Atari-HEAD
Atari Human Eye-Tracking and Demonstration Dataset

Ruohan Zhang*, Calen Walshe, Zhuode Liu, Lin Guan, Karl Muller,
Jake Whritner, Luxin Zhang, Mary Hayhoe, Dana Ballard

The University of Texas at Austin
Carnegie Mellon University

*zharu@utexas.edu

Previous work

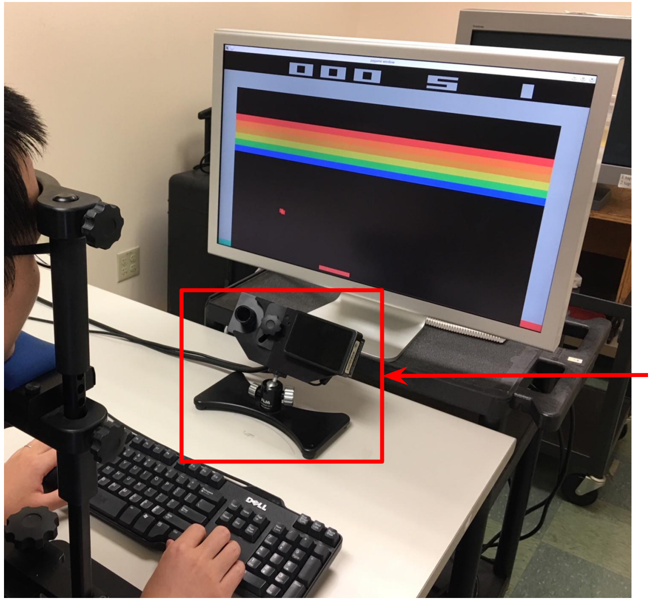
- Arcade Learning Environment (Bellemare, et al. 2013; Machado, et al. 2018)
- Deep Q-Network (Mnih, et al. 2015)
- Rainbow (Hessel, et al. 2018), etc
- Deep Q-learning from demonstration (Hester, et al. 2018)

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?

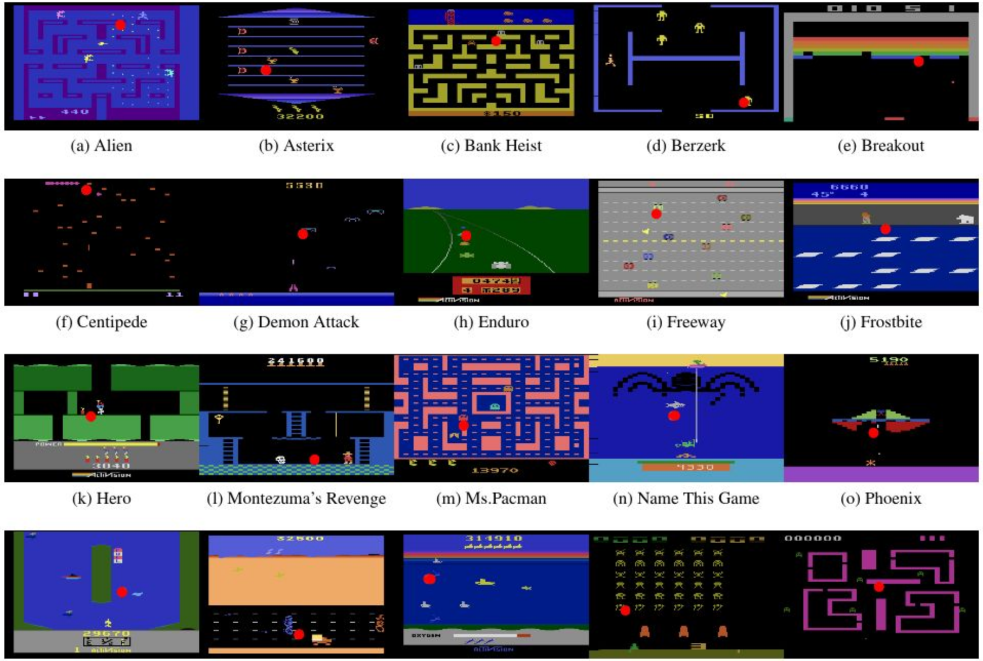
What this is

- **A**tari **H**uman **E**ye-Tracking **A**nd **D**emonstration Dataset



Eyelink-1000 infrared eye tracker

Basic statistics


(a) Alien (b) Asterix (c) Bank Heist (d) Berzerk (e) Breakout
(f) Centipede (g) Demon Attack (h) Enduro (i) Freeway (j) Frostbite
(k) Hero (l) Montezuma's Revenge (m) Ms.Pacman (n) Name This Game (o) Phoenix
(p) River Raid (q) Road Runner (r) Seaquest (s) Space Invaders (t) Venture

20 games, 117 hours of game data

7.97 million actions

328 million gaze locations

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-Δ) ~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

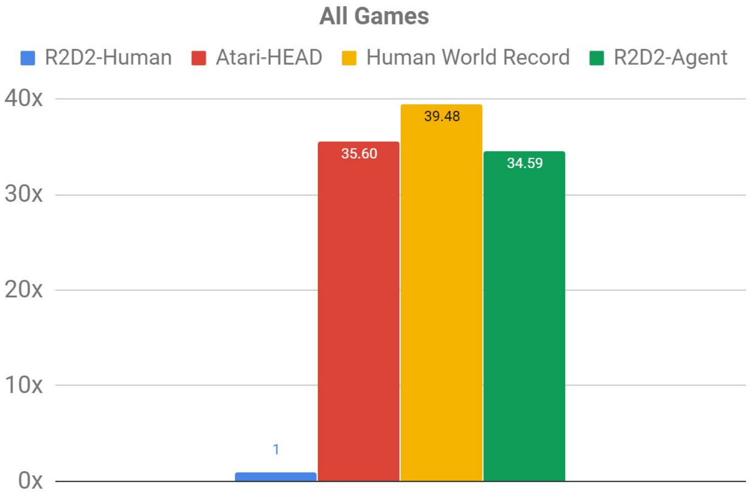
- Game pauses until action
  - Players can hold down a key and the game will run continuously at 20Hz
- Allows multiple eye movements per frame
  - Reduces inattentional blindness
  - Allows sophisticated planning

