Dissertation: A Modular Attention Hypothesis for Modeling Visuomotor Tasks

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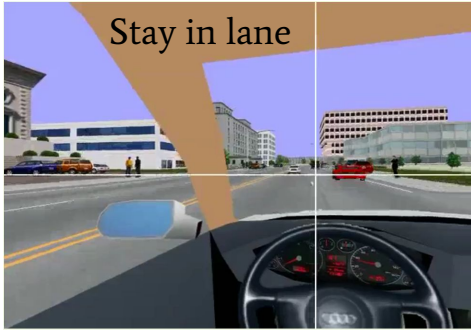
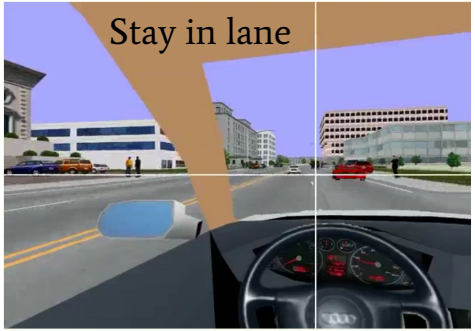
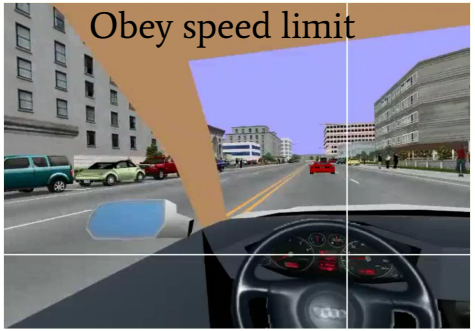
The University of Texas at Austin



Johnson et al., Phil. Trans. of the Royal Society B: Biological Sciences 2014





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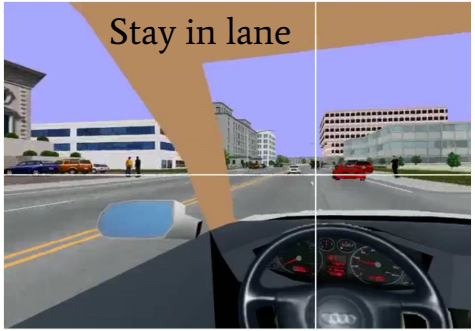

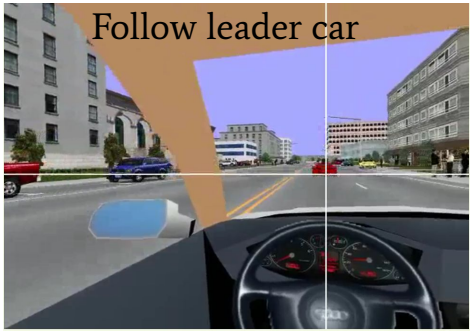

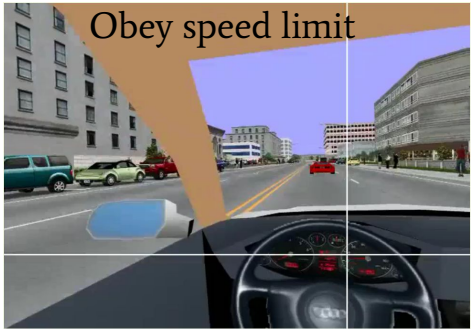

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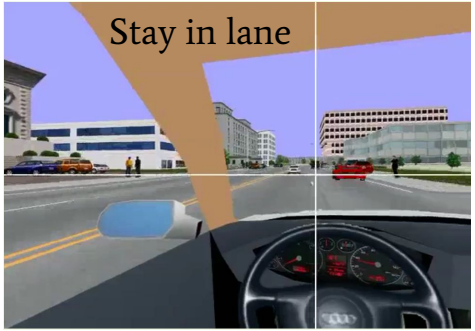

