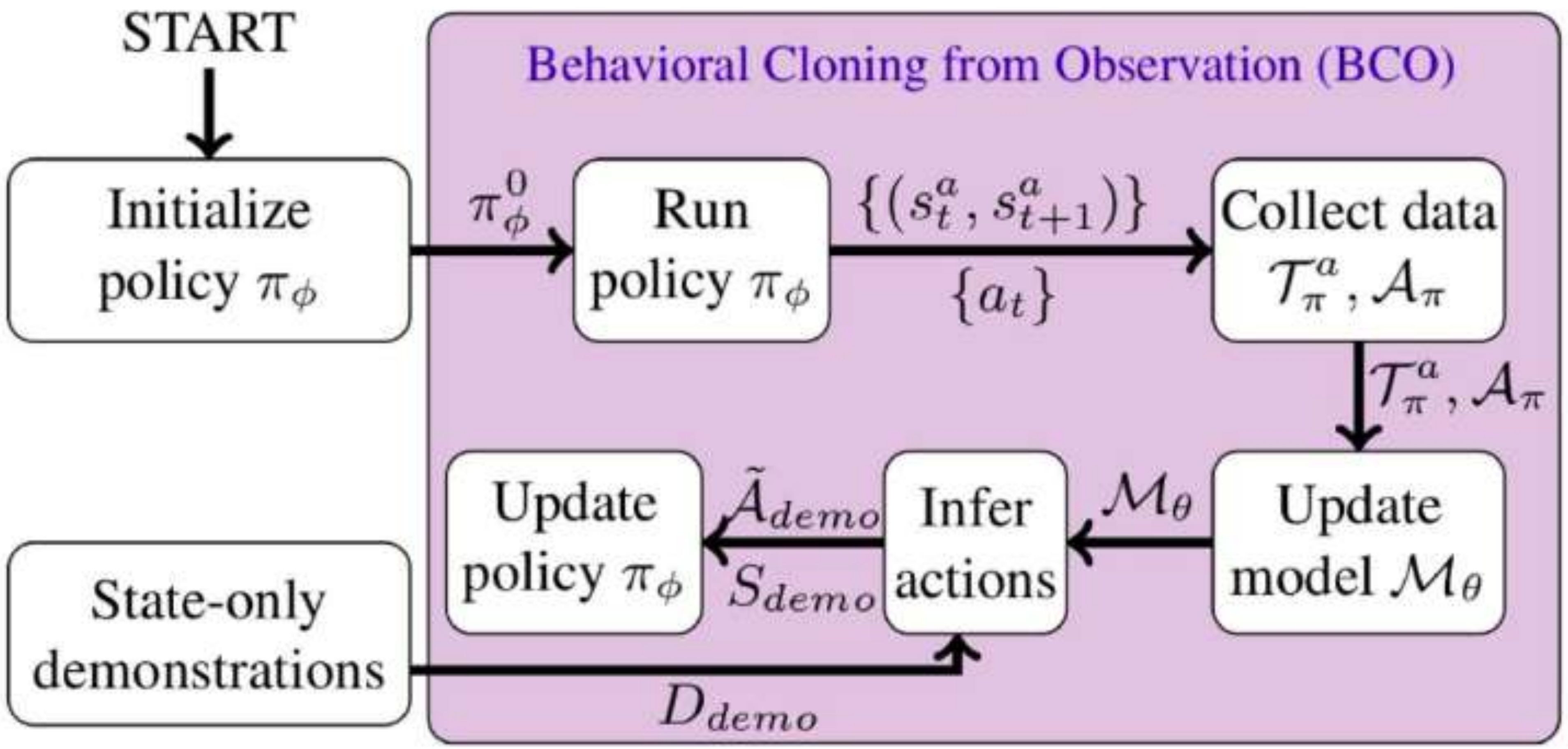
Model-based Approach:

Learn an inverse dynamics model → Infer actions → Perform a conventional IL method

Behavioral Cloning from Observation (BCO)

Algorithm:



Torabi, Warnell, and Stone, IJCAI 2018

Behavioral Cloning from Observation (BCO)

Experimental Results:

- Domain:
  - Mujoco domain "Ant" with 111 dimensional state space and 8 dimensional action space.

Behavioral Cloning from Observation (BCO)

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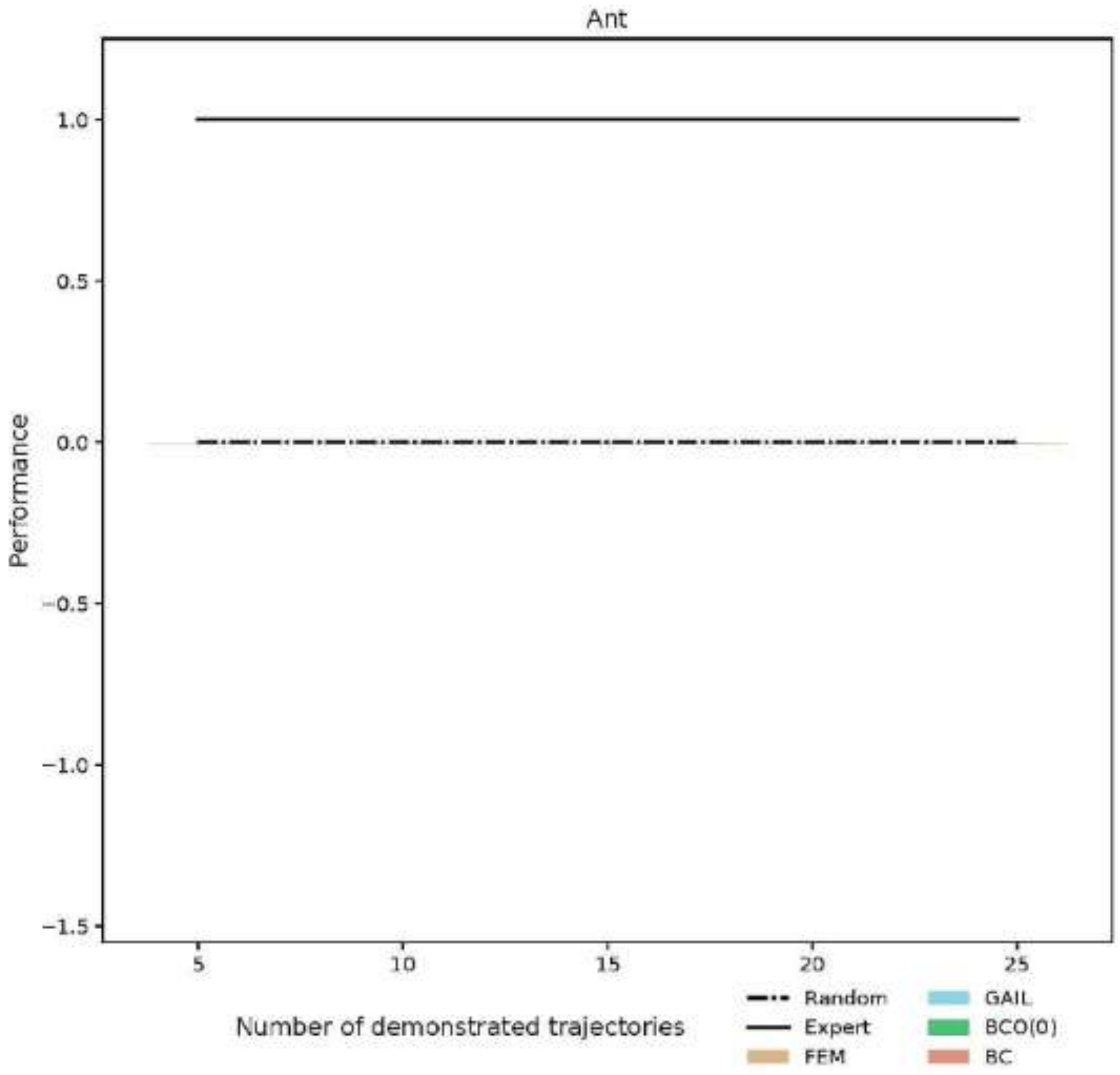

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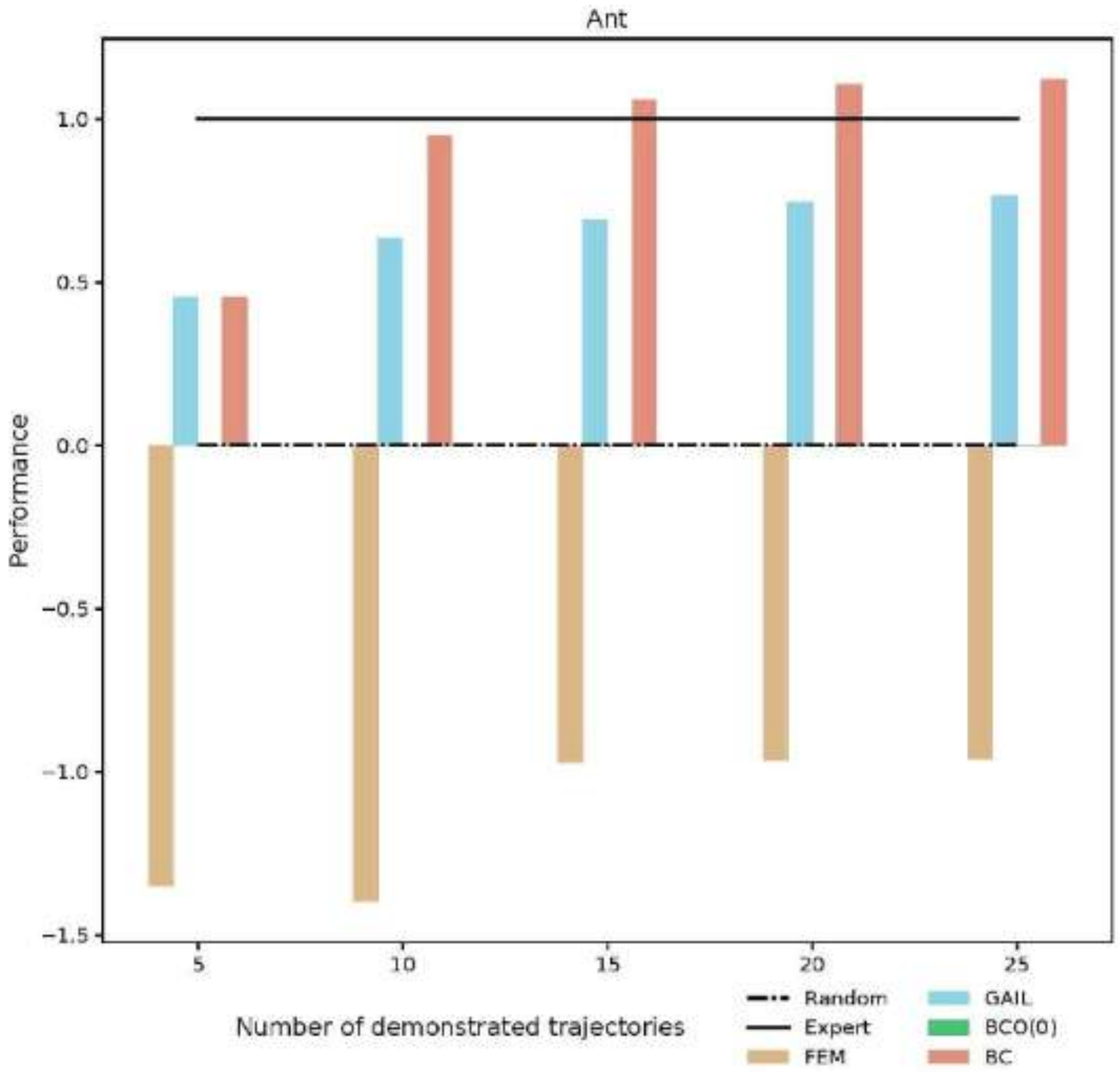

