Robot Skill Learning: Real World to Sim and Back

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

Faraz Torabi

Garrett Warnell

Imitation Learning

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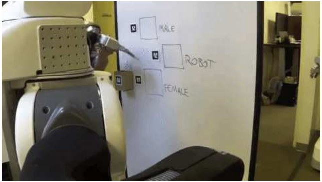

Imitation Learning

Goal:

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

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).

[1] Niekum et al., "Learning and generalization of complex tasks from unstructured demonstrations".

Imitation Learning

Algorithms:

Imitation Learning

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- Behavioral Cloning:

Imitation Learning

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- Behavioral Cloning:
  - End to End Learning for Self-Driving Cars.[2]

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- Behavioral Cloning:
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- Behavioral Cloning:
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- Inverse Reinforcement Learning:
  - Generative Adversarial Imitation Learning.[3]
  - Guided Cost Learning.[4]

[2] Zhang and Cho, "Query-Efficient Imitation Learning for End-to-End Simulated Driving."

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

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

Imitation from Observation

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- Learn how to perform a task given state-only demonstrations.

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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]

[5] Sermanet et al., "Time-contrastive networks: Self-supervised learning from multi-view observation".

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Concentrate on perception; require time-aligned demonstrations.

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Efficient Robot Skill Learning

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Model-based Approach

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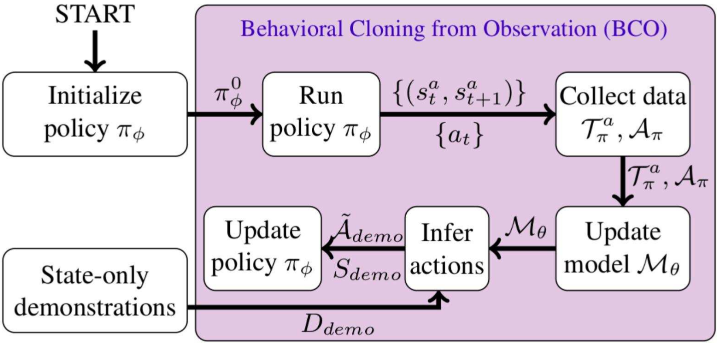
Model-based Approach:

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

Behavioral Cloning from Observation (BCO)

Algorithm:

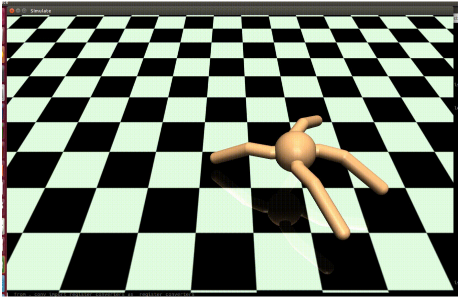


Torabi, Warnell, and Stone, IJCAI 2018

Behavioral Cloning from Observation (BCO)

Experimental Results:

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



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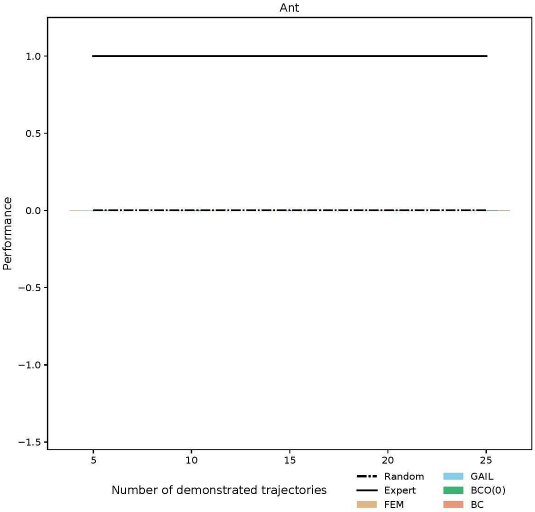