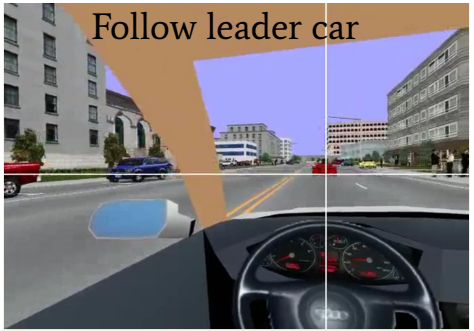

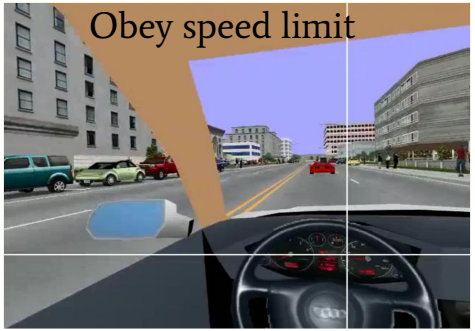

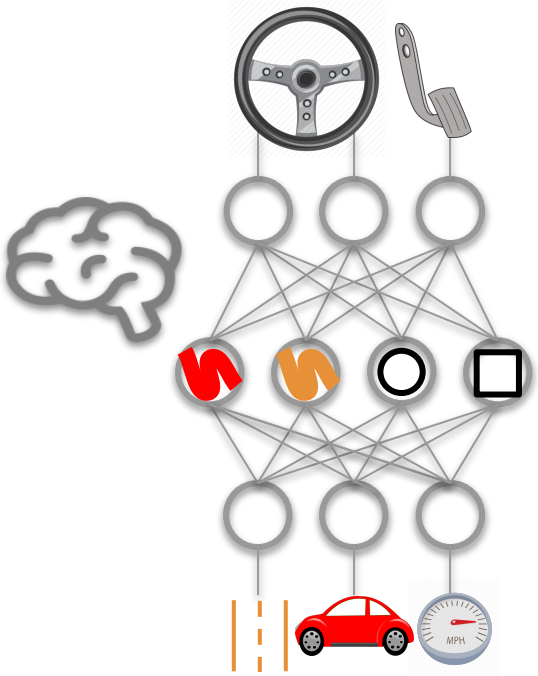

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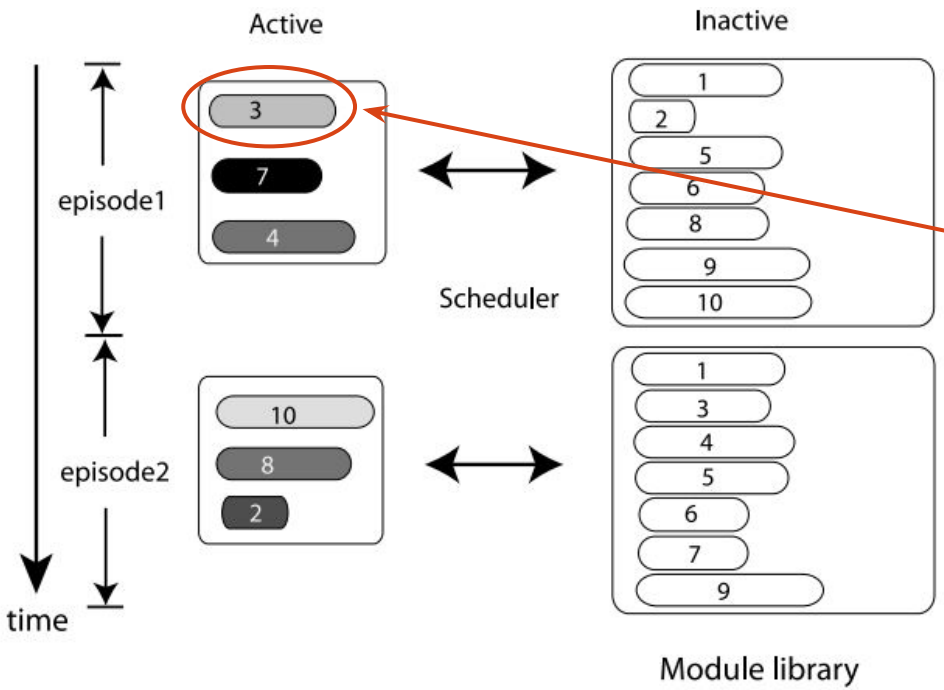
Research question I

RQ-I: How does our brain learn and make decisions to achieve behavioral goals in an information-rich environment, with limited cognitive resources?

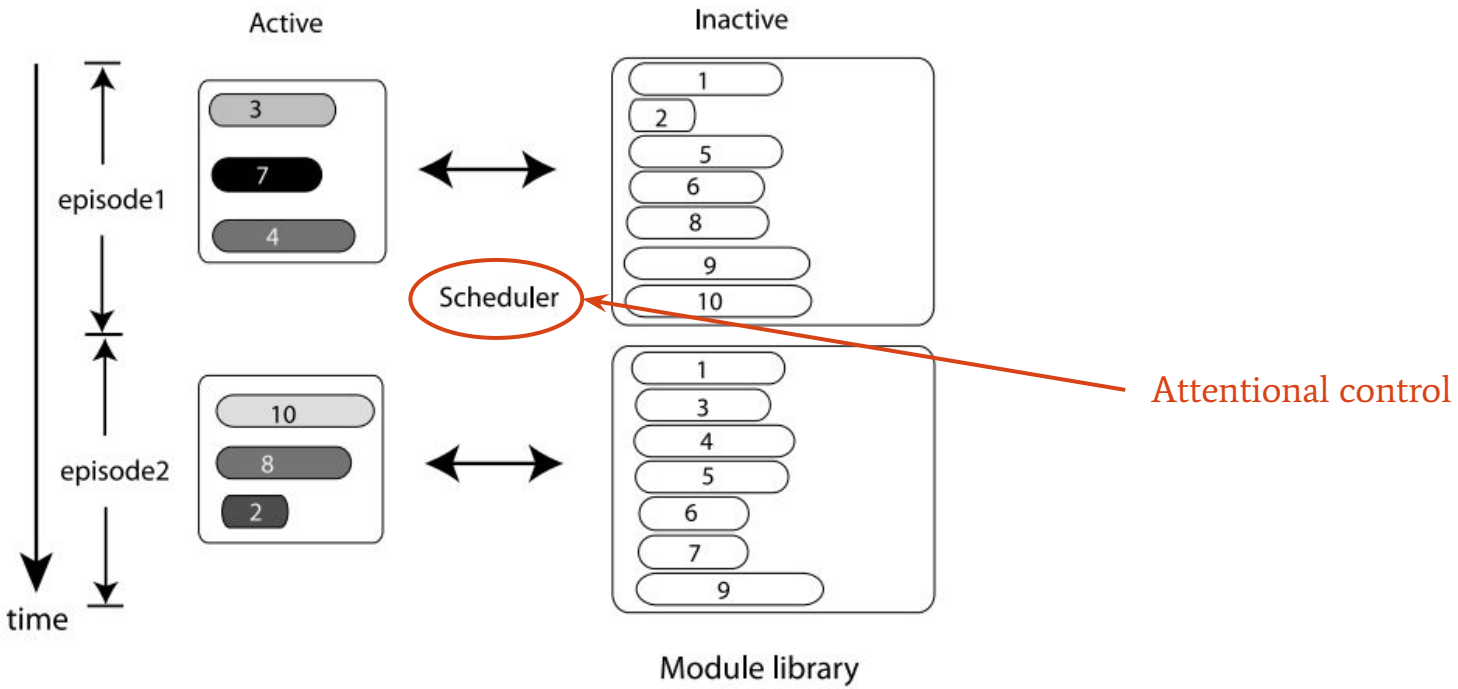
Modularization and attentional control



Modularization hypothesis

Ballard, Brain computation as hierarchical abstraction; Ballard & Zhang, Topics in Cognitive Science 2021

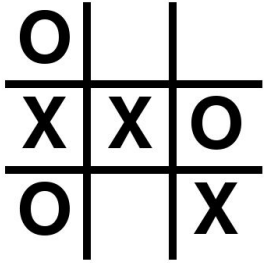
Modularization and attentional control

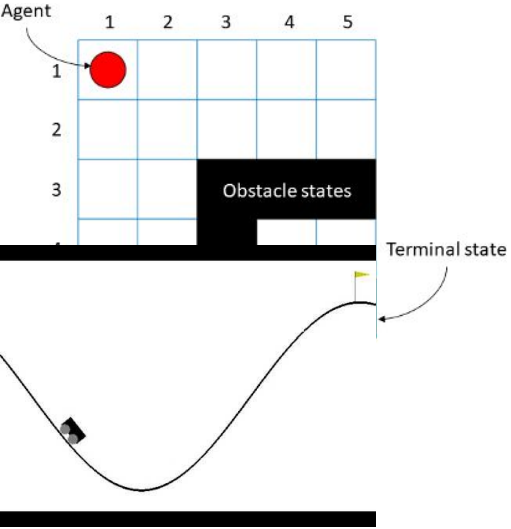


Ballard, Brain computation as hierarchical abstraction; Ballard & Zhang, Topics in Cognitive Science 2021