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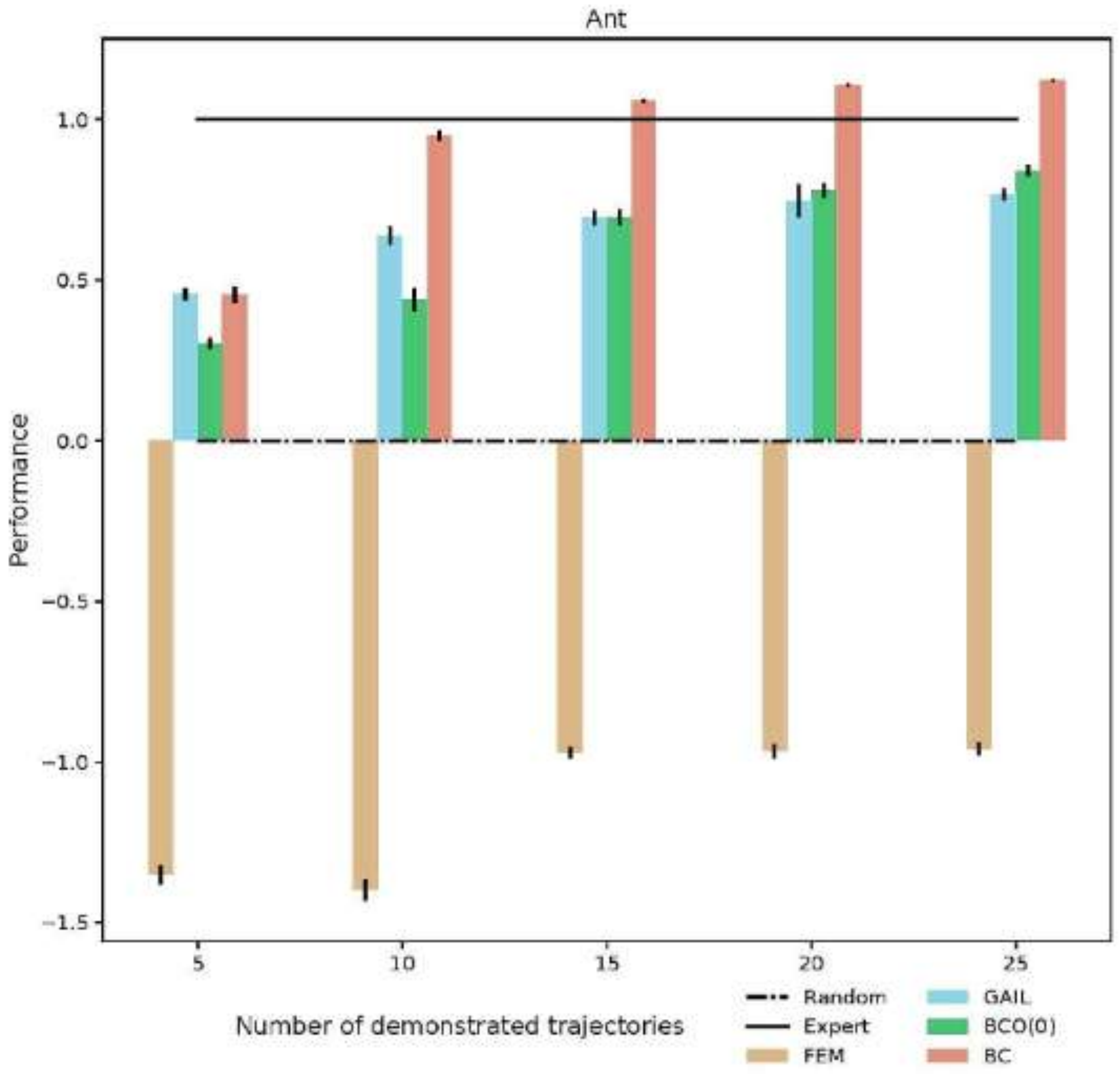

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- Update the model with the learned policy.
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  - Increasing α: increasing the number of interactions allowed at each iteration.

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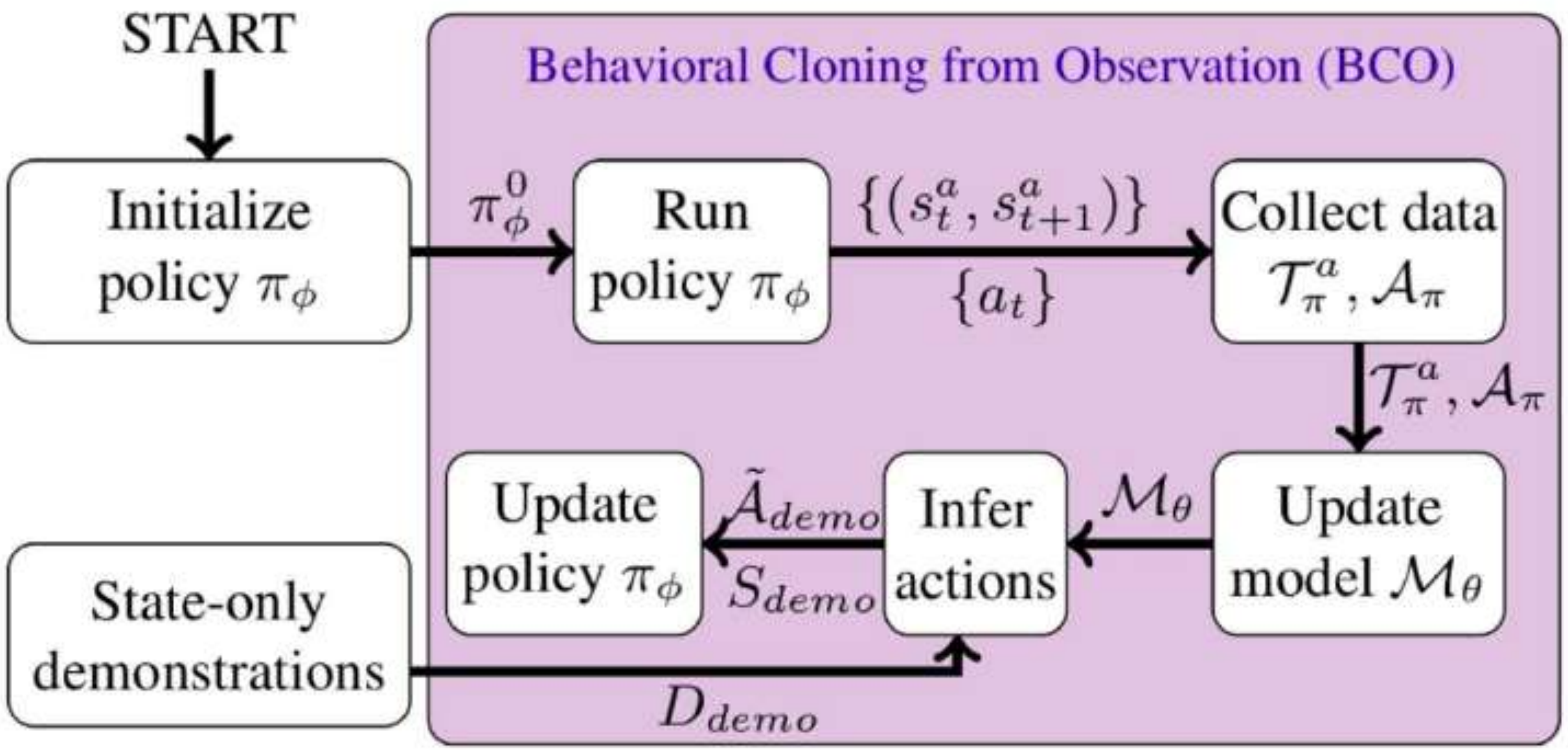

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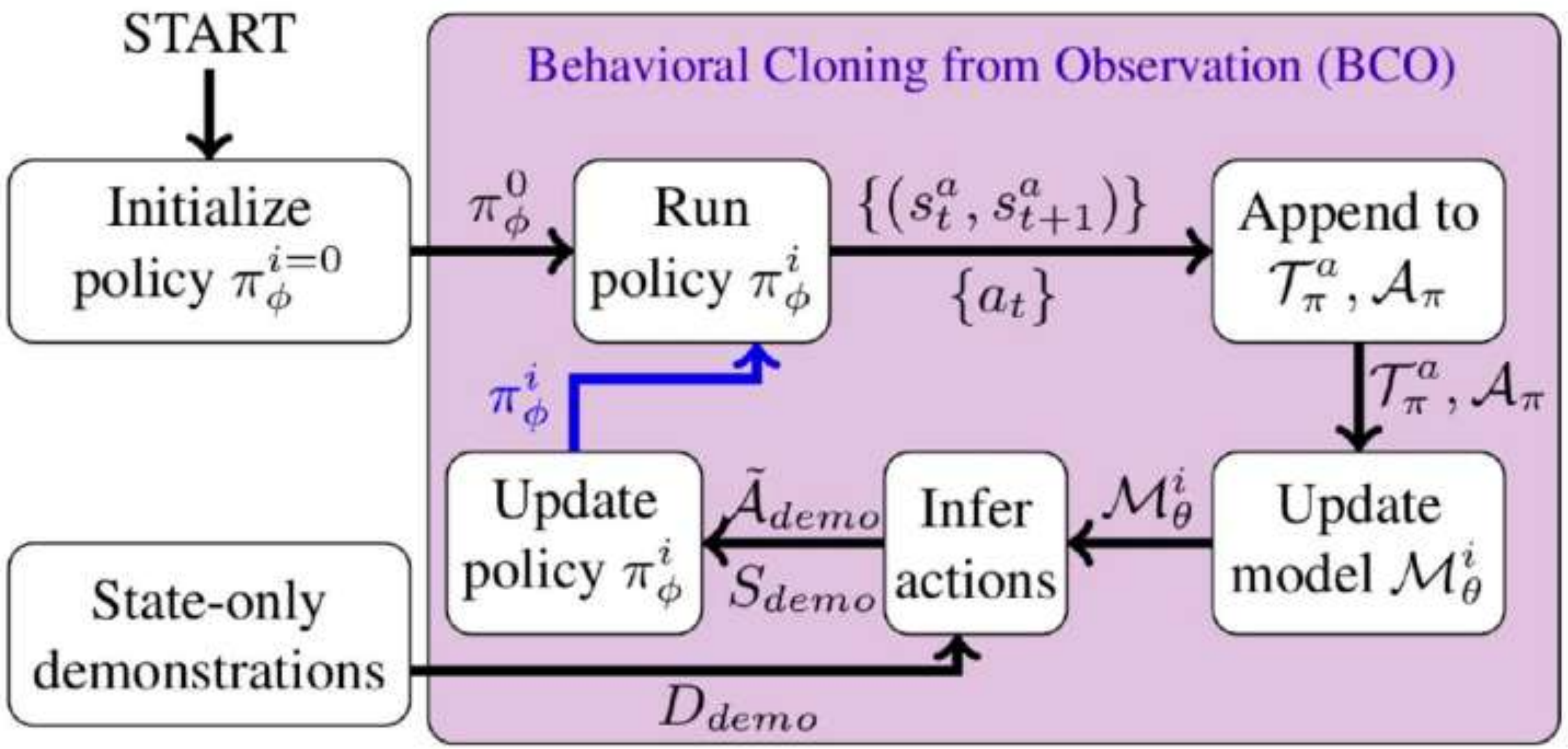