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



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

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

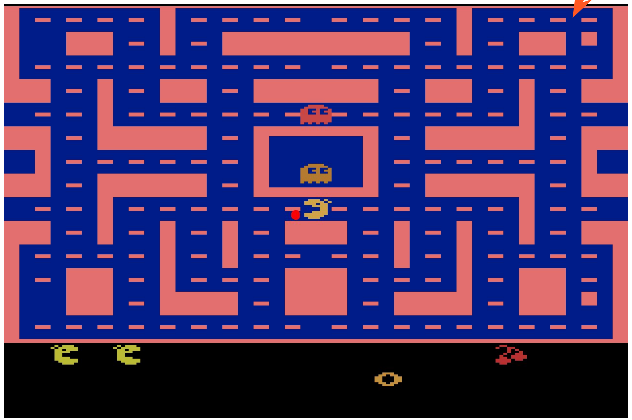
Game scores

	Mnih	Wang	Hester	Kurin	de la Cruz	AtariHEAD 15-min avg.	AtariHEAD 15-min best	AtariHEAD 2-hour	Community Record	RL
alien	6,875	7,127.7	29,160	-	-	27,923	34,980	**107,140**†	103,583	9,491.7
asterix	8,503	8,503.3	18,100	-	14,300	110,133.3	135,000	**1,000,000**‡	**1,000,000**	428,200.3
bank_heist	734.4	753.1	7,465	-	-	5,631.3	6,503	**66,531**†	47,047	1,611.9
berzerk	-	2,630.4	-	-	-	6,799	7,950	55,220⋆	**171,770**	2,545.6
breakout	31.8	30.5	79	-	59	439.7	554	**864**‡	**864**	612.5
centipede	11,963	12,017	-	-	-	45,064	55,932	415,160⋆	**668,438**	9,015.5
demon_attack	3,401	3,442.8	6,190	-	-	7,097.3	10,460	107,045⋆	108,075	**111,185.2**
enduro	309.6	860.5	803	-	-	336.4	392	**4,886**⋆	-	2,259.3
freeway	29.6	29.6	32	-	-	31.1	33	33†	**34**	**34.0**
frostbite	4,335	4,334.7	-	-	-	31,731.5	50,630	**453,880**⋆	418,340	9,590.5
hero	25,763	30,826.4	99,320	-	-	59,999.8	77,185	541,640⋆	**1,000,000**	55,887.4
montezuma	4,367	4,753.3	34,900	27,900	-	38,715	46,000	270,400⋆	**400,000**	384.0
ms_pacman	15,693	15,375.0	55,021	29,311	18,241	28,031	36,061	93,721†	**123,200**	6,283.5
name_this_game	4,076	8,049.0	19,380	-	4,840	7,661.5	8,870	**21,850**†	21,210	13,439.4
phoenix	-	7,242.6	-	-	-	30,800.5	40,780	**485,660**⋆	373,690	108,528.6
riverraid	13,513	17,118	39,710	-	-	20,048	22,590	59,420†	**86,520**	-
road_runner	7,845	7,845	20,200	-	-	78,655	99,400	99,400†	**210,200**	69,524.0
seaquest	20,182	42,054.7	101,120	-	-	52,774	64,710	**585,570**⋆	294,940	50,254.2
space_invaders	1,652	1,668.7	-	3,355	1,840	3,527	5,130	49,340⋆	**110,000**	18,789.0
venture	1,188	1,187.5	-	-	-	8,335	11,800	**28,600**†	-	1,107.0

Eye-tracking accuracy

- Eye tracker calibration every 15 minutes
- Average tracking error: 12 pixels (< 1% stimulus size)
- 1000Hz tracking frequency

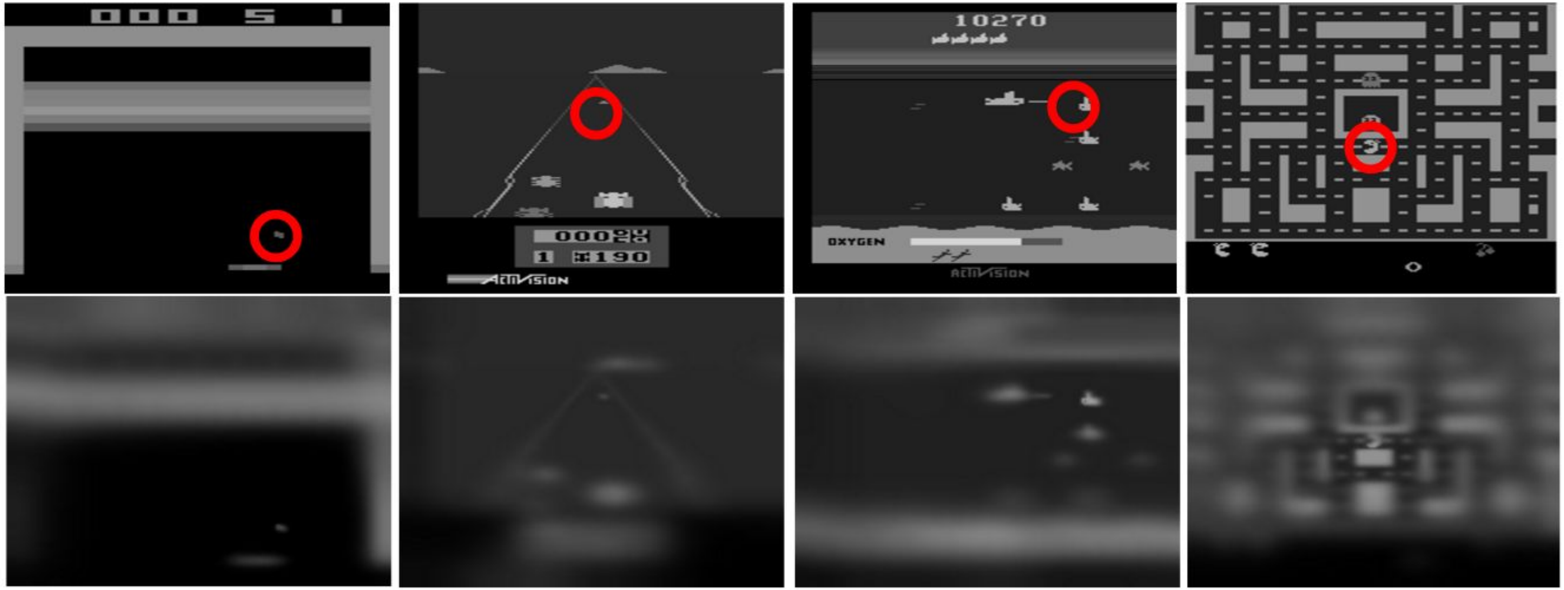
26 pixels



16 pixels

Human perception

- Foveated rendering*: Humans have foveal vision with high acuity for only 1-2 visual degrees