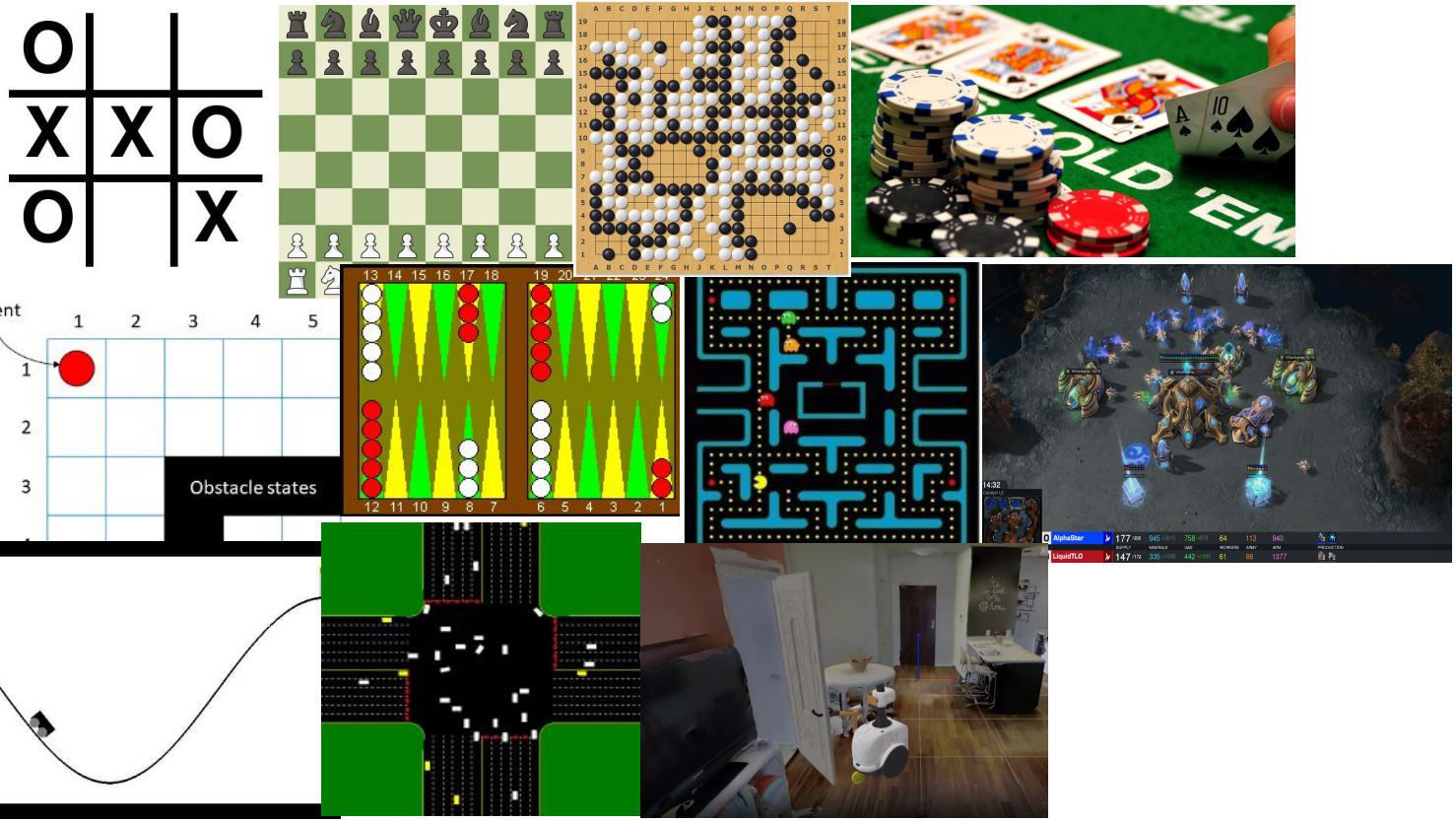
Why should computer scientists care about human cognition?

When AIs move from simple to natural environments





When AIs move from simple to natural environments



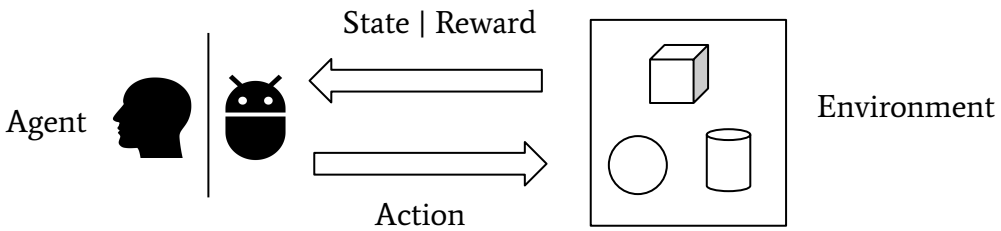
When AIs move from simple to natural environments

Research question II

RQ-II: How can we improve current artificial intelligence (AIs) by studying these mechanisms of the brain, so that AIs can cope with the complexity in the real world?

The reinforcement learning (RL) framework

- A framework widely used in
  - cognitive science to understand animal behaviors;
  - machine learning to train artificial learning agents.



Policy $\pi(a|s)$: tells the agent what action a to take in a given state s

Action value function $Q(s,a)$: tells the agent expected value of taking action a in state s

Roadmap

1. Attentional control

    1.1 Modeling human visual attention

    1.2 Comparing human attention with machine attention

    1.3 Human attention guided learning

2. Modularization hypothesis

3. A theory of their neural basis

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Atari-HEAD Dataset

- Atari Human Eye-Tracking and Demonstration dataset (20 games, 120 hour human data)

Eyelink-1000 infrared eye tracker

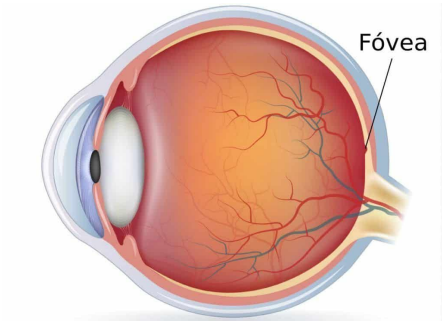
7.97 million actions

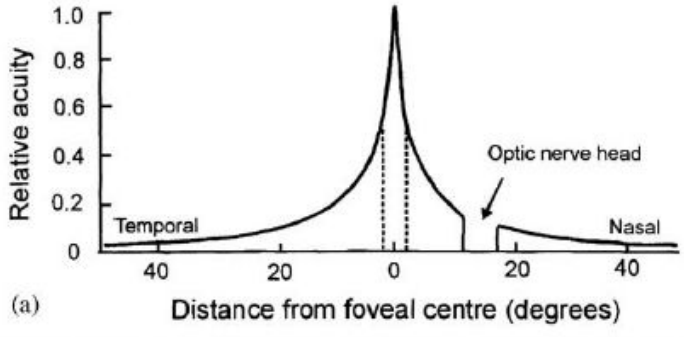
328 million gaze locations

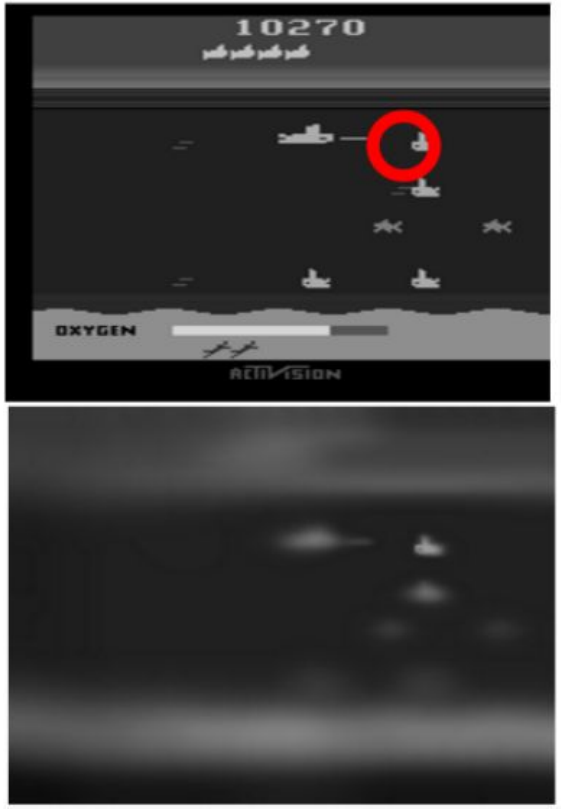
Zhang et al., AAAI 2020

How do humans solve these games?

