Atari-HEAD
Atari Human Eye-Tracking and Demonstration Dataset

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Previous work

- Deep Q-Network (Mnih, et al. 2015)
- Rainbow (Hessel, et al. 2018), etc
- Deep Q-learning from demonstration (Hester, et al. 2018)
Motivations

- [AI] How can we collect demonstration data that better suited for training artificial learning agents?
- [Cognitive ergonomics] What is the level of human performance when the Atari gaming environment is made more friendly to human players?
- [Visuomotor control] How do humans play these games? How do they perceive game images and make decisions?
What this is

- **Atari Human Eye-Tracking And Demonstration Dataset**

Eyelink-1000 infrared eye tracker
Basic statistics

20 games, 117 hours of game data

328 million gaze locations

7.97 million actions
Design: Semi-frame-by-frame game playing

- Game pauses until action
  - Players can hold down a key and the game will run continuously at 20Hz
- Eliminates errors due to sensori-motor delays
  - Which is typically ~250ms (~15 frames at 60Hz game speed)
  - Action $a(t)$ could be intended for a state $s(t-\Delta)$ ~250ms ago
  - Ensuring the action (label) matches the state (input) is important for supervised learning algorithms such as behavior cloning
Design: Semi-frame-by-frame game playing

- Game pauses until action
  - Players can hold down a key and the game will run continuously at 20Hz
- Allows multiple eye movements per frame
  - Reduces inattentional blindness
  - Allows sophisticated planning
Design

- Rest for 15 minutes after every trial (15 minutes)
- Display size & brightness
- Comfortable keyboard
Human performance

- A new human performance baseline
  - Previous human baseline*: Expert’s performance in a challenging environment
  - Atari-HEAD baseline: Amateur’s performance in a friendly environment

*Kapturowski, et al. ICLR 2019; Human World Record: Twin Galaxies

2-hour experiment time limit reached before game terminated (potential higher score if continue to play)
## Game scores

<table>
<thead>
<tr>
<th>Game</th>
<th>Mnih</th>
<th>Wang</th>
<th>Hester</th>
<th>Kurin</th>
<th>de la Cruz</th>
<th>AtariHEAD 15-min avg.</th>
<th>AtariHEAD 15-min best</th>
<th>AtariHEAD 2-hour</th>
<th>Community Record</th>
<th>RL</th>
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<td>11,800</td>
<td>28,600†</td>
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<td>1,107.0</td>
</tr>
</tbody>
</table>
- Eye tracker calibration every 15 minutes
- Average tracking error: 12 pixels (< 1% stimulus size)
- 1000Hz tracking frequency
- Foveated rendering*: Humans have foveal vision with high acuity for only 1-2 visual degrees

*Perry & Geisler, Electronic Imaging 2002
Dataset: Additional measurements

- Decision time
- Immediate and cumulated rewards
- Eyelink software further supports extracting the following from the raw eye-tracking data:
  - Subtypes of eye-movements: Fixations, saccades, smooth pursuits
  - Blinks: Fatigue level/boredness
  - Pupil size (fixed luminance): Arousal level/surprise/excitement
Modeling question I

- [Vision] How well can we model human visual attention in Atari games by leveraging recent progress in saliency research?
Saliency prediction: Previous work

- Visual saliency research*
  - Task-free data: MIT saliency benchmark (Bylinskii et al. 2014), CAT2000 (Borji & Itti 2015), SALICON (Jiang et al. 2015), etc

- What about visual attention in interactive, reward-seeking tasks?

*Itti & Koch, Vision Research 2000
Gaze prediction: Gaze network

- A standard saliency prediction problem
Quantitative results

- Highly accurate
- avg. AUC across 20 games = 0.97
- Significantly better than baseline models
Results & visualization

- Highly accurate, avg. AUC across 20 games = 0.97 (random = 0.5; max = 1)
- Model captures predictive eye movements
- Model identifies the target object from a set of visually identical objects
- Model captures divided attention
Gaze model across subjects
Modeling question II

- [AI] Is human visual attention information a useful signal in training decision learning agents?
Action prediction: Policy network

- Imitation learning: behavior cloning
- Hypothesis: Attention information could help with action prediction

Zhang et al., ECCV 2018
Results

- Incorporating human attention improves human action prediction accuracy
- Average: +0.07
Results

- Incorporating human attention improves task performance (game score)
  - Average: +115.3%
  - Most profound for
    - Games in which the task-relevant objects are very small (e.g., “ball”)
      - Gaze helps extract feature for a neural network during training
    - Games that rely heavily on multitasking

Kurin et al., 2017; Hester et al., 2018
Why visual attention helps

- Resolves ambiguity by indicating the target of the current decision
More imitation learning

- For gaze-assisted inverse reinforcement learning and behavior cloning from observation, please see another paper/poster#22
Related work: Similar datasets

- Human eye tracking + decisions
  - Meal preparation (Li, Liu, & Rehg 2018)
  - Urban driving (Alletto et al. 2016)
Related work: AGIL in cooking, driving & walking

Alleto et al., 2016; Yu et al., 2018; Xia et al., 2019; Chen et al., 2019; Liu et al., 2019; Matthis, Yates, & Hayhoe, 2018
Future work: Human vs. machine attention

- We have methods* to visualize where a deep neural network pays attention to given an input image
- Questions:
  - Is the RL agent’s attention similar to human’s?
  - Especially in the states where it made mistakes
  - Is there anything the agent fails to capture?

*Grimm et al., ICLR 2018; Greydanus et al., ICML 2018
Future work: Attention-guided learning

- Can we improve the performance of learning agents using human attention?
- Example - state compression*: Use human attention as a prior to help identify features that need to be preserved during compression

*Lerch & Sims, arXiv 2018; Abel et al., AAAI 2019
Future work: Attention-guided reinforcement learning
Future work: Attention-guided reinforcement learning
Future work: Attention-guided reinforcement learning

- An exciting possibility: Human attention + AI control
Summary

- [Cognitive ergonomics] A new human performance baseline
- [Vision science] A dataset for studying task-driven saliency
- [AI] A high-quality dataset that is more suited for training learning agents
- [AI] Human attention-guided decision learning algorithms
Acknowledgment

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