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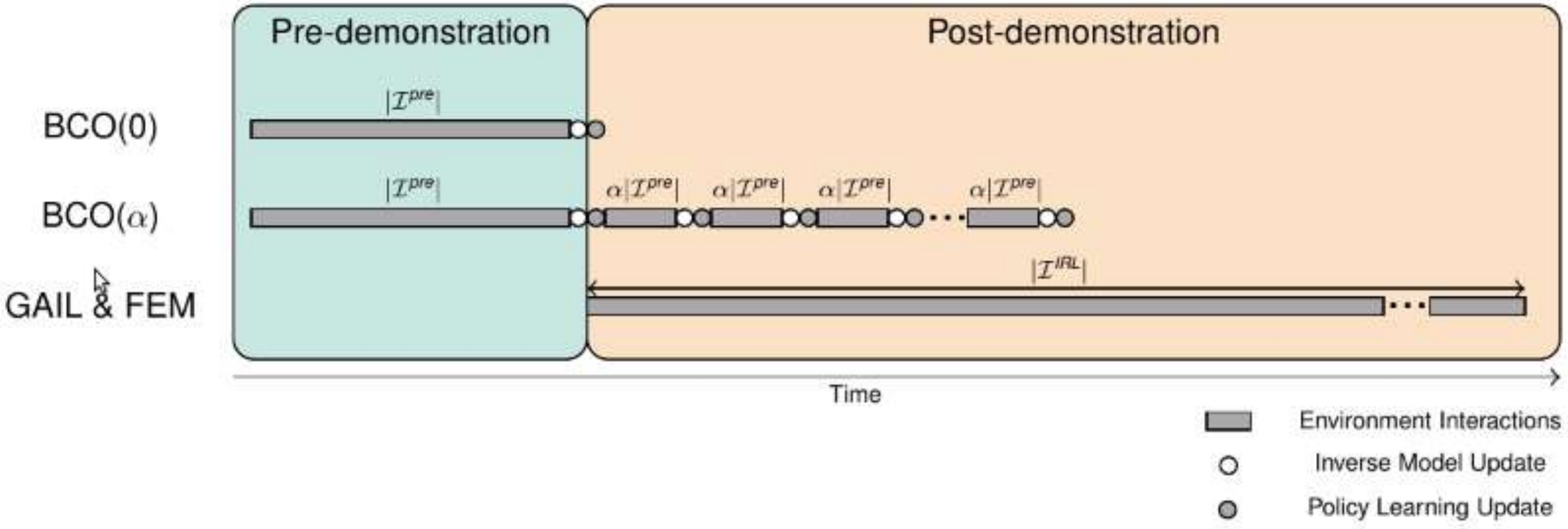
Interaction time:



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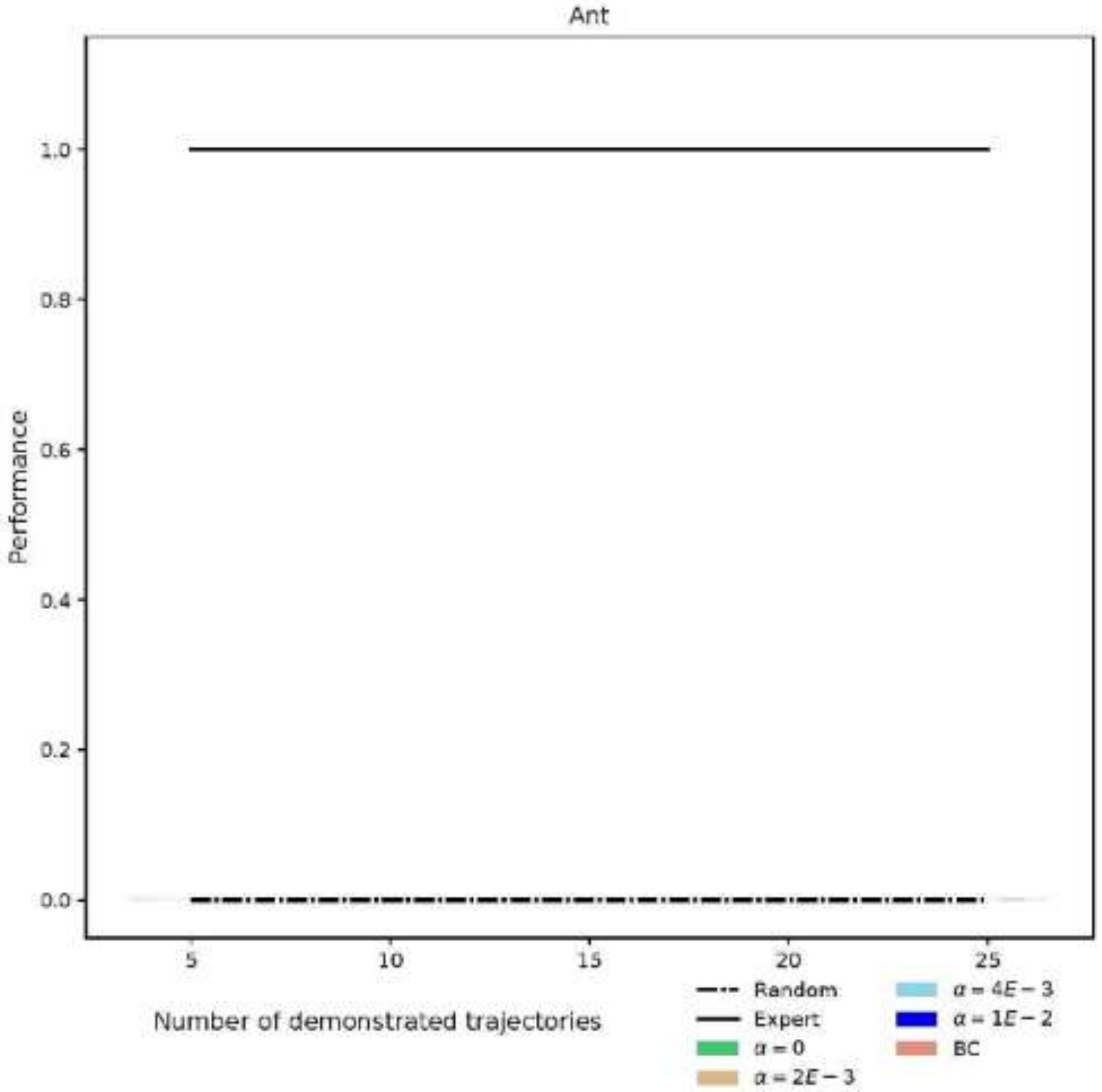
Effect of varying α on BCO(α):



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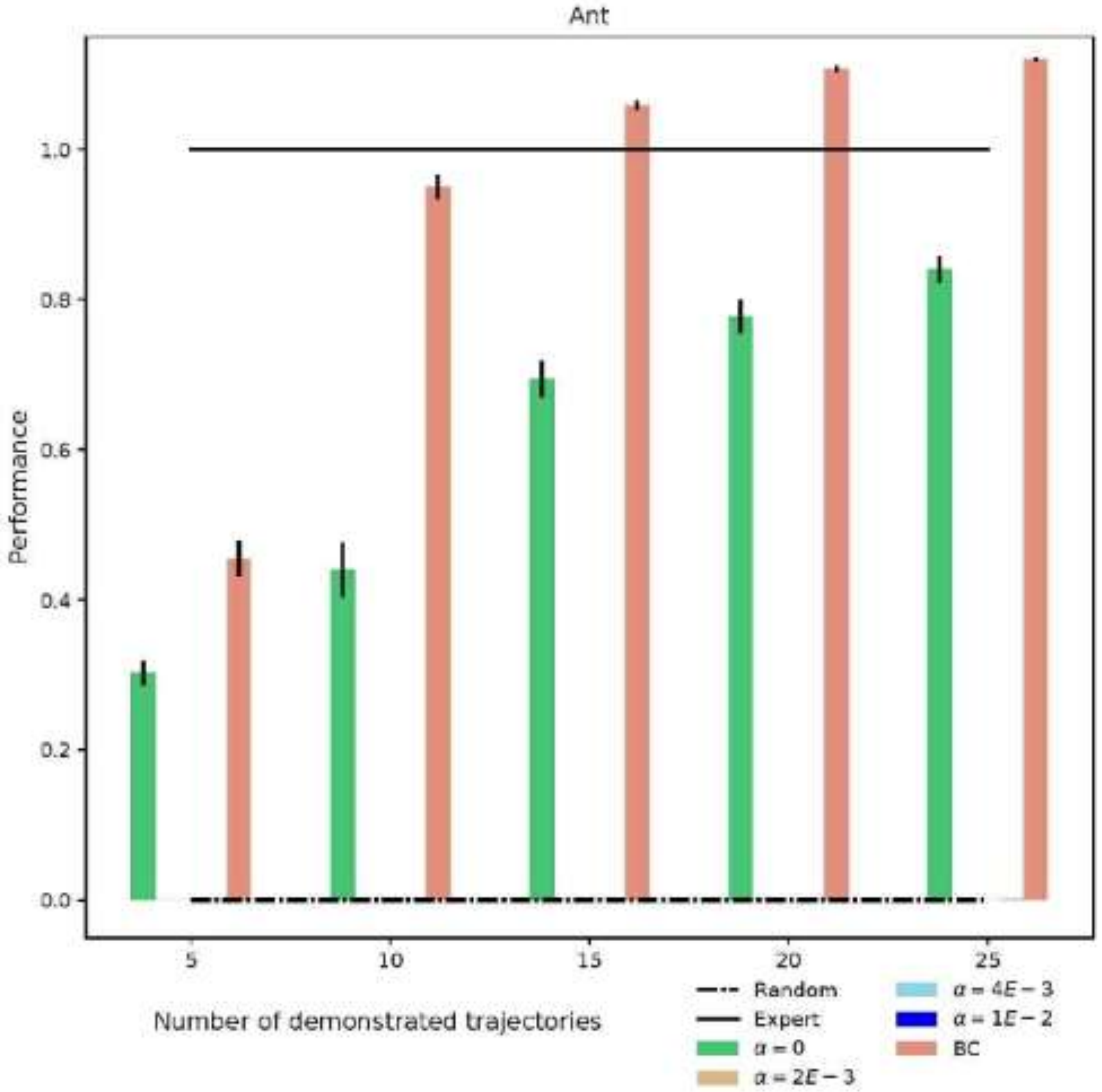

