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Presented by Lin Guan
A Reinforcement Learning Problem: Montezuma’s Revenge
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Find an optimal **policy**, i.e., the action to take in an observed state that maximizes expected long-term reward.
Montezuma’s Revenge: Imitation Learning

[Image of a game level from Montezuma's Revenge]

Lin Guan (UT Austin)
Survey Scope

- 64 papers, 5 types of human guidance that...
Survey Scope

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- Are beyond conventional step-by-step action demonstrations
Survey Scope

- 64 papers, 5 types of human guidance that...
- Are beyond conventional step-by-step action demonstrations
- Have shown promising results in training agents to solve deep reinforcement learning tasks
1. Introduction

2. Learning from Human Evaluative Feedback

3. Learning from Human Preference

4. Hierarchical Imitation

5. Imitation from Observation

6. Learning Attention from Human

7. Conclusion
Montezuma’s Revenge: Evaluative Feedback
While the true reward is delayed and sparse, human evaluative feedback is immediate and dense.
Representative Works

Interpreting human feedback as:

- Reward function, replacing reward provided by the environment
- TAMER: Training an agent manually via evaluative reinforcement [Knox and Stone, 2009, Warnell et al., 2018]
Representative Works

Interpreting human feedback as:

- Direct policy labels
  - Advise [Griffith et al., 2013, Cederborg et al., 2015]
Representative Works

Interpreting human feedback as:
- Direct policy labels
  - Advise [Griffith et al., 2013, Cederborg et al., 2015]
- Advantage function
  - COACH: Convergent actor-critic by humans [MacGlashan et al., 2017]
  - This interpretation explains human feedback behaviors better in several tasks
  - Still an unresolved issue that requires carefully designed human studies
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Montezuma’s Revenge: Human Preference

[Diagram of Montezuma’s Revenge game showing two paths: Path 1 and Path 2, with an arrow indicating a preference for Path 2]
Motivation

Ranking behaviors is easier than rating them. And sometimes the ranking can only be provided at the end of a behavior trajectory.
[Christiano et al., 2017]: As an inverse reinforcement learning problem, i.e., learn human reward function from human preference rather than from demonstration.
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Query selection? Preference elicitation [Zintgraf et al., 2018]
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Query selection? Preference elicitation [Zintgraf et al., 2018]

Many good works on preference-based reinforcement learning [Wirth et al., 2017]
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Montezuma’s Revenge: Hierarchical Imitation
Motivation

Human is good at specifying high-level abstract goals while the agent is good at performing low-level fine-grained controls.
Representative Works

- High-level + low-level demonstrations [Le et al., 2018]

- A promising combination:
  - High-level: Imitation learning, e.g., DAgger [Ross et al., 2011]
  - Low-level: Reinforcement learning, e.g., DQN [Mnih et al., 2015]
Representative Works

- High-level + low-level demonstrations [Le et al., 2018]
- High-level demonstrations only [Andreas et al., 2017]
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Motivation

To utilize a large amount of human demonstration data that do not have action labels, e.g., YouTube videos
Representative Works

- **Challenge 1: Perception**
  - Viewpoint [Liu et al., 2018, Stadie et al., 2017]
  - Embodiment [Gupta et al., 2018, Sermanet et al., 2018]
Representative Works

- Challenge 1: Perception
  - Viewpoint [Liu et al., 2018, Stadie et al., 2017]
  - Embodiment [Gupta et al., 2018, Sermanet et al., 2018]

- Challenge 2: Control
  - Model-based: Infer the missing action given a state transitions \((s, s')\) by learning an inverse dynamics model [Nair et al., 2017, Torabi et al., 2018a]
  - Model-free: e.g., bring the state distribution of the imitator closer to that of the trainer using generative adversarial learning [Merel et al., 2017, Torabi et al., 2018b]
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Please see paper#10945: **Recent Advances in Imitation Learning from Observation** [Torabi et al., 2019]
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Montezuma’s Revenge: Human Attention
Motivation

Human visual attention provides additional information on *why* a particular decision is made, e.g., by indicating the current object of interest.
Representative Works

- AGIL: Attention-guided imitation learning [Zhang et al., 2018]

- Including attention does lead to higher accuracy in imitating human actions
Representative Works

(a) Cooking [Li et al., 2018]

(b) Driving [Palazzi et al., 2018, Xia et al., 2019]
An agent can learn...

- From human evaluative feedback
- From human preference
- From high-level goals specified by humans
- By observing human performing the task
- From human visual attention
Future Directions

- Shared datasets and reproducibility
- Understanding human trainers' behaviors, e.g., [Thomaz and Breazeal, 2008]
- A unified lifelong learning framework [Abel et al., 2017]

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Thank You!
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