Atari-HEAD:
Atari Human Eye-Tracking and Demonstration Dataset

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Abstract

We present a large-scale dataset of human actions and eye movements while playing Atari videos games. This dataset currently has 44 hours of gameplay data from 16 games and 2.97 million demonstrated actions. In order to obtain near-optimal decisions, human subjects played games in a frame-by-frame manner. Raw game frame, player eye movements, action (keyboard strokes), reaction time, and immediate reward are recorded every frame. This dataset could be useful imitation learning, reinforcement learning, and visual saliency research.

Keywords: Visual Attention; Eye Tracking; Imitation Learning

Motivation

- Imitation learning: extracting initial biases as well as strategies how to approach a visuomotor task from demonstrations of humans [Schaal, 1999]
- Humans have foveal vision with high acuity for only 1-2 visual degrees

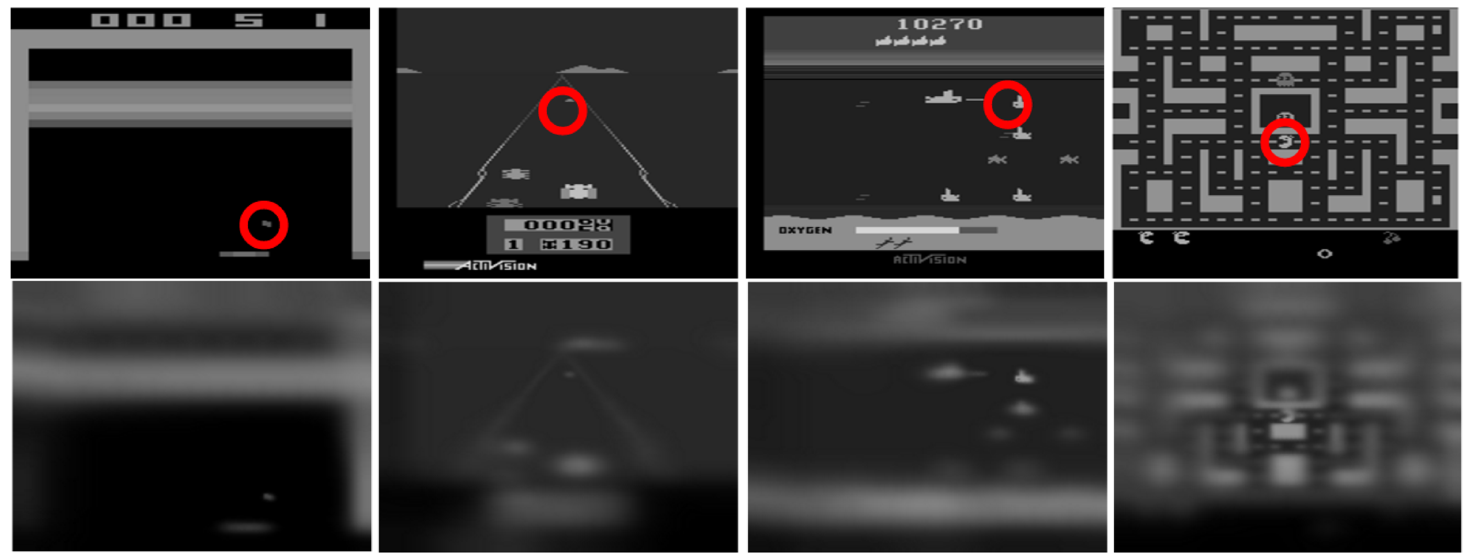


Figure 1: Foveal vision, generated using the foveated rendering algorithm [Perry and Geisler, 2002]

- Foveal vision leads to eye movements/gaze behaviors, which reveal the underlying visual attention mechanism of humans
- **Research question: Is human visual attention useful for teaching AIs?**
- Proposal: Learn a visual attention model from human gaze data, then use the learned model to guide the process of learning actions

Data Collection

- 16 Atari video games from the Arcade Learning Environment [Bellemare et al., 2012].
- Game image frames, human keystroke action, reaction time, gaze positions, and immediate reward received are recorded
- Gaze positions are recorded using EyeLink 1000 eye tracker at 1000Hz; average gaze positional error: 0.41 visual degrees (< 1% of the image size)
- **Semi-frame-by-frame game mode**: To maximize human performance, the game pauses at every frame, until an keyboard action is taken by the human player. However, human can hold down a key and the game will run continuously at 20Hz.
- 4 amateur players, 44 hours, 175 15-minute trials (must rest at least 30 minutes between trials), 2.97 million demonstrated actions
- Dataset link: QR code or https://zenodo.org/record/2603190