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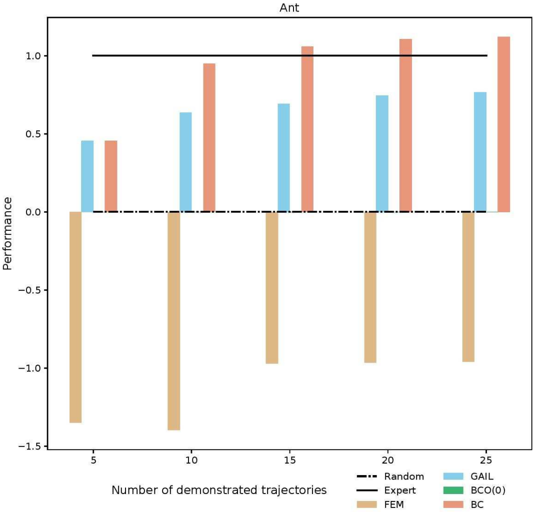

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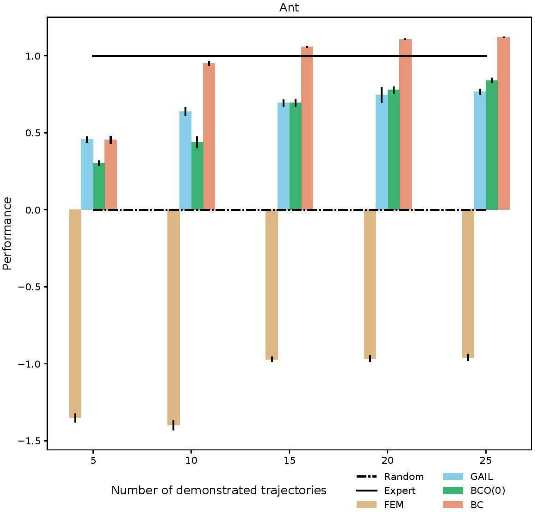

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  - $\alpha = 0$: no post-demonstration interaction.

Behavioral Cloning from Observation (BCO(α))

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- Inverse dynamics model is learned using a random policy.

Solution: BCO(α)

- Update the model with the learned policy.
- Parameter α controls tradeoff between performance and environment interactions
  - $\alpha = 0$: no post-demonstration interaction.
  - Increasing α: increasing the number of interactions allowed at each iteration.

Behavioral Cloning from Observation (BCO(α))

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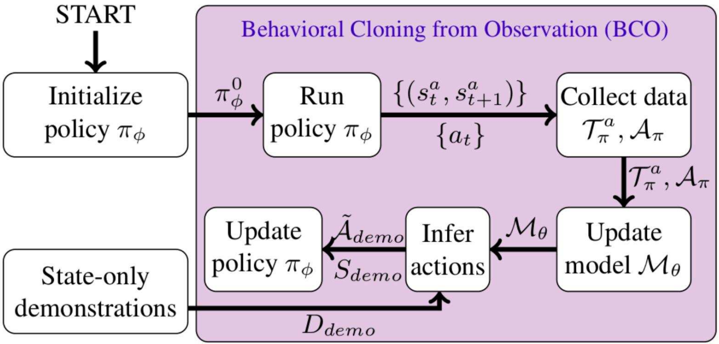