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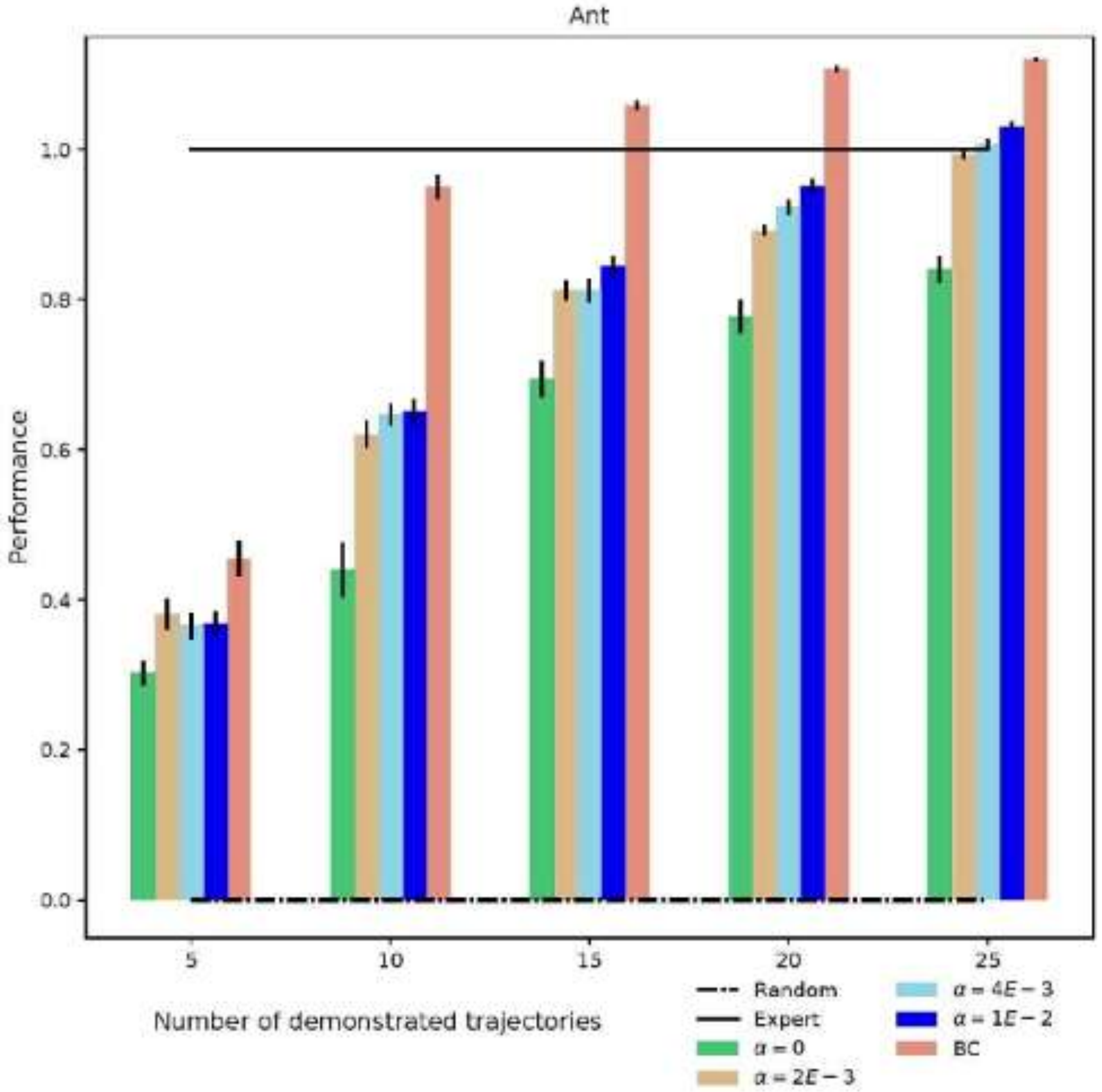

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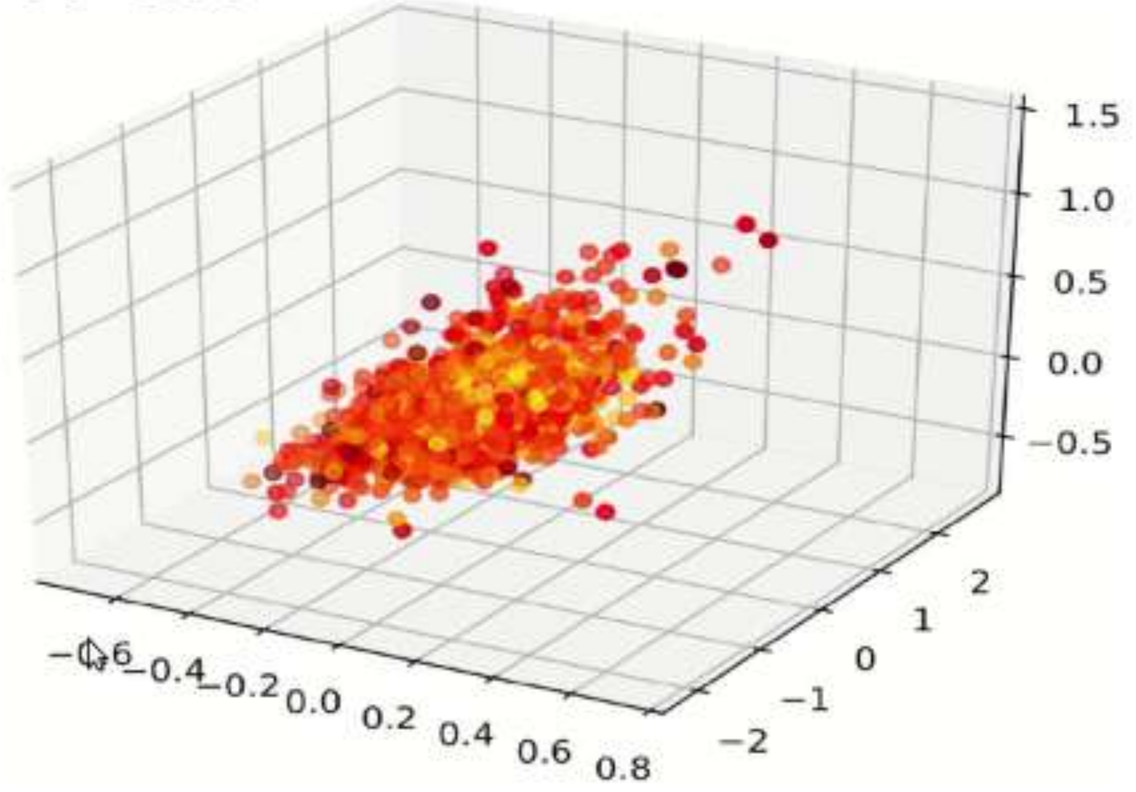
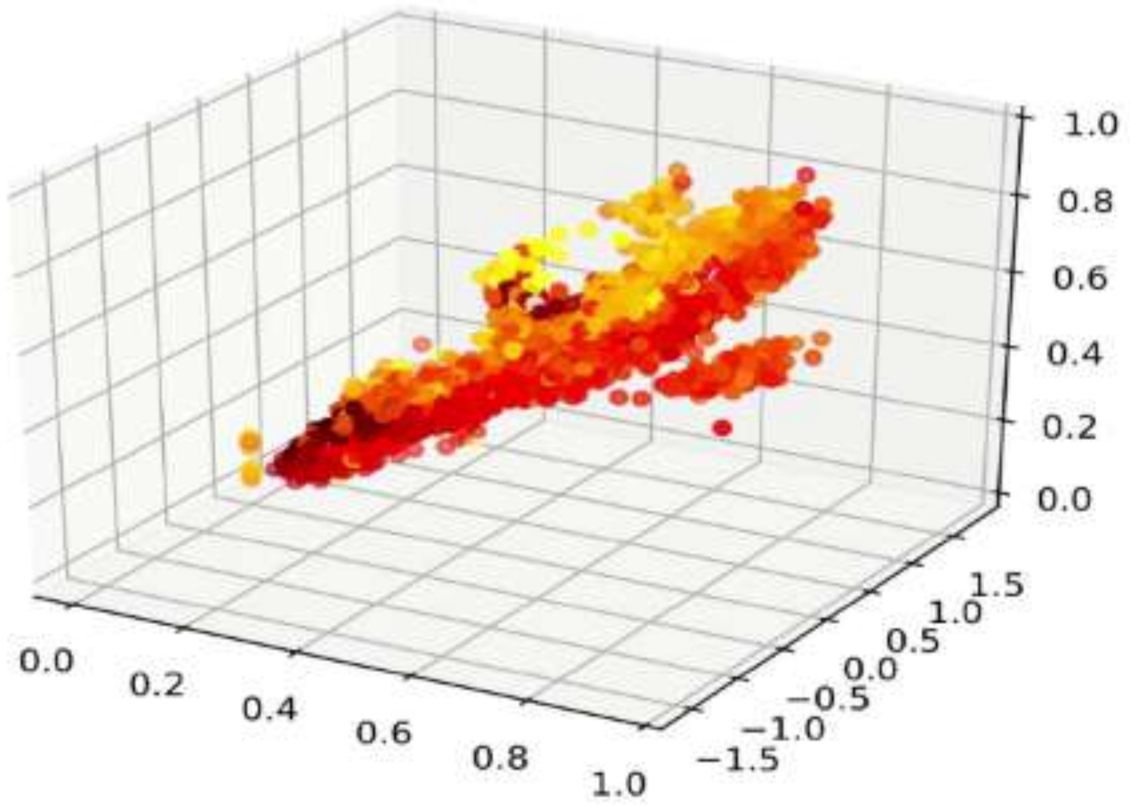
Gen. Adversarial Imitation from Observation (GAIfO)

Motivation:



(a) Random Policy



(b) Demonstration

Figure: State transition distribution in Hopper domain.