*Perry & Geisler, Electronic Imaging 2002

Dataset: Additional measurements

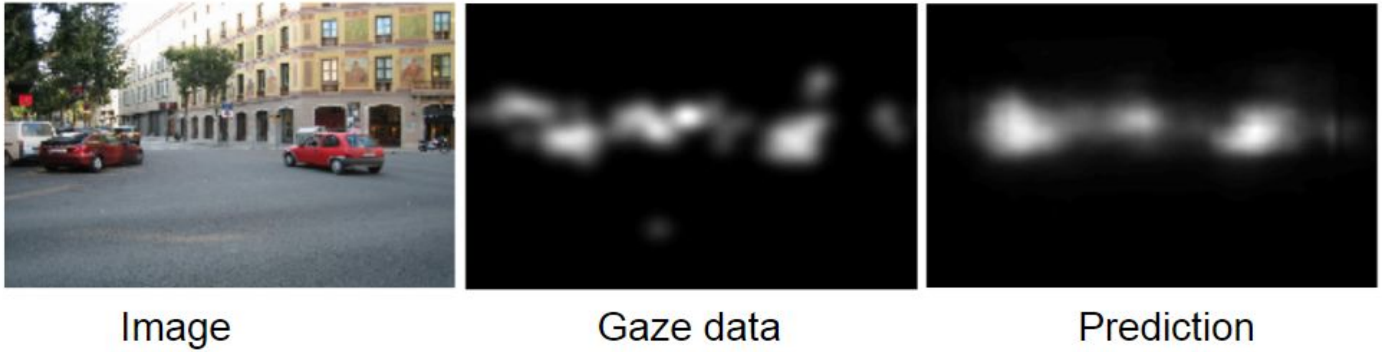
- Decision time
- Immediate and cumulated rewards
- Eyelink software further supports extracting the following from the raw eye-tracking data:
  - Subtypes of eye-movements: Fixations, saccades, smooth pursuits
  - Blinks: Fatigue level/boredness
  - Pupil size (fixed luminance): Arousal level/surprise/excitement

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

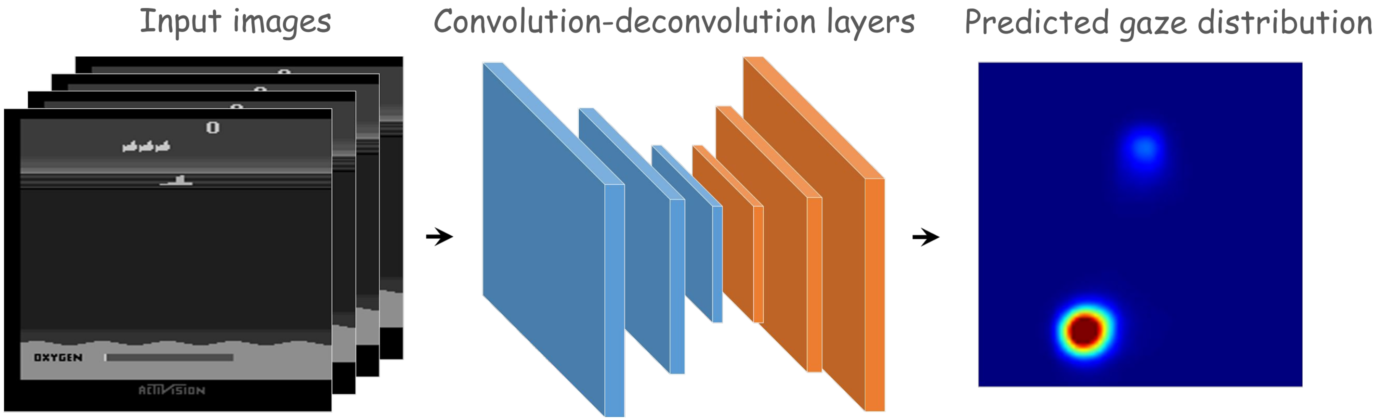


- What about visual attention in interactive, reward-seeking tasks?