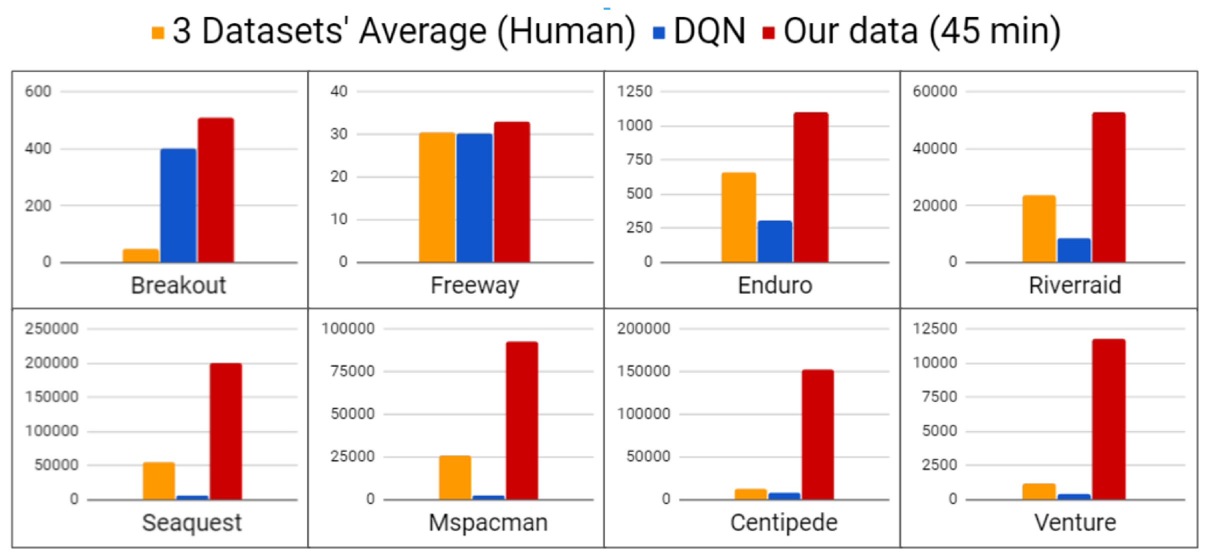
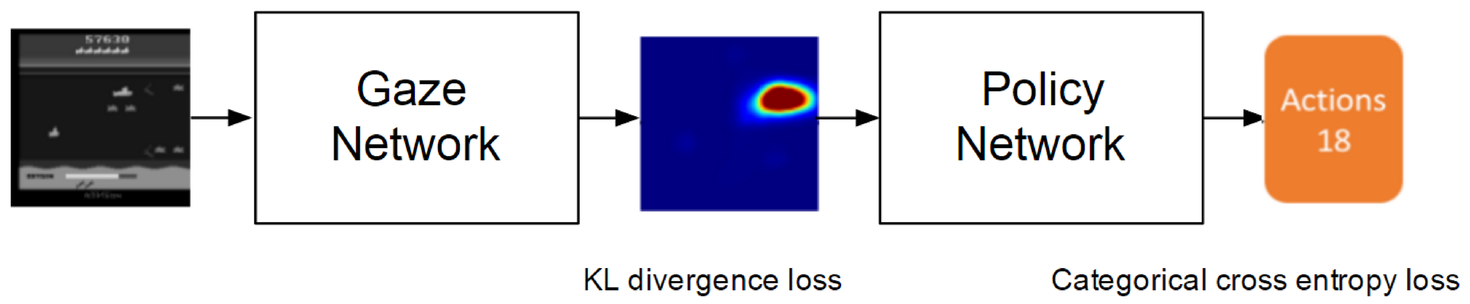


Figure 2: The way we collected data results significantly better human performance than previous datasets and deep Q-Network [Mnih et al., 2015, Wang et al., 2016, Hester et al., 2018]. Potentially, imitation learning agent could also perform better when learning from these demonstrations.