Gen. Adversarial Imitation from Observation (GAIfO)

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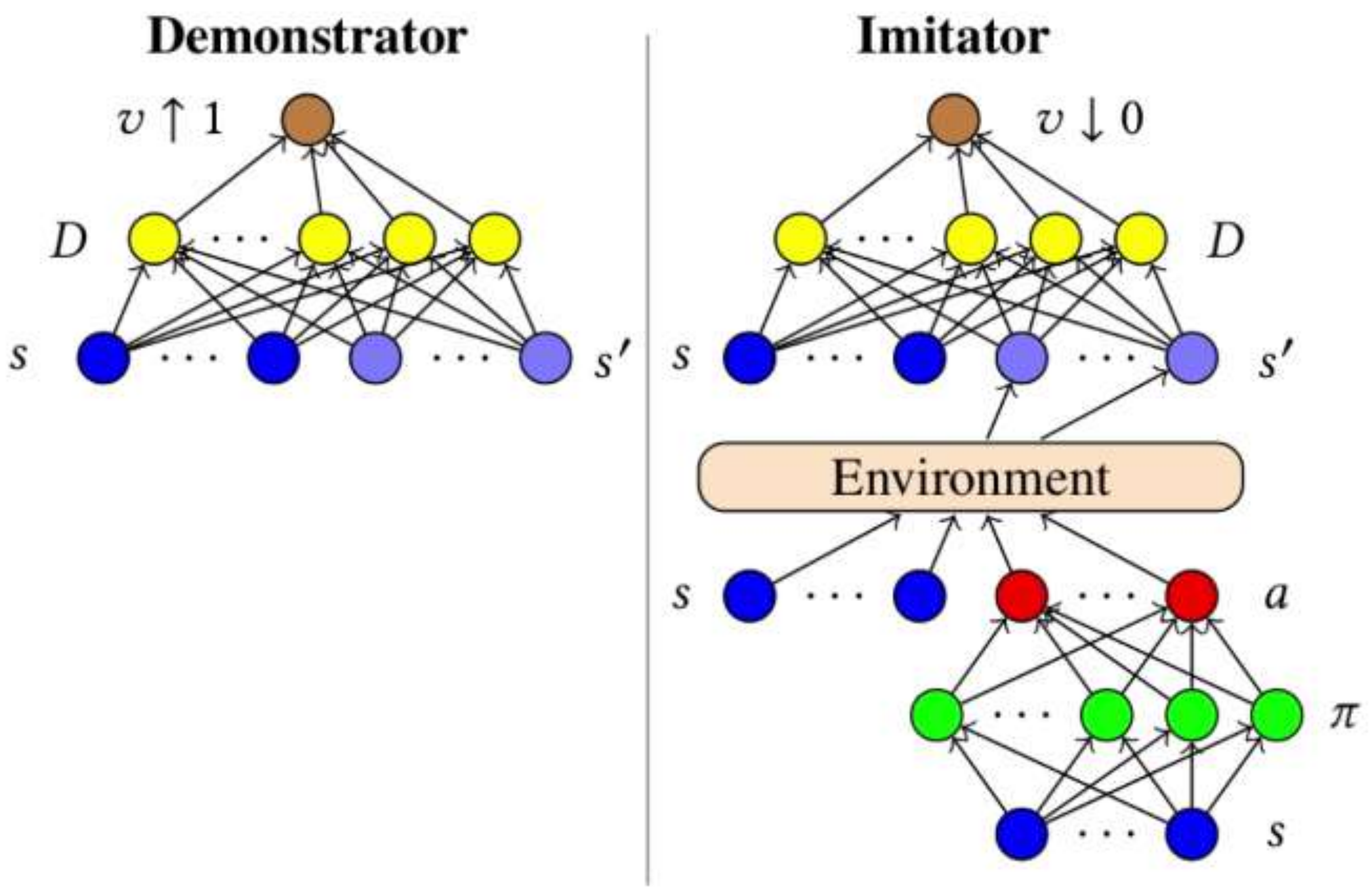
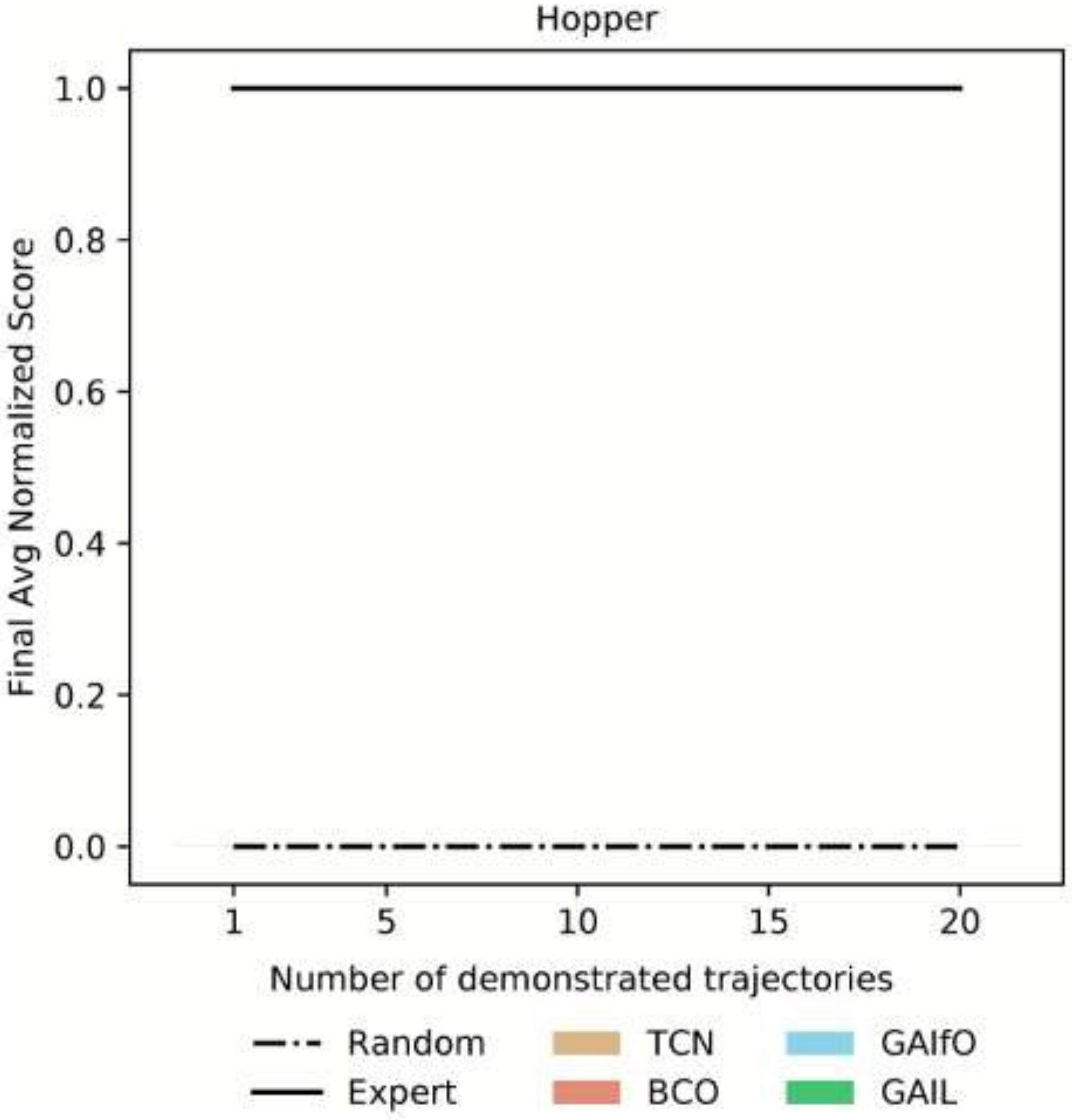


Gen. Adversarial Imitation from Observation (GAIfO)

Comparison against other IfO approaches and GAIL:



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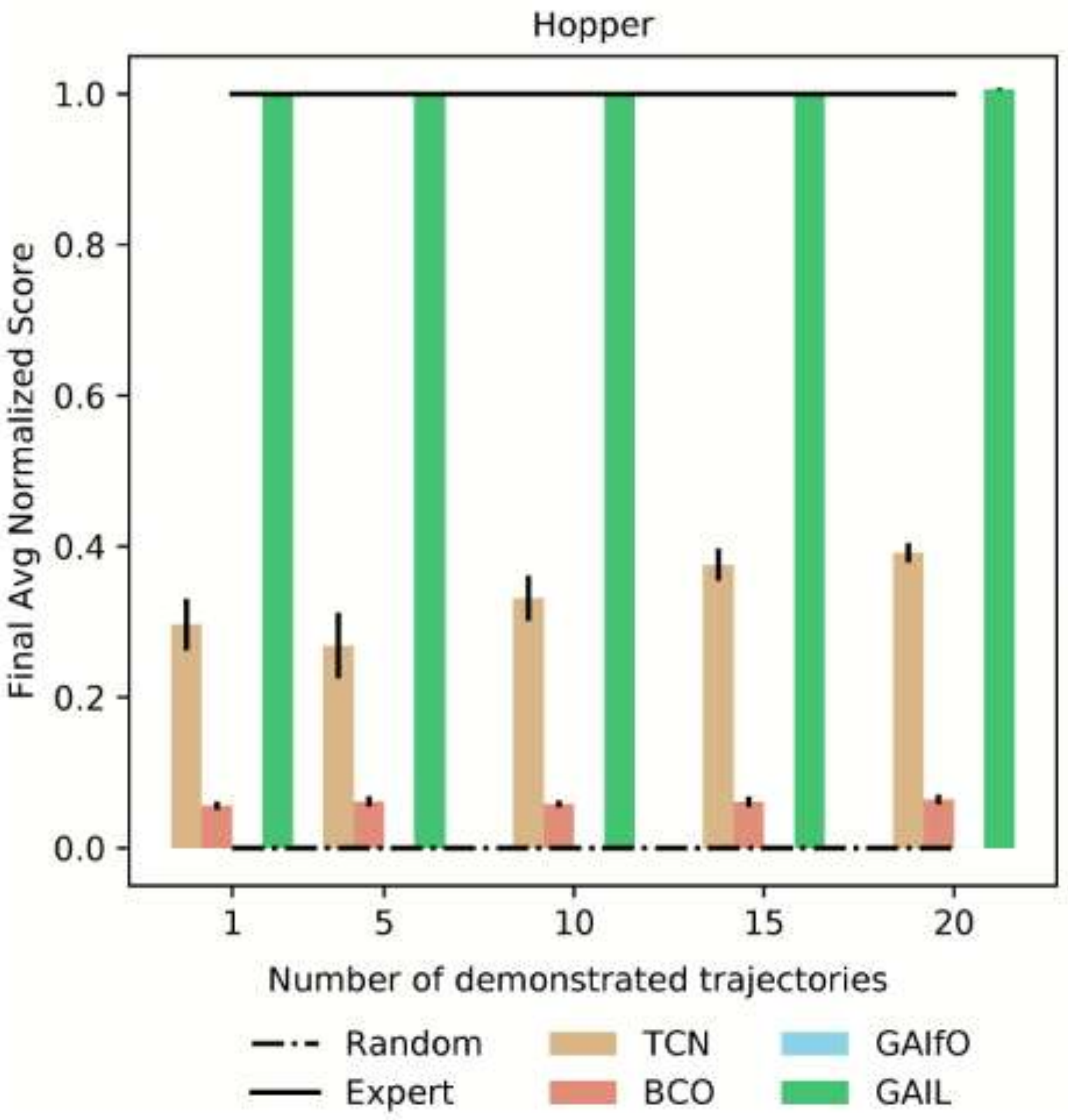