*Itti & Koch, Vision Research 2000

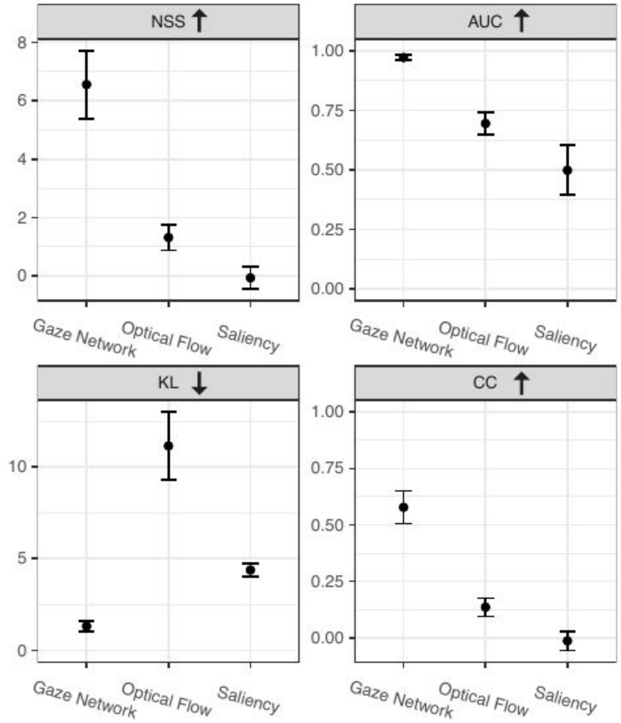
Gaze prediction: Gaze network

- A standard saliency prediction problem



Quantitative results

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

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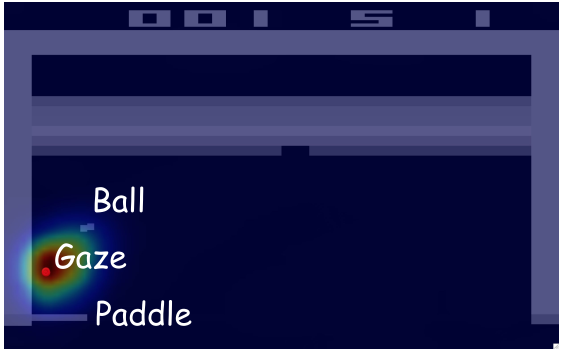
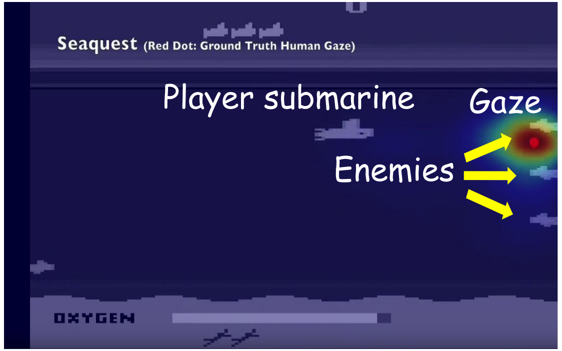
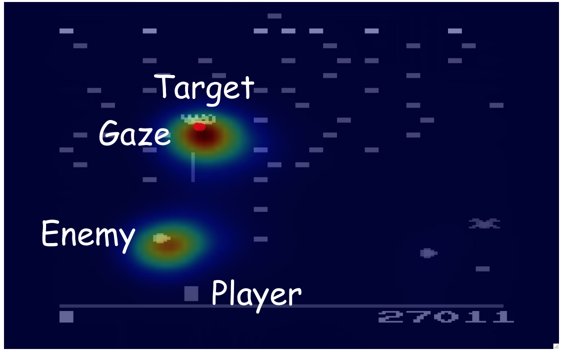
OXYGEN
ACTIVISION

Results & visualization

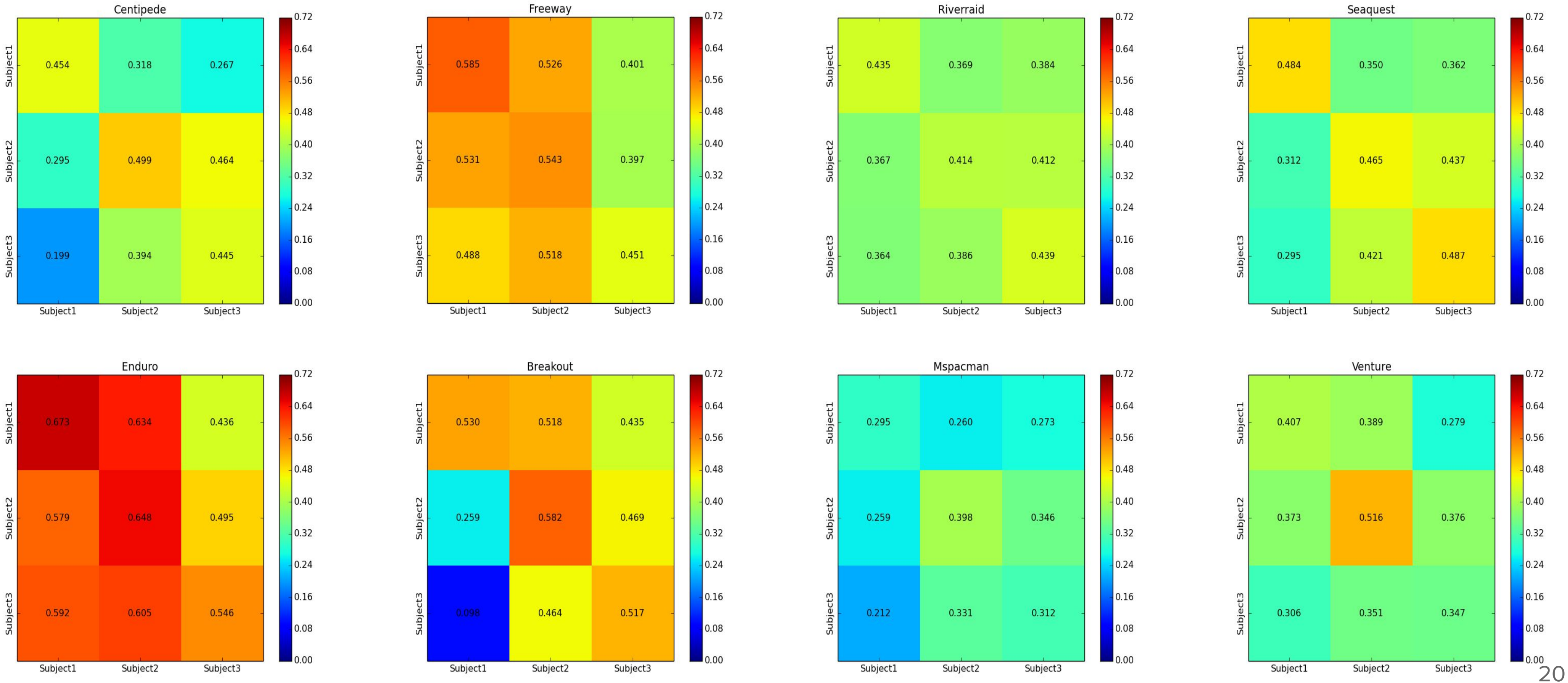
- Highly accurate, avg. AUC across 20 games = 0.97 (random = 0.5; max = 1)
- Model captures predictive eye movements
- Model identifies the target object from a set of visually identical objects
- Model captures divided attention