- See the world in the eyes of the players
  - Foveal vision: has high acuity for only 1-2 visual degrees
  - Visual acuity decreases as a function of distance from foveal center



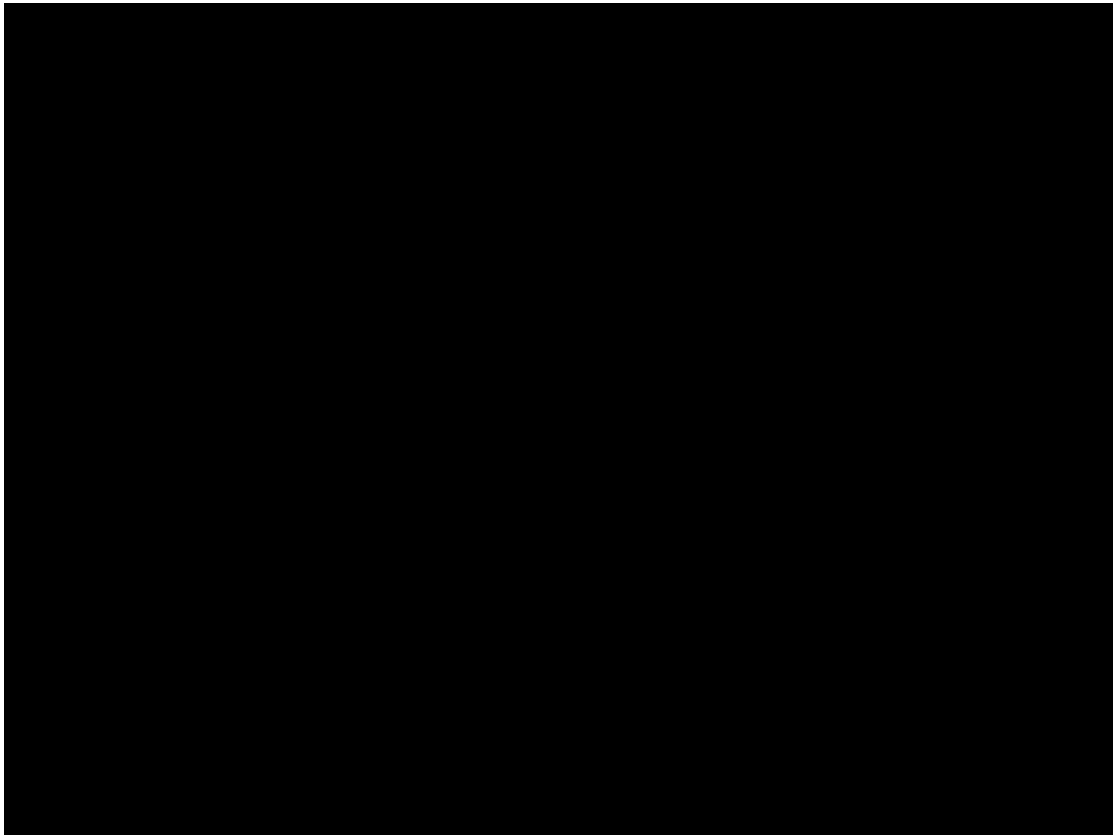




89 visual degrees

Perry & Geisler, Electronic Imaging 2002; Zhang et al., ECCV 2018

Consequence: Eye movements



Cons:

- Partial observability
- Rely on memory and prediction to survive

Pros:

- Require less computational resources
- Does not require spatial invariance as CNNs do

Reveals the current underlying behavioral goal of the decision maker

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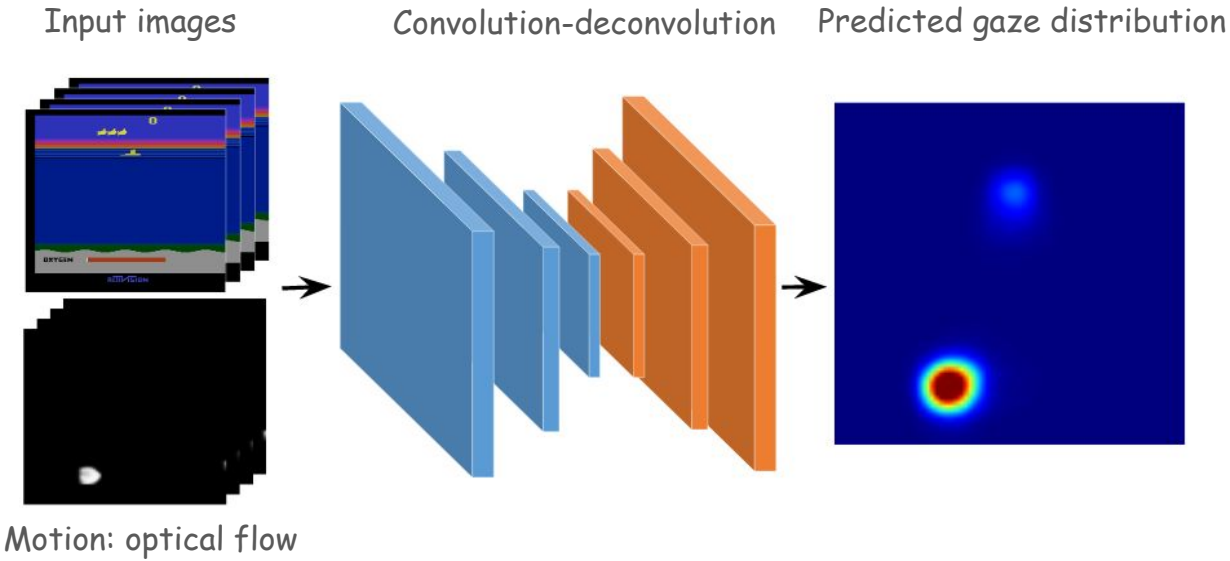
Gaze prediction: Gaze network

- How do we predict human gaze in video games?
- Adding motion information to the previous deep saliency prediction networks*
- Highly accurate, avg. AUC score across 20 games = 0.97 (random = 0.5; max = 1)



Zhang et al., ECCV 2018; *Alletto et al., CVPR 2016

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How do AIs solve these games?

- AIs nowadays can solve some of these games on their own using deep reinforcement learning*
- With human gaze data and models, we can ask:
  - Do humans and RL agents attend to the same visual features when performing the same task?