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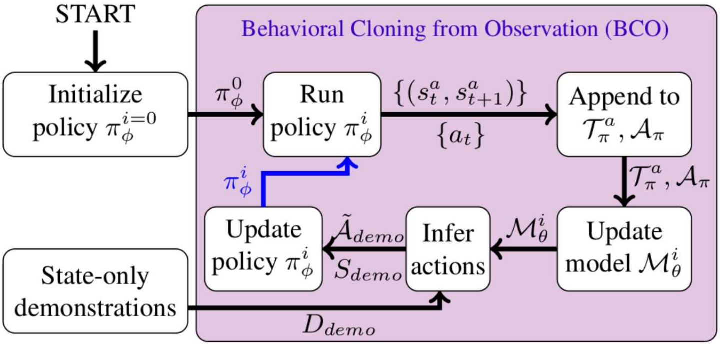
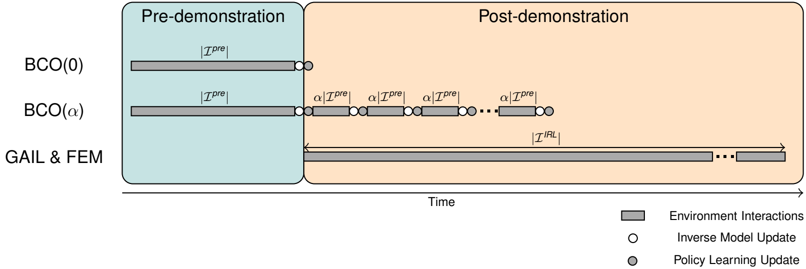


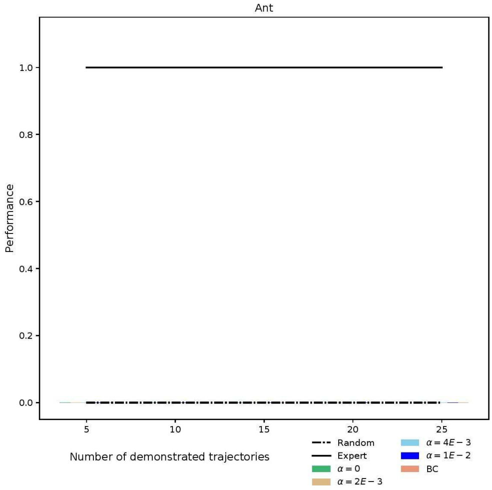
Behavioral Cloning from Observation (BCO(α))

Interaction time:



Behavioral Cloning from Observation (BCO(α))

Effect of varying α on BCO(α):



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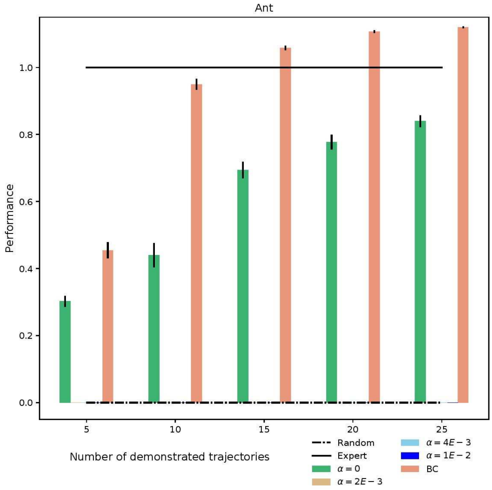

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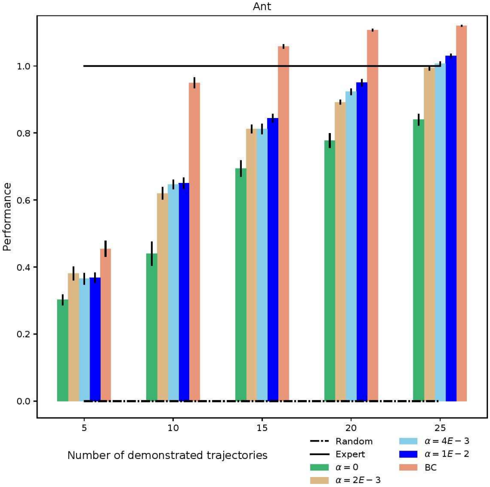