Gaze model across subjects

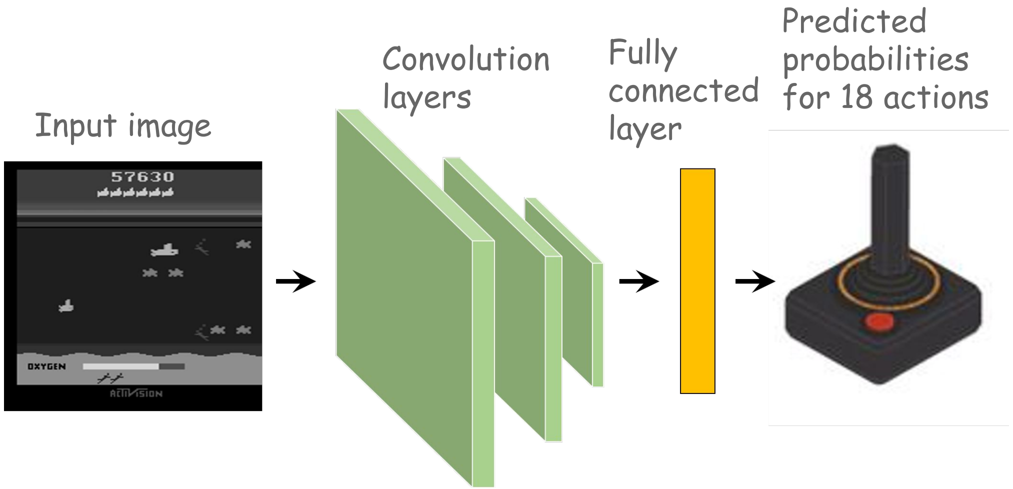


Modeling question II

- [AI] Is human visual attention information a useful signal in training decision learning agents?

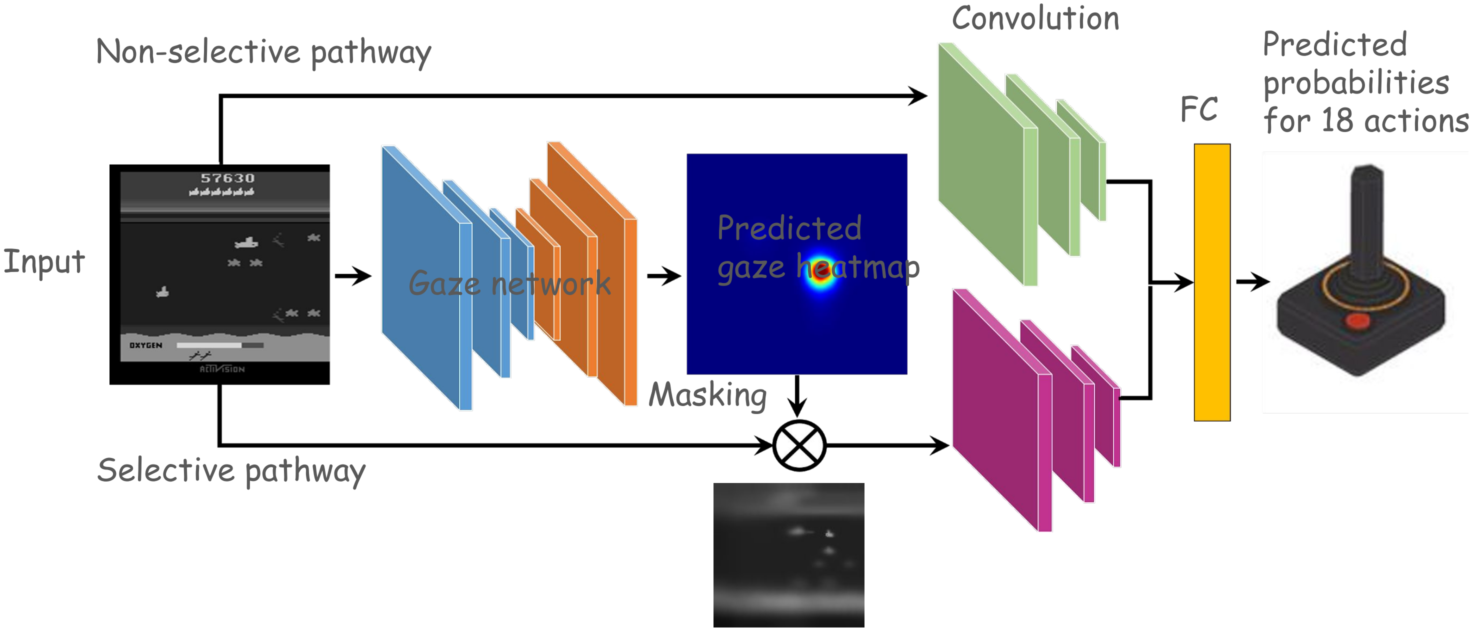
Action prediction: Policy network

- Imitation learning: behavior cloning



Attention-guided imitation learning (AGIL)

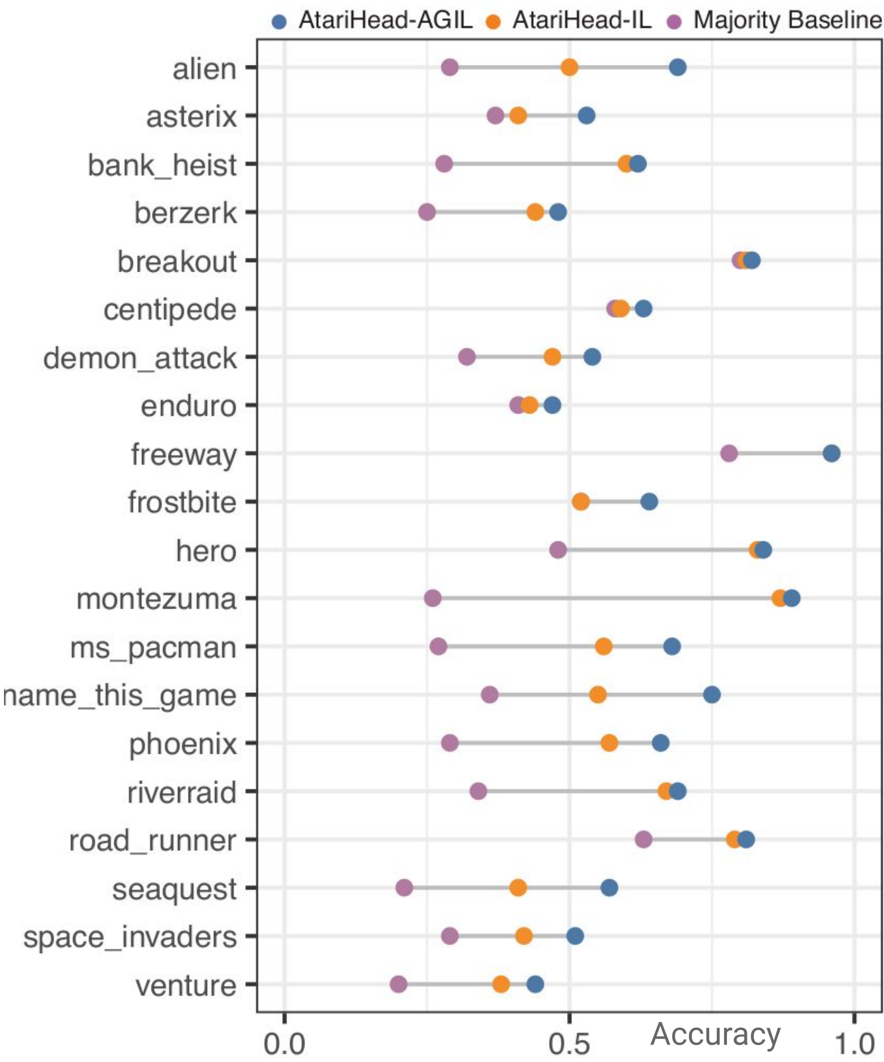
- Hypothesis: Attention information could help with action prediction