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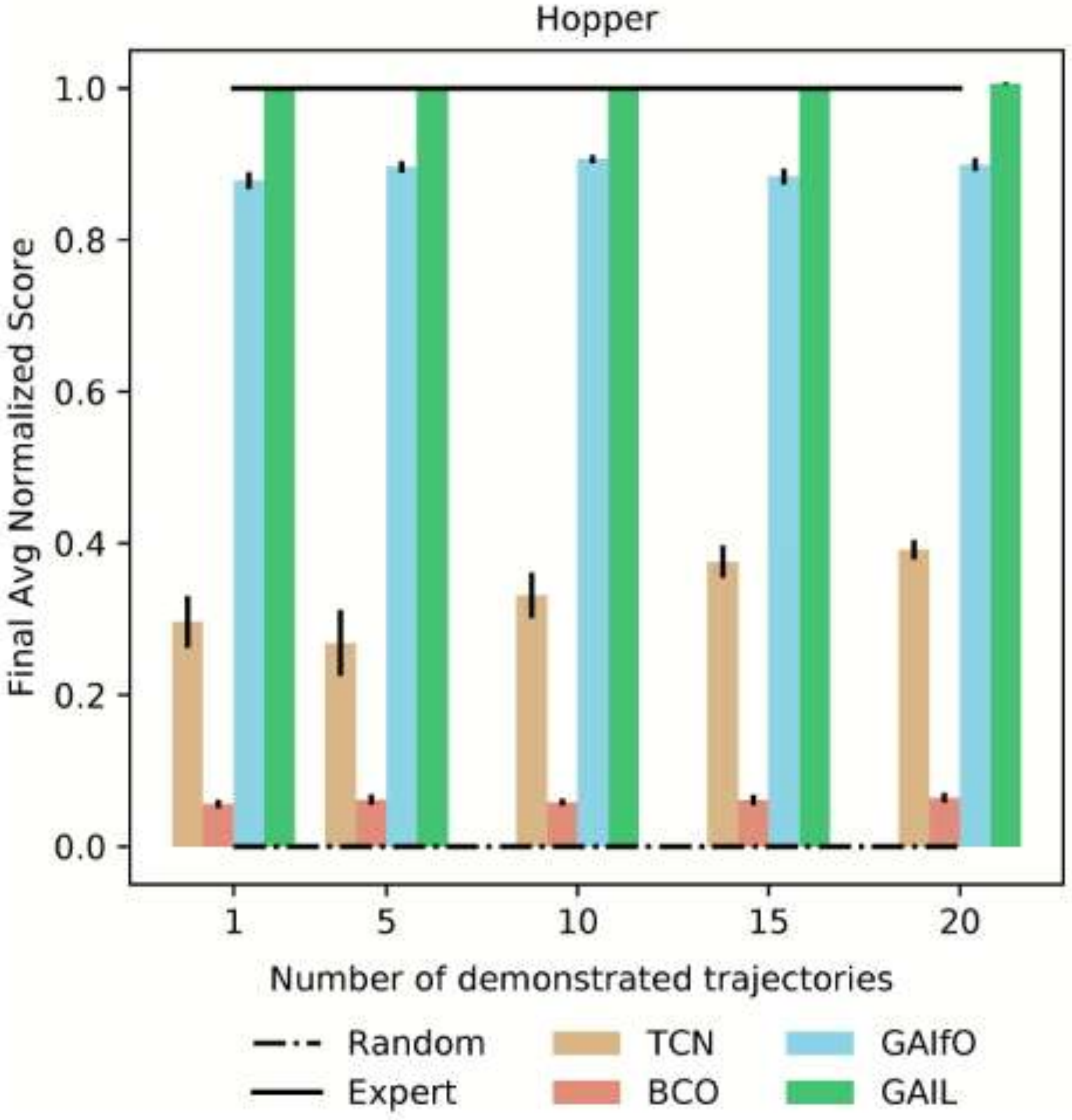

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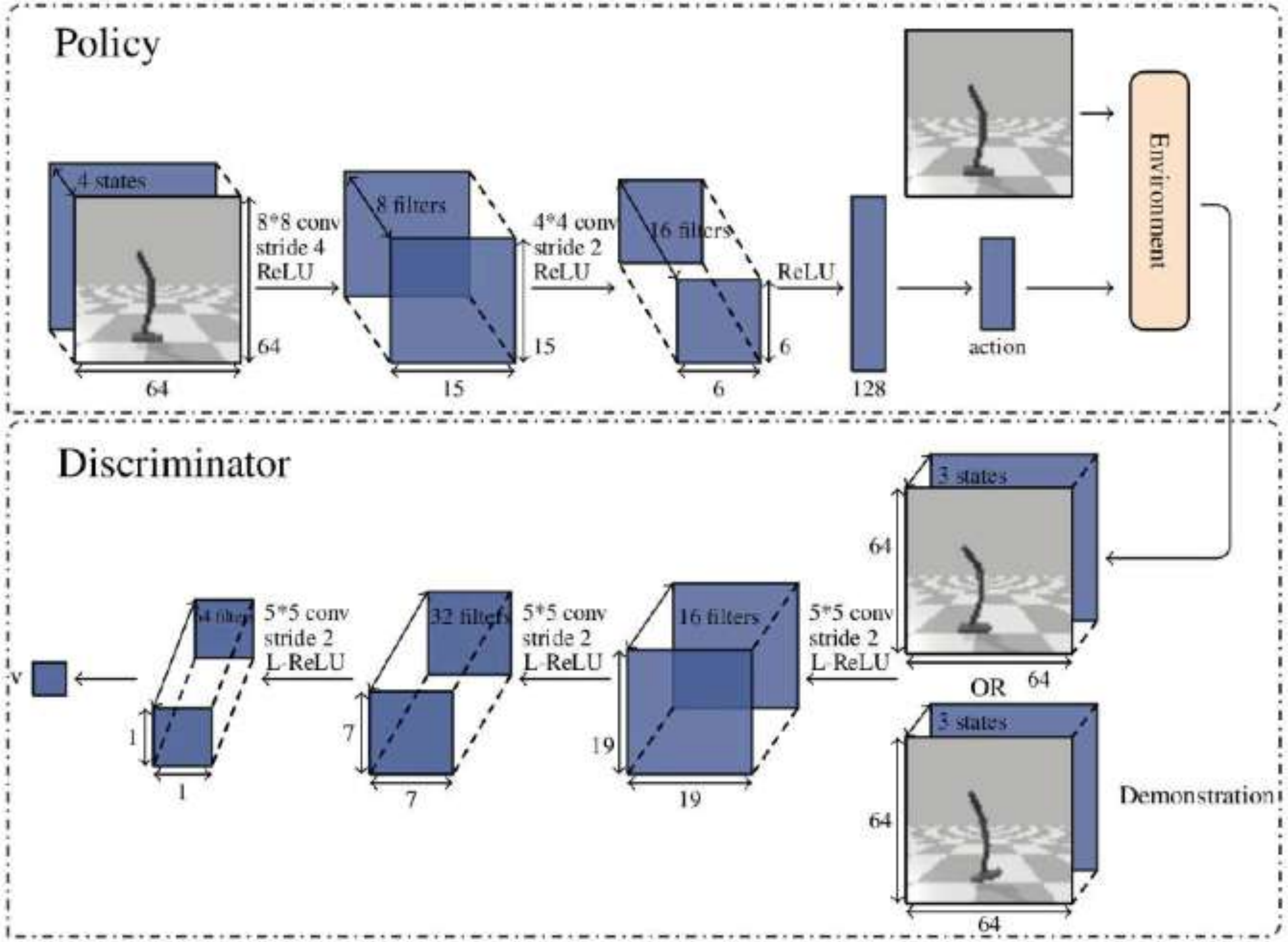

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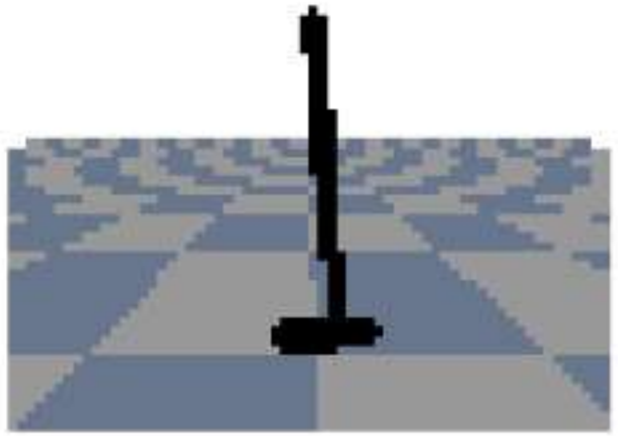

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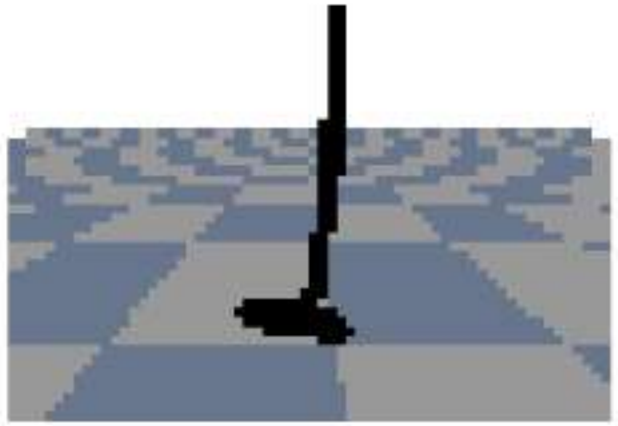
Learned Policy:



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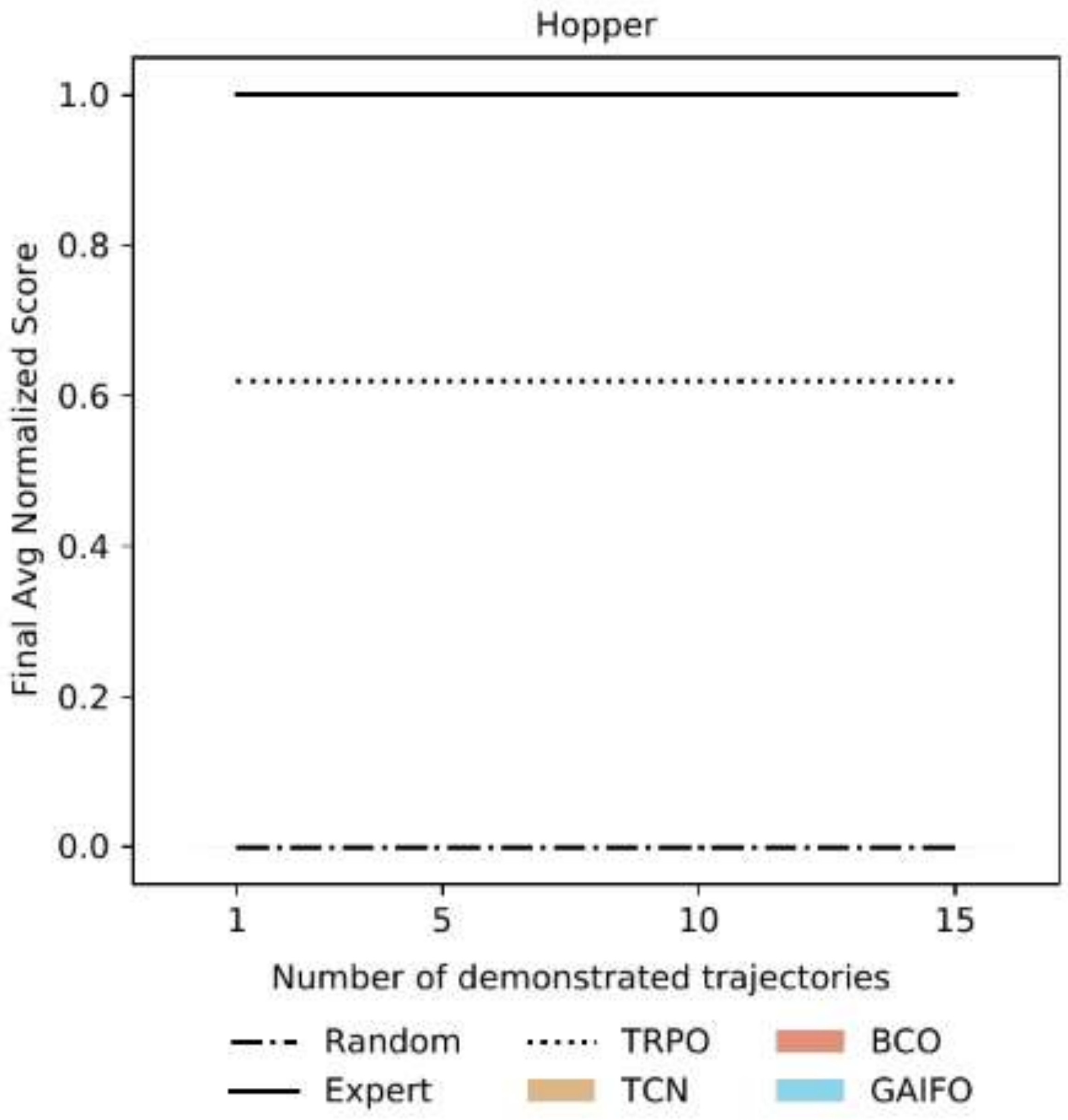