*Mnih et al. Nature 2015;

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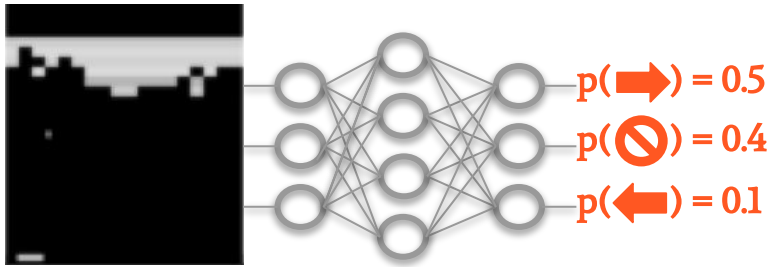
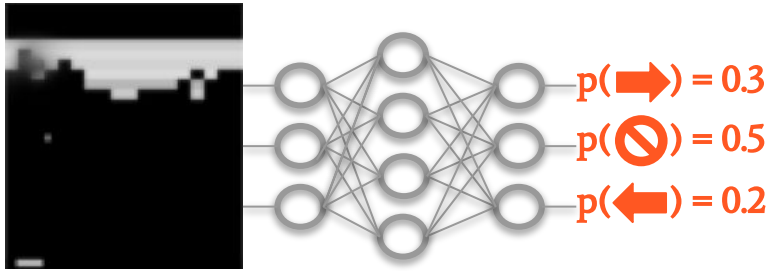
- With human gaze data and models, we can ask:
  - Do humans and RL agents attend to the same visual features when performing the same task?
  - Does the similarity explain RL agents' performance?
  - What factors affect RL agents' attention?

*Mnih et al. Nature 2015;

How do we get RL agent's attention?

- Deep RL attention*
  - Alter the input image by blurring the region around a pixel
  - Calculate how much it changes the output policy of a trained deep RL network
  - The more the change, the more important that pixel is
  - Do this for every pixel for a given image and get the RL agent's attention map





*Greydanus et al. ICML 2017

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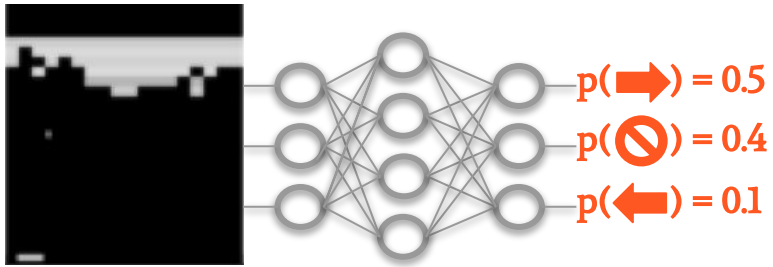
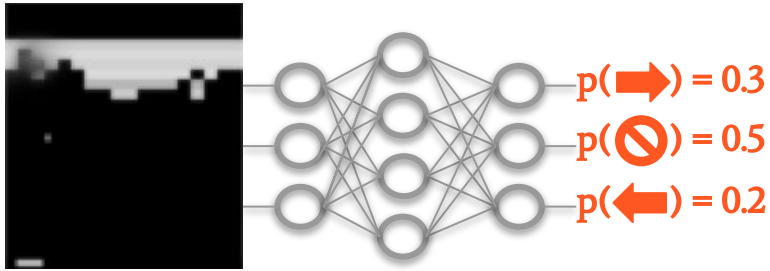
  - Do this for every pixel for a given image and get the RL agent's attention map
- There was no useful reference to tell whether the resulted attention was good or bad
  - Our human gaze dataset makes quantitative comparisons possible





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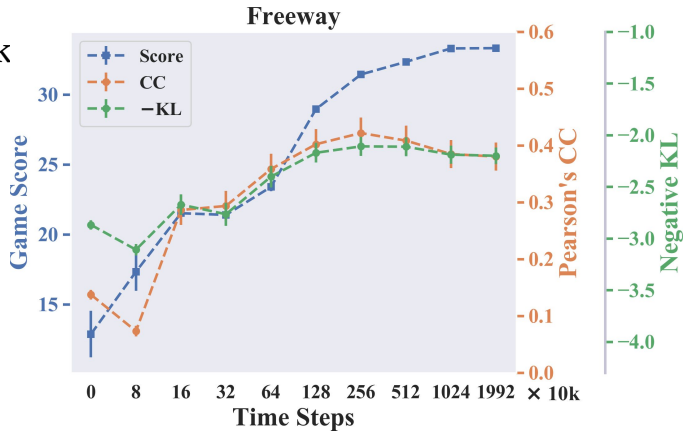
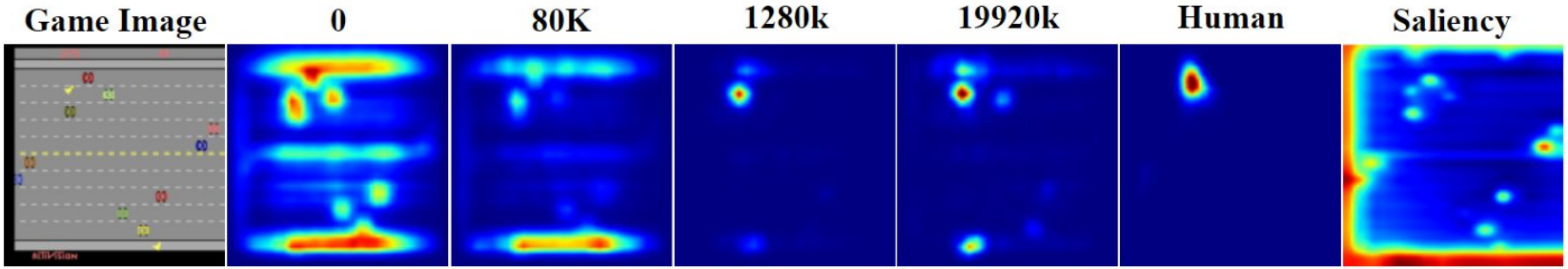
Human vs. RL attention - learning

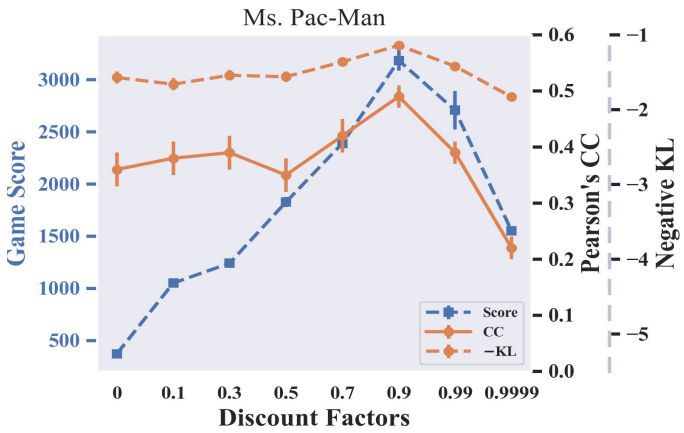
- RL (PPO2) agent's attention gradually becomes more human-lik during training
- RL attention is similar to the bottom-up saliency map at the beginning, and it gradually learns to focus on the task-relevant object like humans do
- Agent's performance is highly correlated with similarity measures, average correlation = 0.81/0.79 (CC/-KL, 6 games)