Zhang et al., ECCV 2018

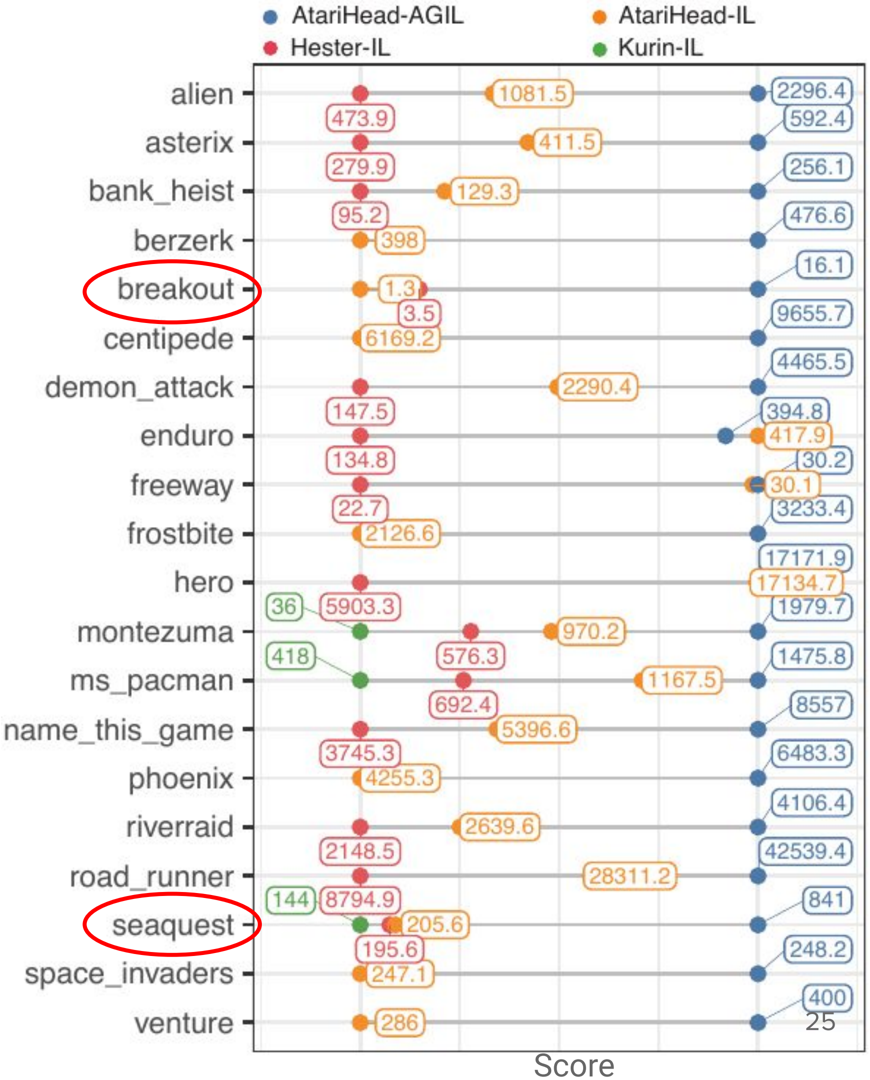
Results

- 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

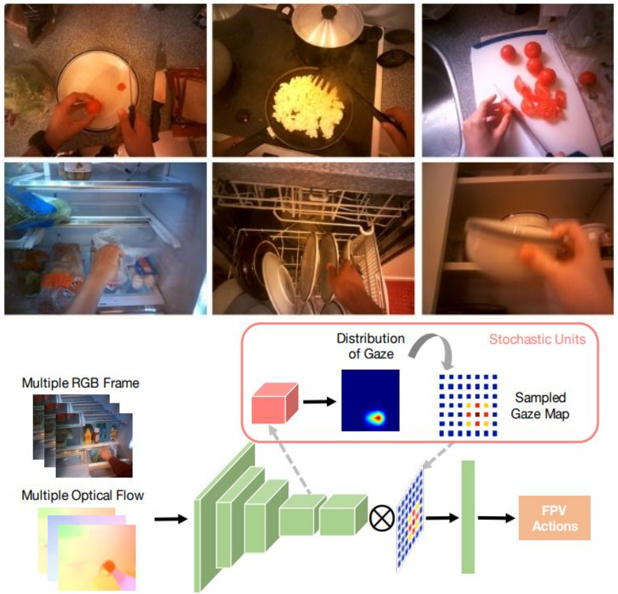
More imitation learning

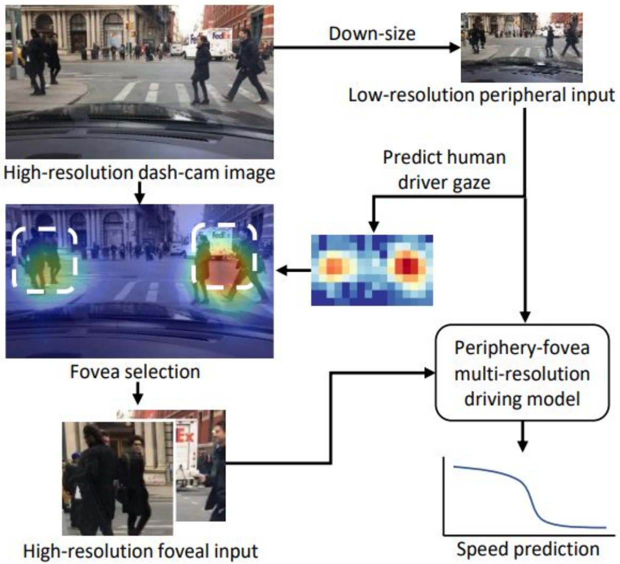
- For gaze-assisted inverse reinforcement learning and behavior cloning from observation, please see another paper/poster#22