Learning to Predict Human Visual Attention and Decisions



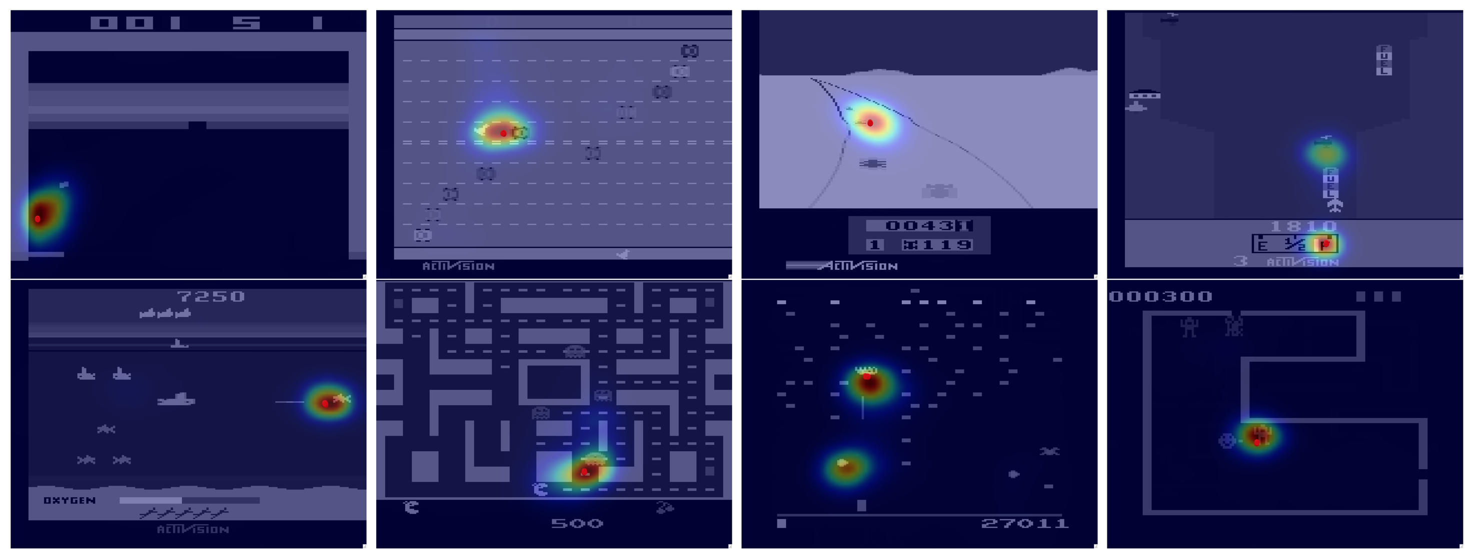
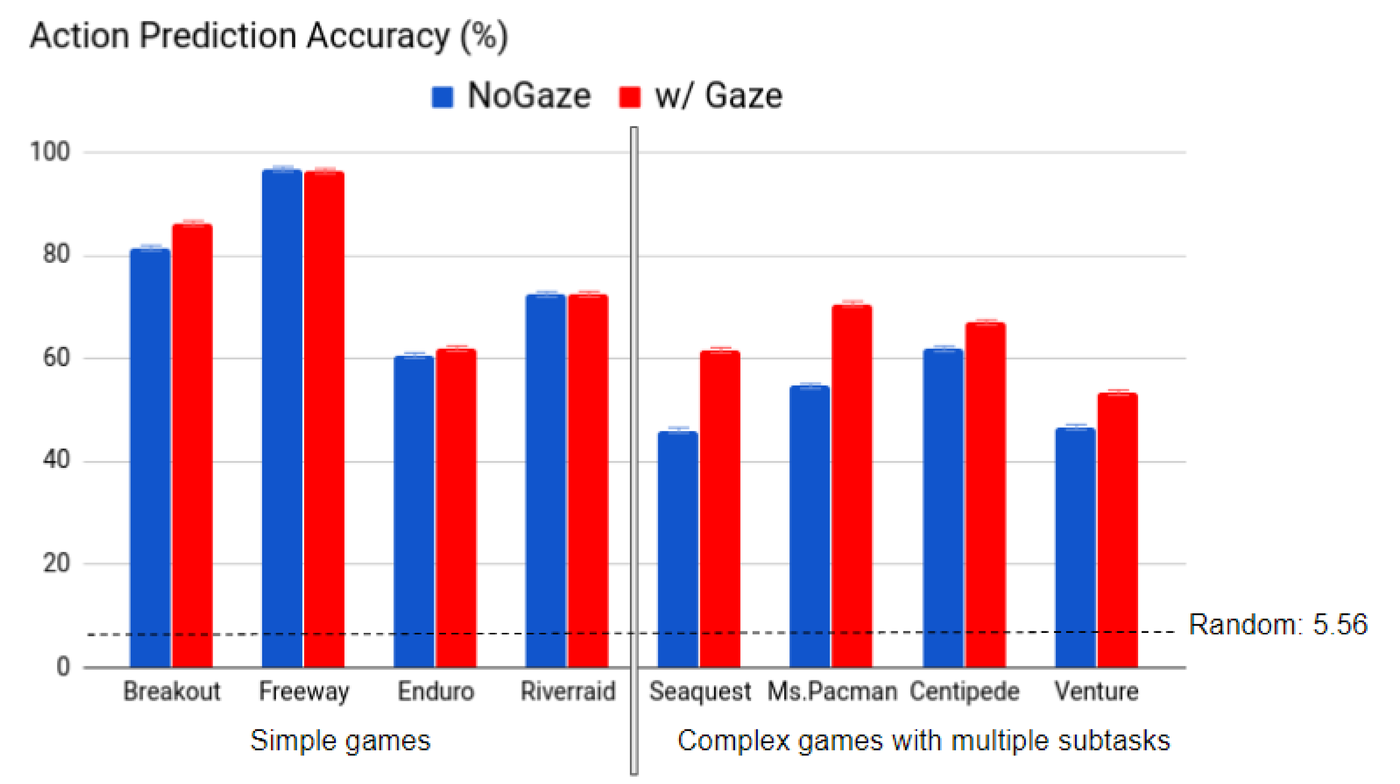