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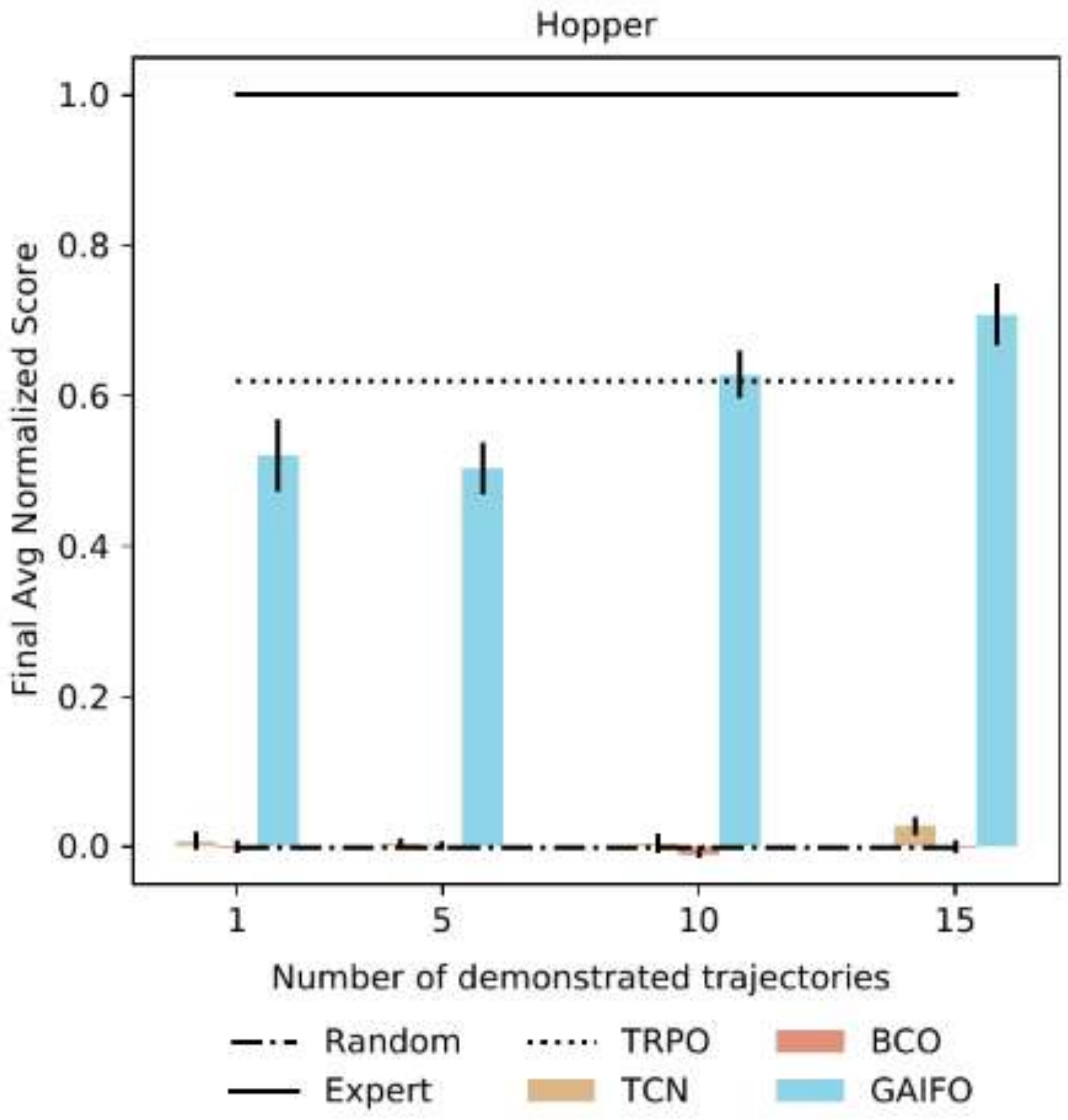

Ongoing Work

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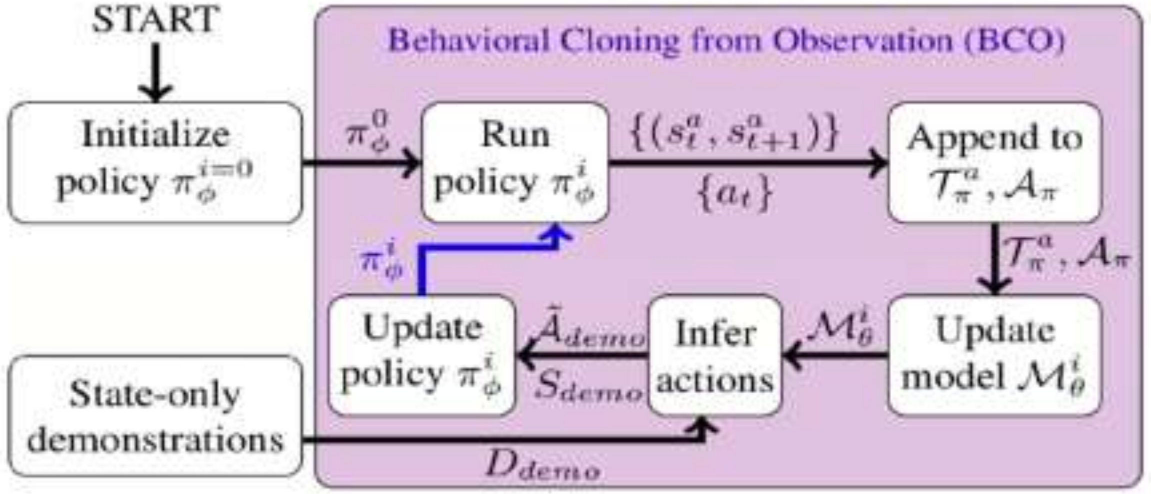
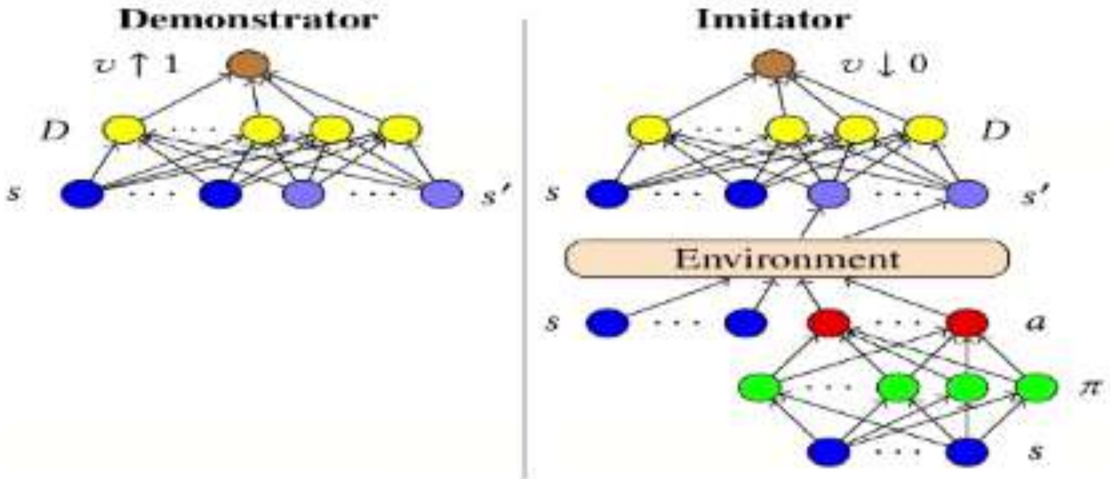
- Sim-to-real transfer using the algorithms.

Imitation Learning Summary



(a) BCO



(b) GAIfO

Faraz Torabi

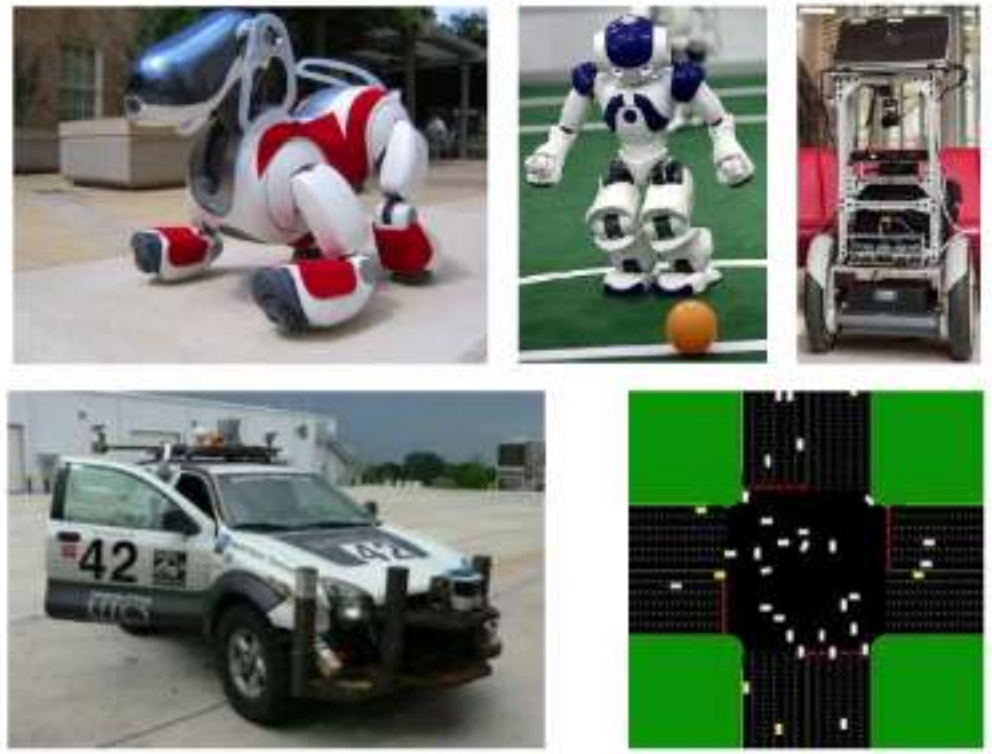
Garrett Warnell

Research Question

To what degree can autonomous intelligent agents learn in the presence of teammates and/or adversaries in real-time, dynamic domains?