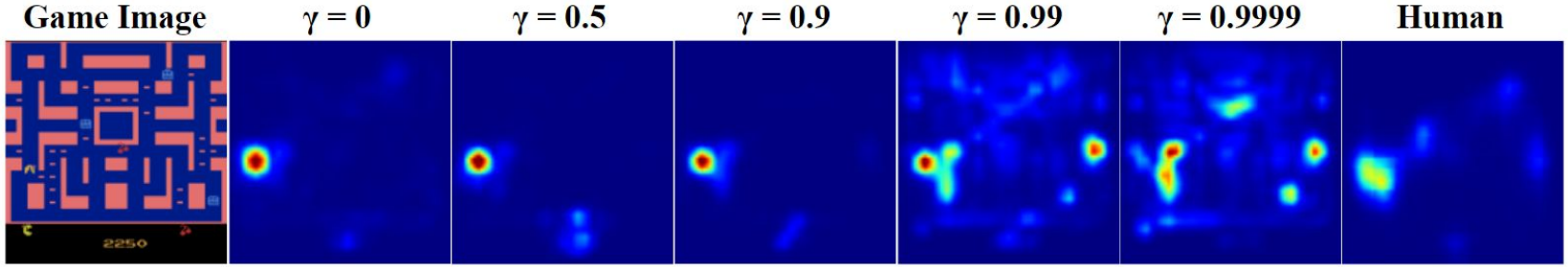




Human vs. RL attention - discount factor

- How much the agent weighs future reward comparing to current reward (planning horizon)
- Intermediate discount factor values produce more human-like attention
  - These values are likely to be the “planning horizons” of human attentional control system
- Deviating from the default value (0.99) could lead to better performance

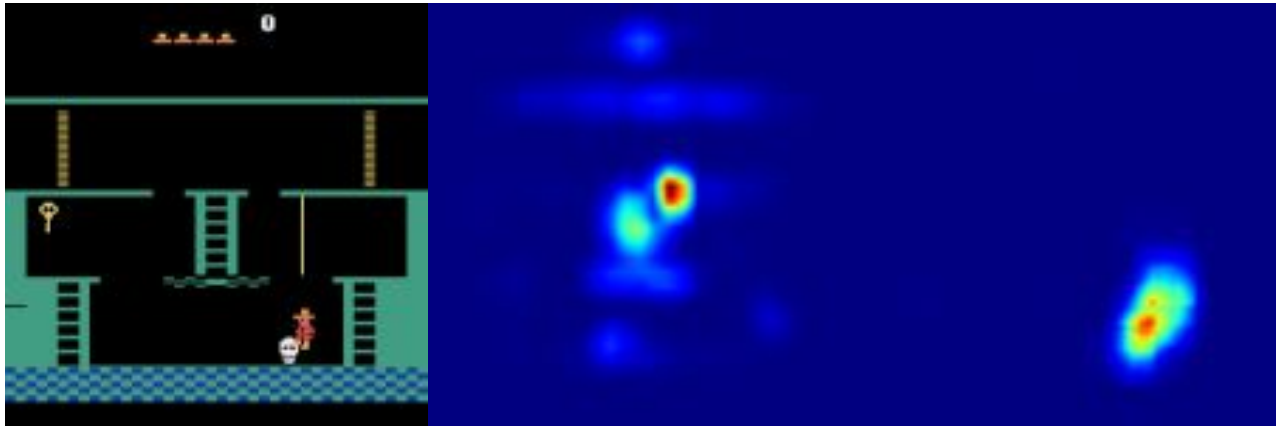




Why do RL agents make mistakes?

- Human attention can help us tell whether the agent's attention is correct when they make mistakes
- We record the states when the RL agent is about to make a mistake
- If RL agent's attention in these states is quantitatively very different from humans, the mistake is likely due to wrong perception

Game Image **RL** **Human**



CC=-0.05
KL=4.33

Insights for vision science research

- RL agents trained from scratch with only images and reward signals can develop attention maps that are similar to humans, even though they have very little prior knowledge.

Zhang et al. arXiv 2021; *Cross et al., 2020

Insights for vision science research

- RL agents trained from scratch with only images and reward signals can develop attention maps that are similar to humans, even though they have very little prior knowledge.
- This result is complementary to a recent study* that compares human fMRI data with deep RL agents' learned feature maps, suggesting that deep RLs can learn biologically plausible representations and can be used as models for human gaze, decision, and brain activities.

Zhang et al. arXiv 2021; *Cross et al., 2020

Insights for RL research

- We highlight the importance of choosing appropriate discount factors.
  - It is beneficial to have an adaptive discount factor (Badia et al., 2020) or multiple discount factors (Fedus et al., 2019).

Zhang et al. arXiv 2021

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- Failure analysis could identify states where agent's attention drastically differs from expert humans.
  - These are the states that may need human intervention

Zhang et al. arXiv 2021

Insights for RL research

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- Failure analysis could identify states where agent's attention drastically differs from expert humans.
  - These are the states that may need human intervention
- ★ The task performance and similarity to human attention are highly correlated, suggesting that one could use human attention to guide the learning process of the agents.

Zhang et al. arXiv 2021

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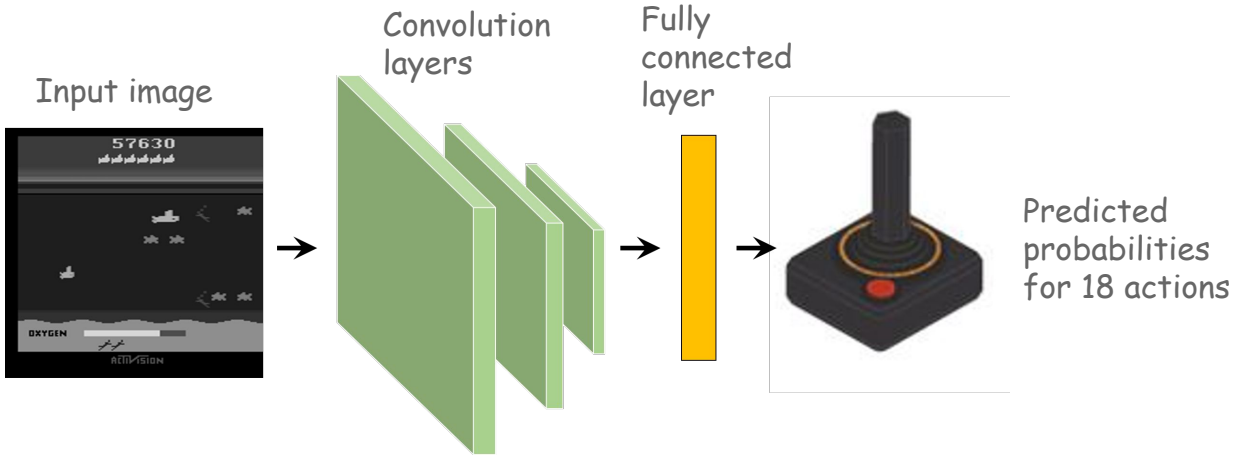
Incorporating attention into learning