Figure 3: Visualization of gaze prediction results for eight games. The solid red dot indicates the ground truth human gaze position. The heatmap shows the model's prediction as a saliency map, computed using the gaze network. Average area under the curve (AUC) score across 8 games on testing dataset: **0.965**.



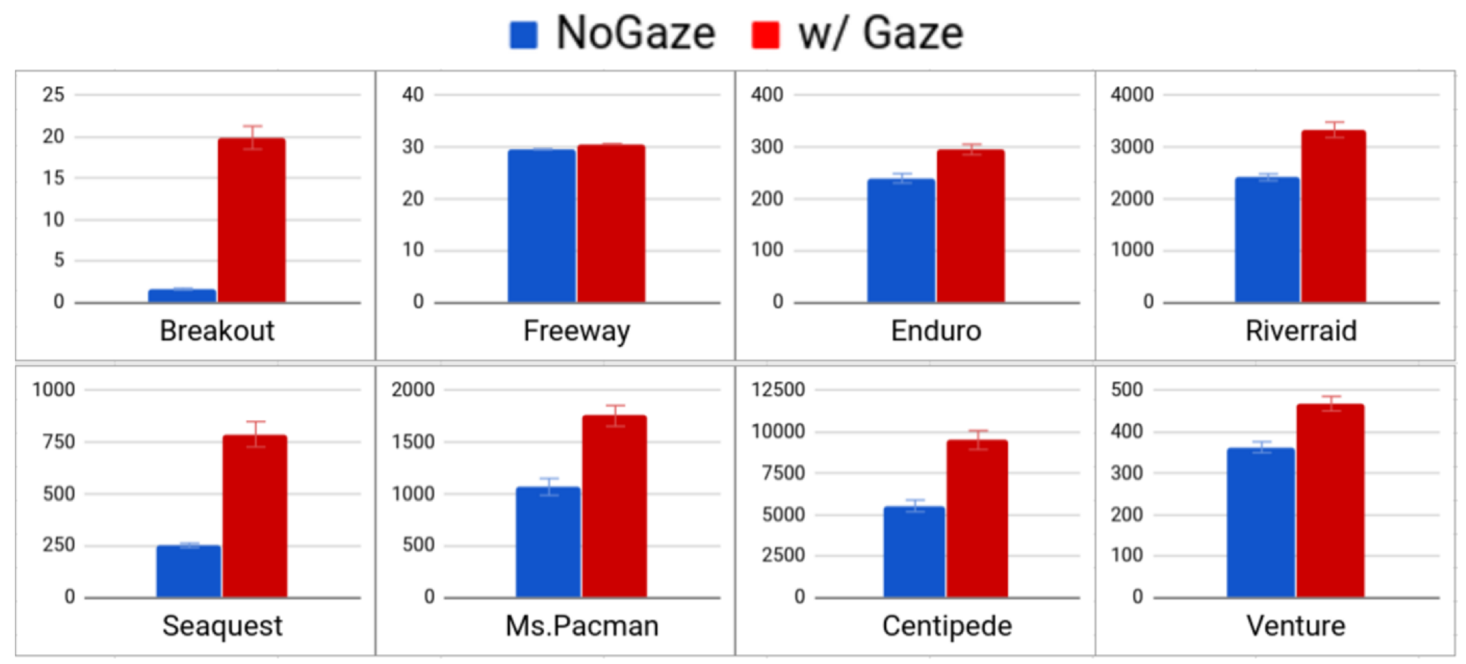


Figure 4: Game scores across 8 games. Visual attention can help the imitator learn better from human demonstration.

- Hypothetically, visual attention simplifies the learning problem by indicating the object of interest for the current decision

Work in Progress

- More data: Novice vs. experienced players; more games
- Human decision time is an useful source of information as well, how do we model and use it for imitation learning?
- There is still a large performance gap between the human player and the learning agent, what else is missing from an imitation learning perspective?
- Visual attention + reinforcement learning: Applying learned attention model to speedup the learning process of RL algorithms.

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