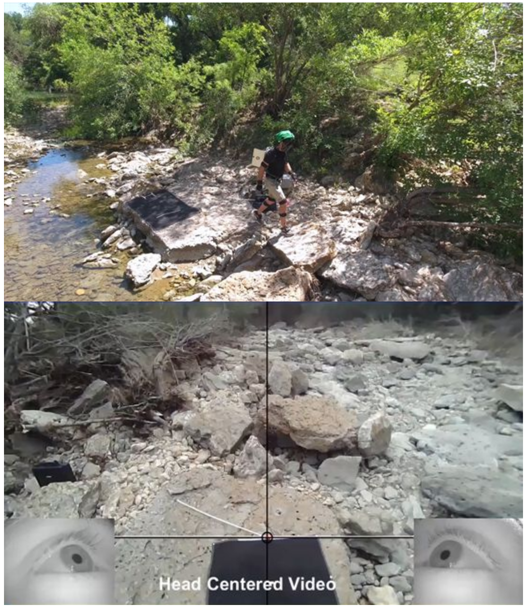
Related work: Similar datasets

- Human eye tracking + decisions
  - Meal preparation (Li, Liu, & Rehg 2018))
  - Urban driving (Alletto et al. 2016)

Related work: AGIL in cooking, driving & walking



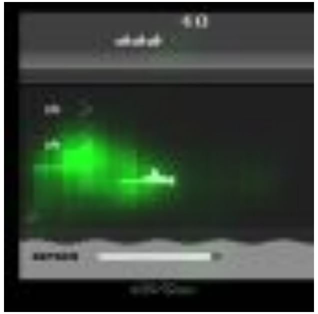




Alleto et al., 2016; Yu et al., 2018; Xia et al.,2019; Chen et al., 2019; Liu et al., 2019; Matthis, Yates, & Hayhoe, 2018

Future work: Human vs. machine attention

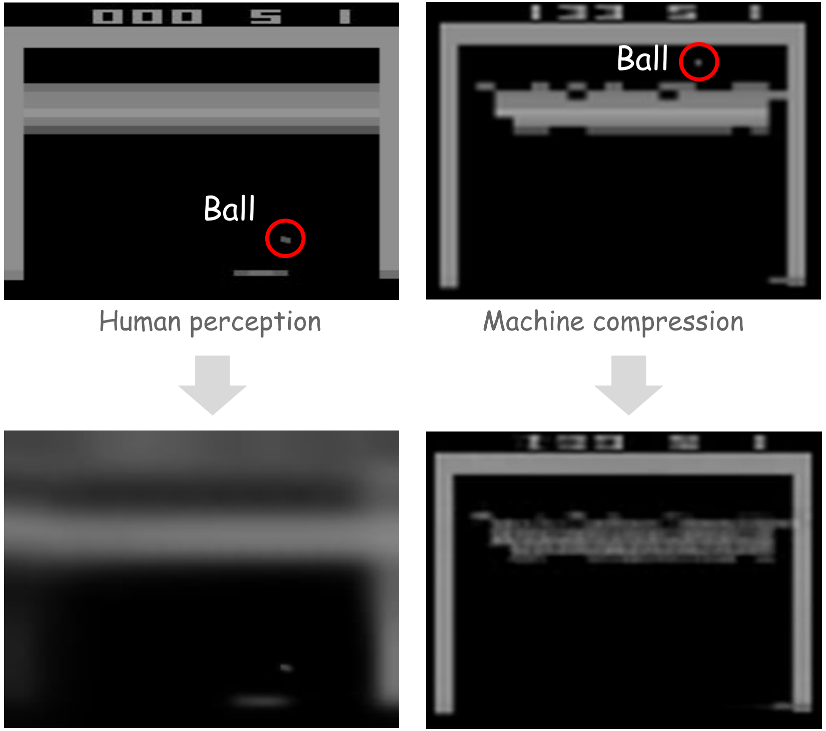
- We have methods* to visualize where a deep neural network pays attention to given an input image
- Questions:
  - Is the RL agent's attention similar to human's?
    - Especially in the states where it made mistakes
    - Is there anything the agent fails to capture?



*Grimm et al., ICLR 2018; Greydanus et al., ICML 2018

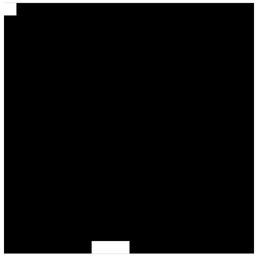
Future work: Attention-guided learning

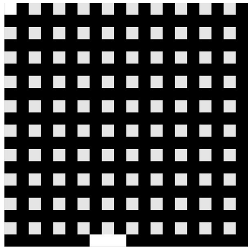
- Can we improve the performance of learning agents using human attention?
- Example - state compression*: Use human attention as a prior to help identify features that need to be preserved during compression

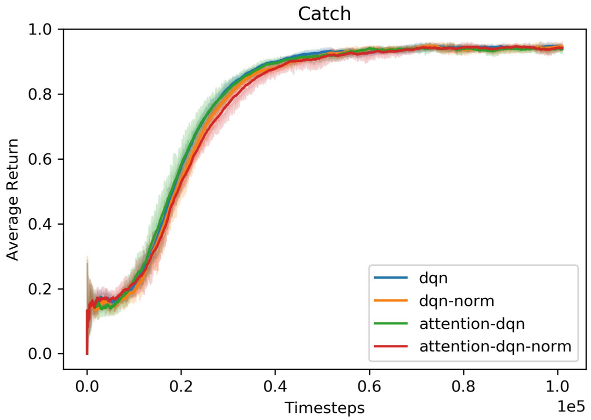


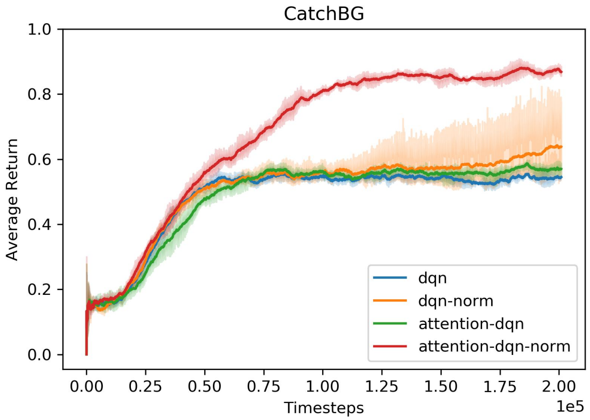
*Lerch & Sims, arXiv 2018; Abel et al., AAAI 2019