Research Areas

- Autonomous agents
- Multiagent systems
- Machine learning
  - **Reinforcement learning**
- **Robotics**



Selected other RL Contributions

- Human interaction
  - Advice, Demonstration
  - Positive/Negative Feedback

[Knox & Stone, '09]

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  - Sample efficient; real-time
  - Continuous state; delayed effects
- Deep RL in continuous action spaces [Hausknecht & Stone, '16]

Selected MAS Contributions

- Autonomous traffic management
- Trading Agent Competition (PowerTAC)
- Ad Hoc Teamwork

Ad Hoc Teams

- Ad hoc team player is an individual
  - Unknown teammates (programmed by others)
- Teammates likely sub-optimal: no control

Challenge: Create a good team player

- Introduced as AAAI Challenge Problem [AAAI'10]
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Benchmarking Robot Cooperation without Pre-Coordination in the RoboCup Standard Platform League Drop-In Player Competition

Katie Genter*, Tim Laue°, Peter Stone*

* University of Texas at Austin, Austin, TX, USA

° University of Bremen, Germany

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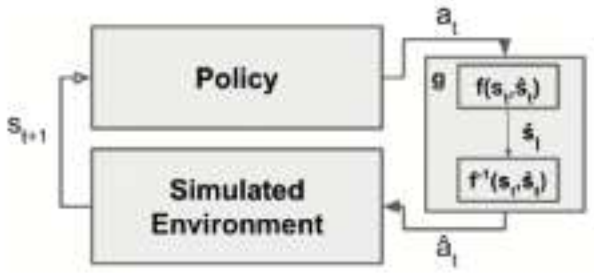
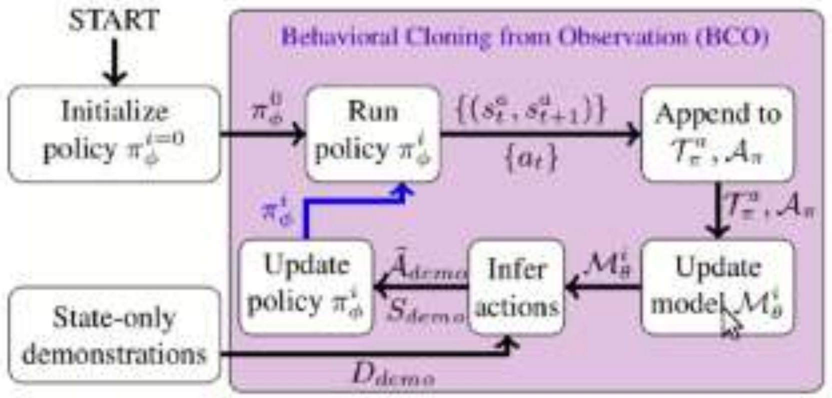
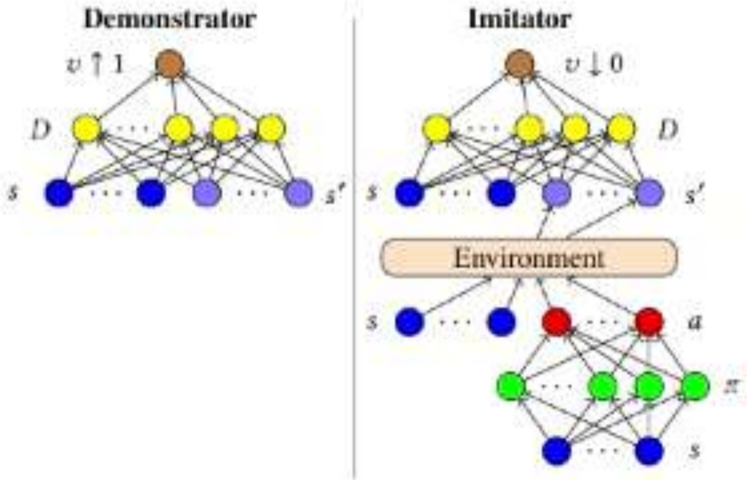
Efficient Robot Skill Learning: GSL and IfO

To what degree can autonomous intelligent agents learn in the presence of teammates and/or adversaries in real-time, dynamic domains?







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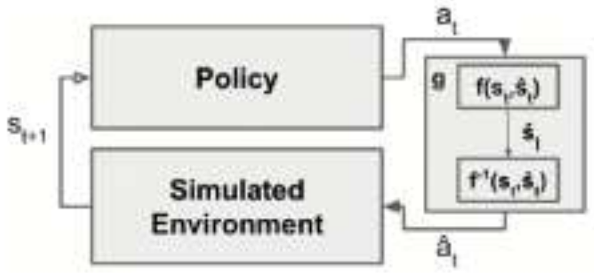

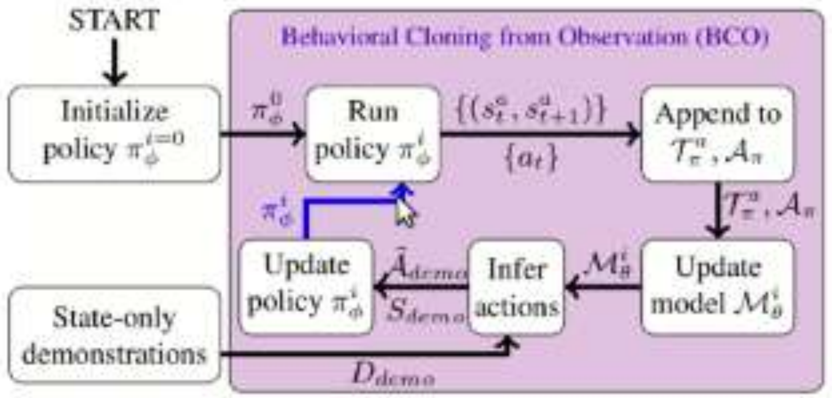

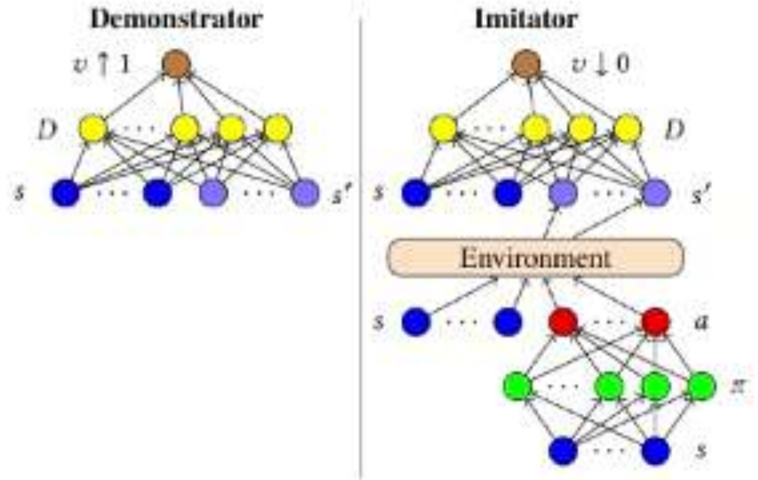

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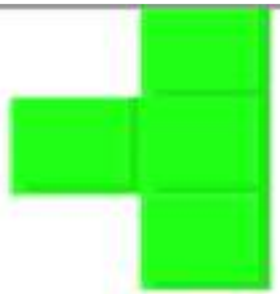

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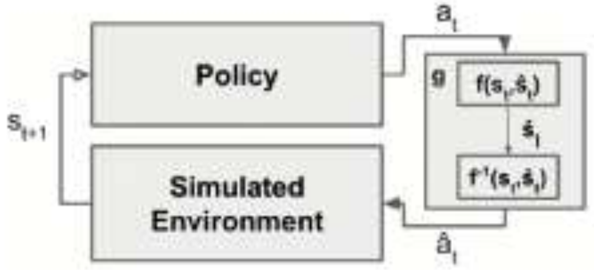

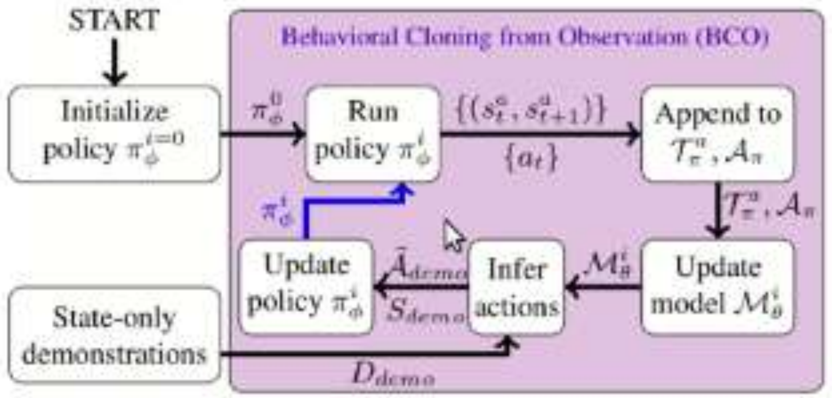

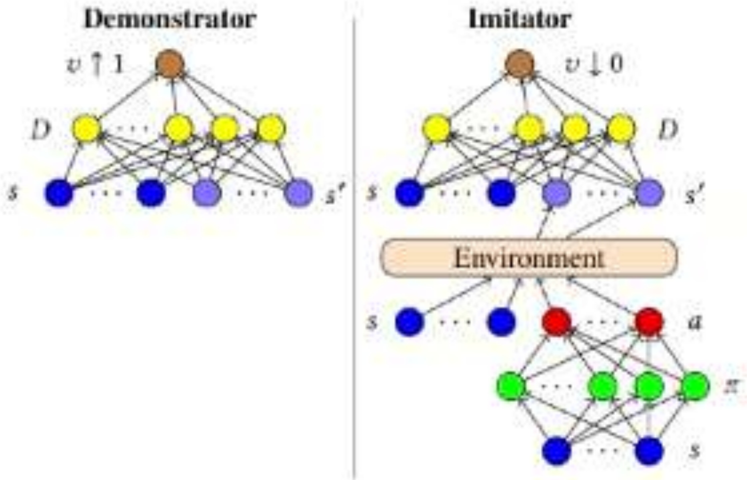

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