- Human gaze is useful for establishing joint attention in teaching and learning*

*Yu & Smith, Cognition 2012

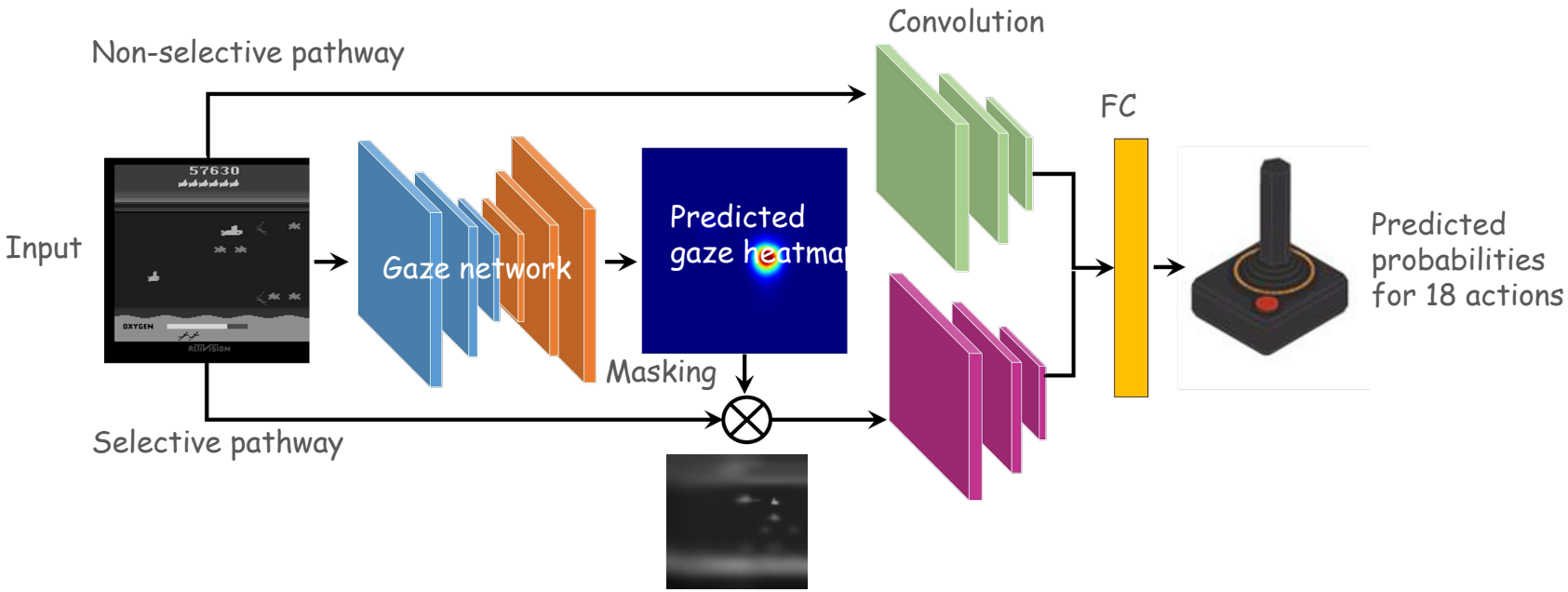
Imitation learning: behavioral cloning (BC)

- Imitation learning: learning to imitate human teacher's actions
- Behavioral cloning: imitation learning as supervised learning



Attention-guided imitation learning (AGIL)

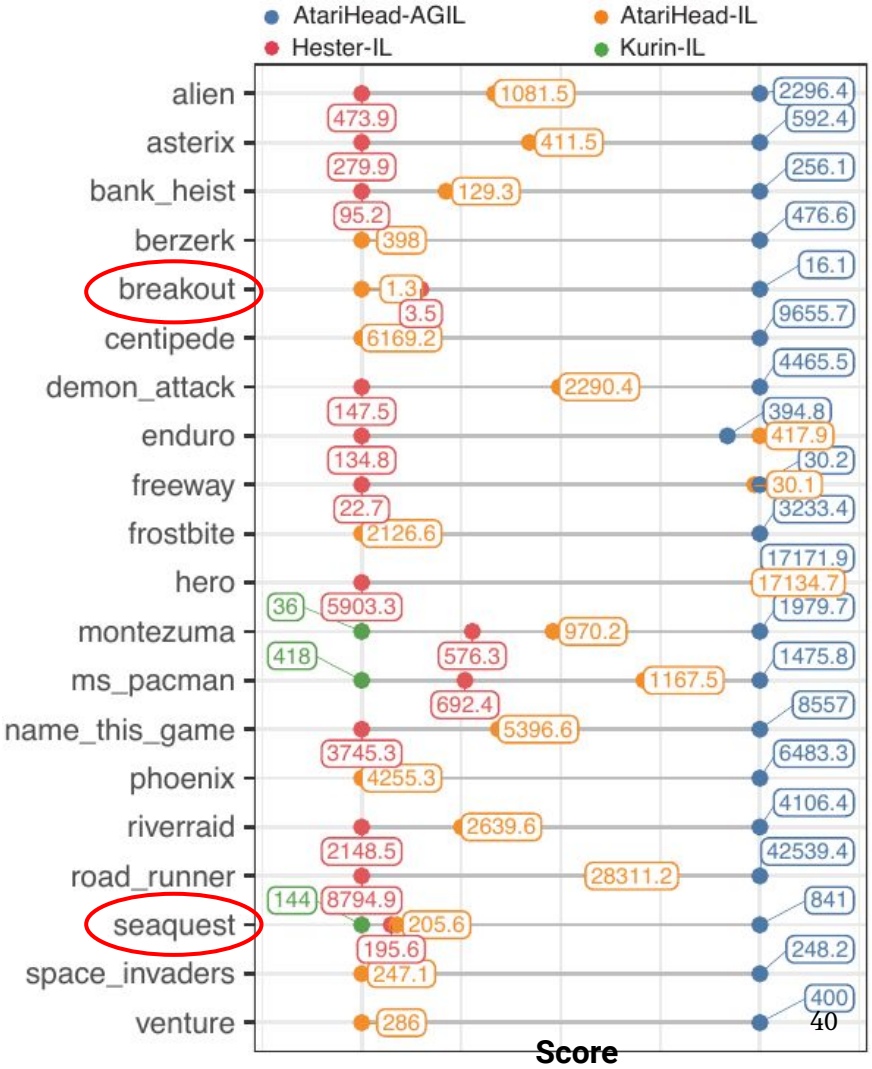
- A biology-inspired two-pathway learning agent