Future work: Attention-guided reinforcement learning

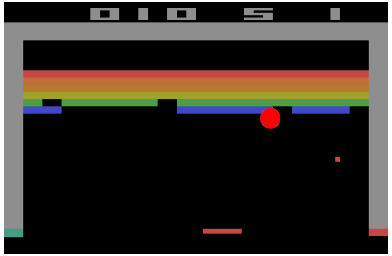


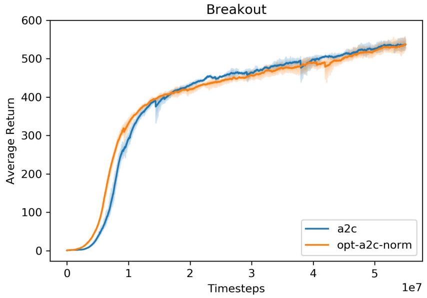


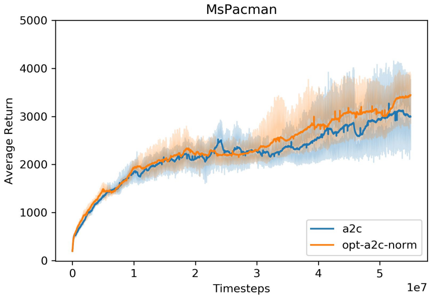


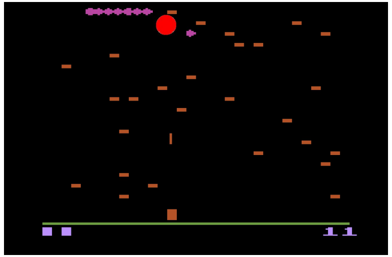


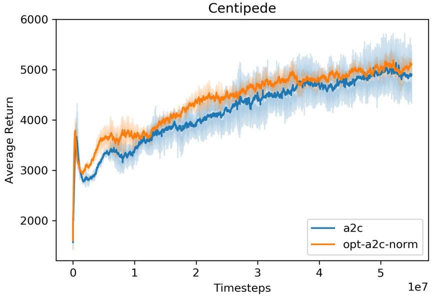
Future work: Attention-guided reinforcement learning

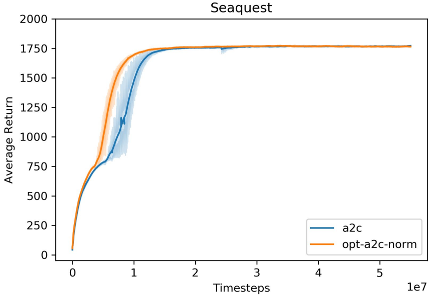






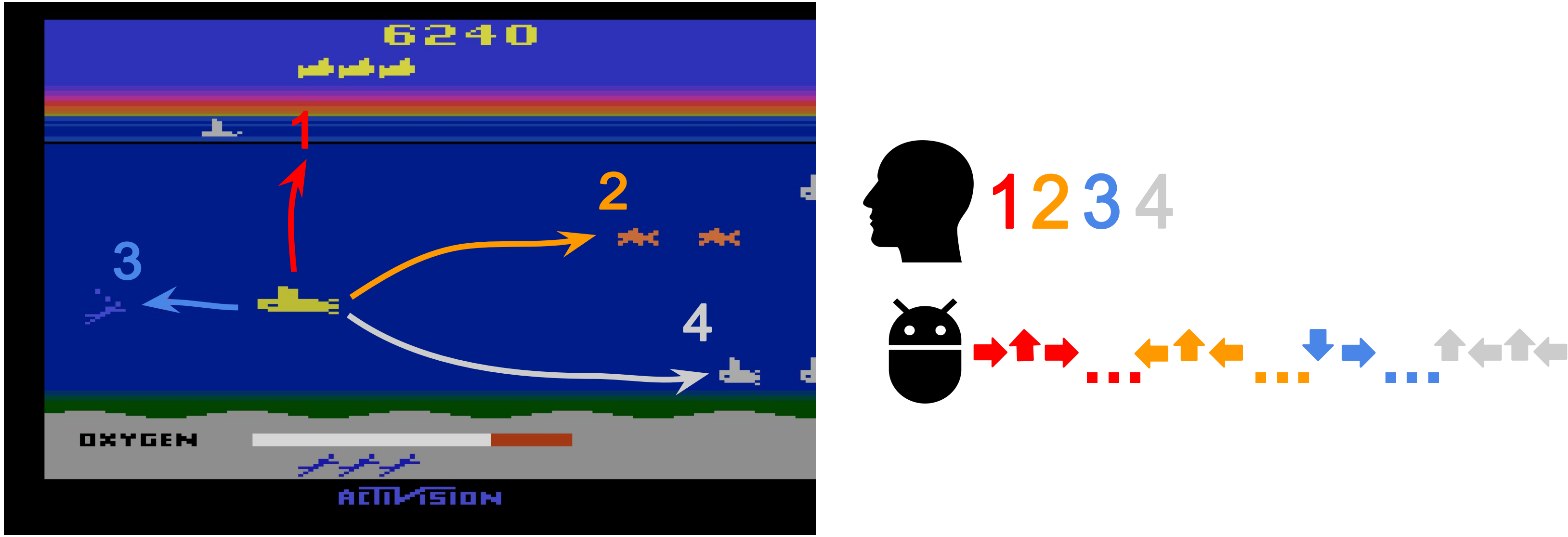






Future work: Attention-guided reinforcement learning

- 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

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