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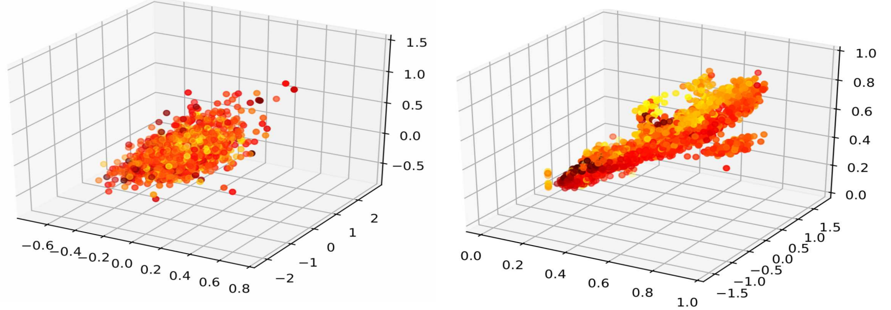
  - **Model-free approach**: GAIfO

Gen. Adversarial Imitation from Observation (GAIfO)

Motivation:



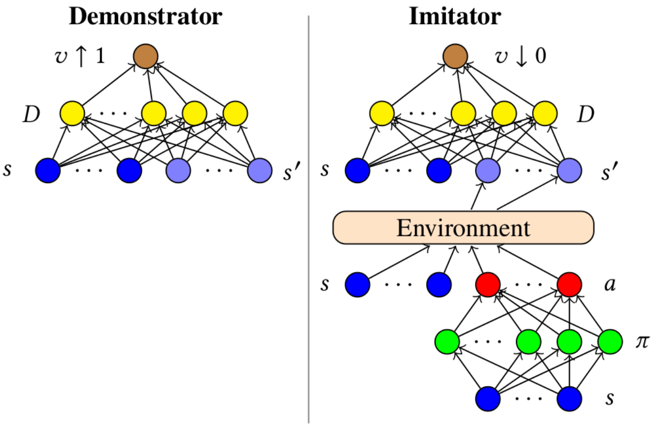
(a) Random Policy

(b) Demonstration

Figure: State transition distribution in Hopper domain.

Gen. Adversarial Imitation from Observation (GAIfO)

Algorithm:



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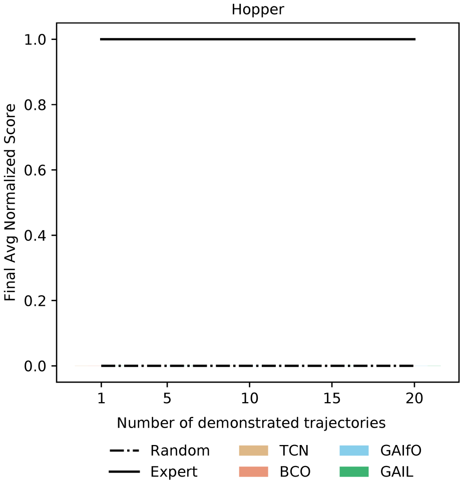
Comparison against other IfO approaches and GAIL:



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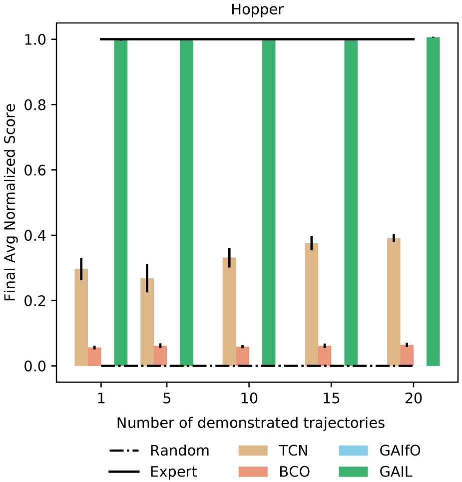

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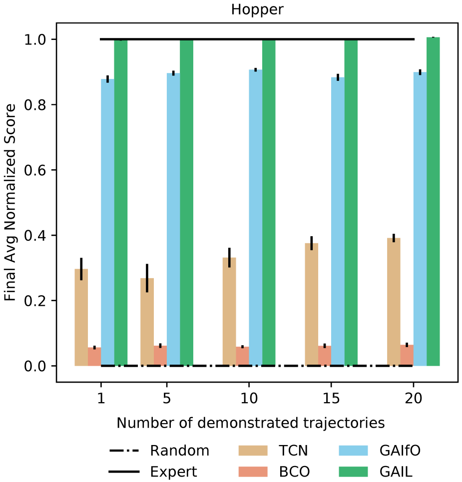

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Challenges:

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Solution:

- Stack four frames.

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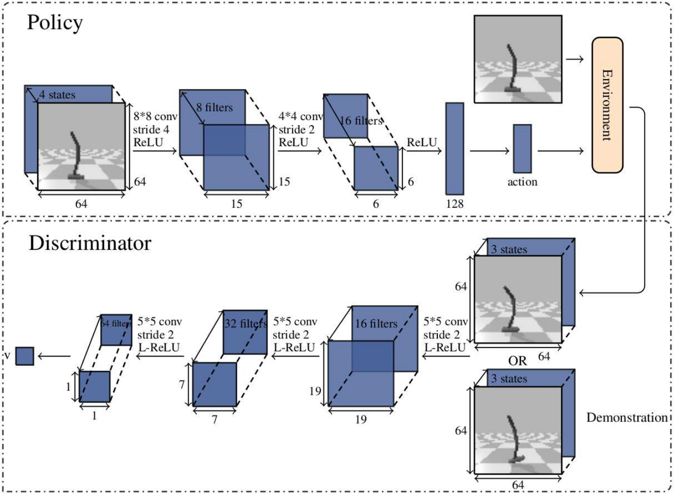

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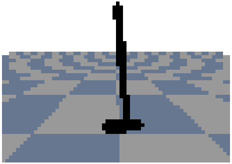

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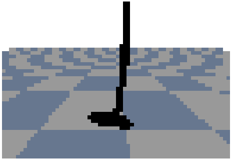
Learned Policy:



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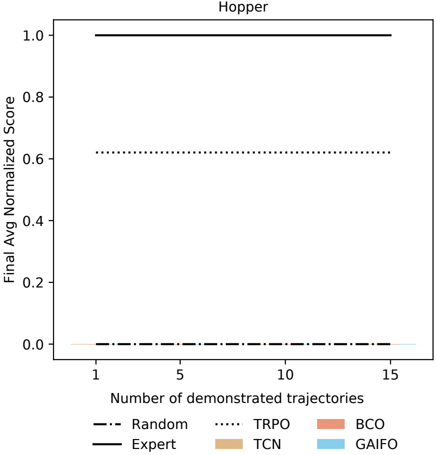

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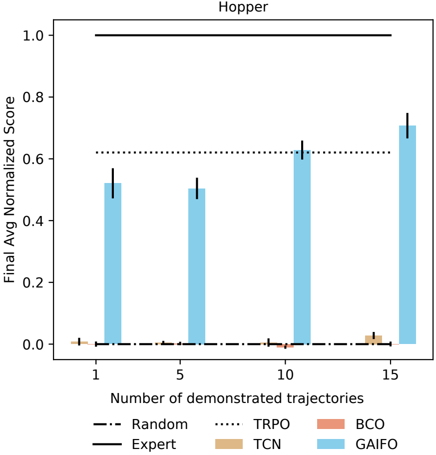

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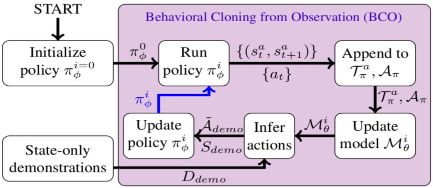
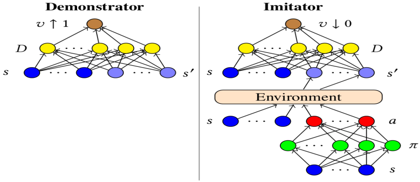
- Adapt algorithms for physical robots.
- Sim-to-real transfer using the algorithms.

Imitation Learning Summary



(a) BCO



(b) GAIfO

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