Zhang et al., ECCV 2018; Zhang et al., AAAI 2020

Results

- Incorporating human attention significantly improves task performance (game score)
- More improvement for
  - Games in which the task-relevant objects are very small (e.g., “ball”)
  - Multitasking games

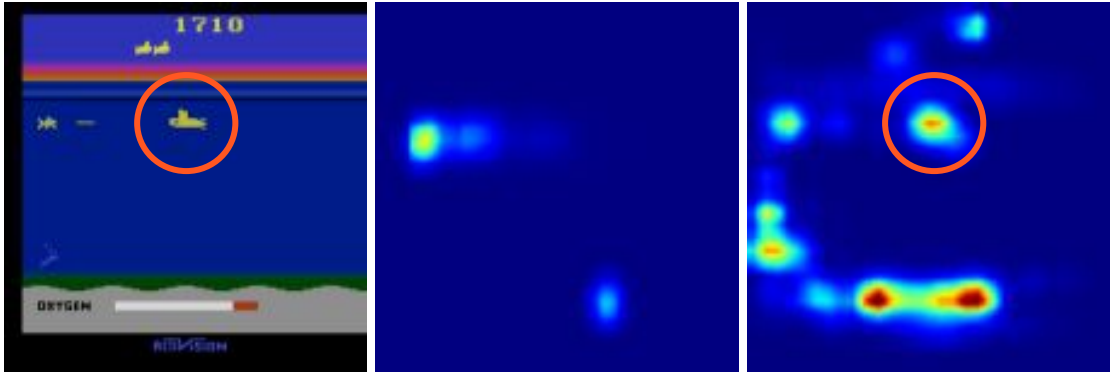


Zhang et al., AAAI 2020; Kurin et al., 2017; Hester et al., 2018

Issues with AGIL

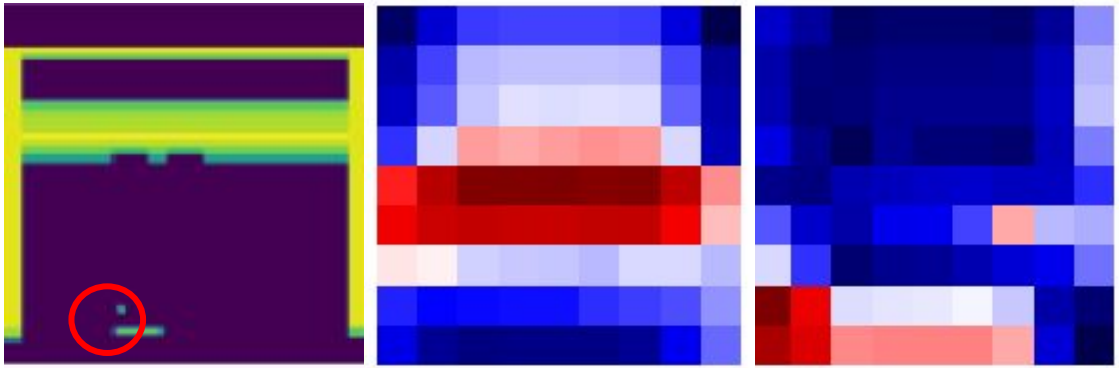
- ✗ AGIL uses gaze by masking so it eliminates information in the periphery
  - Such information still matters for an agent without memory
- AGIL increases model complexity (two pathways)
  - Part of the performance improvement may come from these additional parameters.

Game Image **Human** **RL**



Coverage-based Gaze Loss (CGL)

- Idea: Penalize the agent only if it fails to attend to human attended regions, it is ok for it to pay attention to more things
  - Using a KL-divergence loss (sensitive to false negatives) to force CNN feature maps to be activated at human attended regions
  - Add this KL loss as an auxiliary loss function to the original loss function

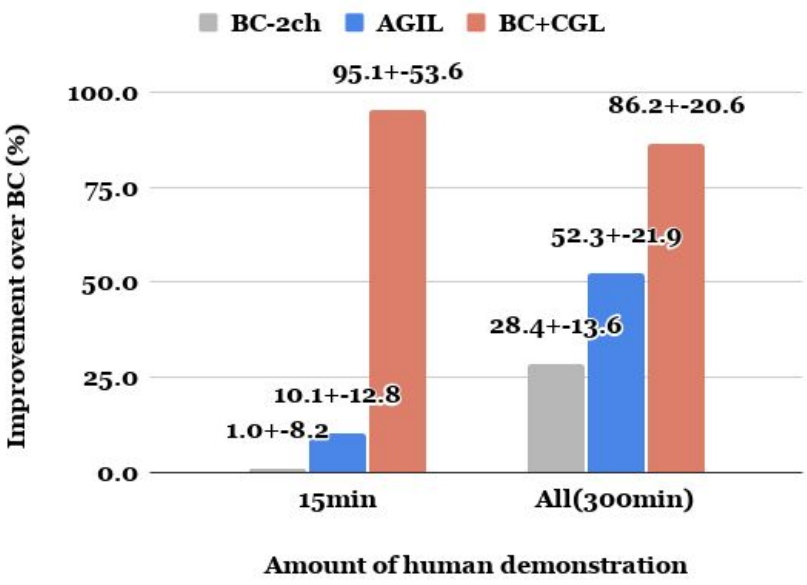


Trained CNN layer 3 feature maps without vs. with CGL

Saran, Zhang, et al., AAMAS 2021

CGL + behavioral cloning

- Performs better than AGIL
  - Especially when training data is limited
- A control study confirms that part of AGIL performance improvement does come from the extra model parameters (BC-2ch)



CGL + BCO / IRL

- Human attention benefits other imitation learning algorithms as well.
- Behavioral cloning from observation*
  - Average improvement compared to a baseline without human attention: +344%
- Inverse reinforcement learning (T-REX**)
  - Average improvement: +374%

Saran, Zhang, et al., AAMAS 2021; *Torabi et al., IJCAI 2018; **Brown et al., ICML 2019

Why attention helps: Causal relationship learning

- Does attention help identify the correct causal chain in learning?
  - e.g., ball coming -> move left
  - Causal confusion happens when the learned policies misidentify the causes of the demonstrator's actions.
  - The "causal confusion trap" in previous works*
    - Add past action labels (often correlated with the current action) to the images
    - Replace original training images with these confounded ones to see how much it degrades the performance

*de Haan et al., NeurIPS 2019

Why attention helps: Causal relationship learning

- Behavioral cloning (BC) performance when confounded: -48%
- BC + attention (CGL) performance when confounded: -34%
- CGL outperforms BC by 571% when facing the causal confusion trap
- Attention does help identify the correct causal relation

*Saran, Zhang, et al., AAMAS 2021

Summary

- *RQ-I: How does the brain learn and make decisions to achieve behavioral goals in an information-rich environment, with limited cognitive resources?*
    - We publish a large-scale, high-quality dataset of human decisions along with their eye movements while playing Atari video games.

Summary

- *RQ-I: How does the brain learn and make decisions to achieve behavioral goals in an information-rich environment, with limited cognitive resources?*
    - We publish a large-scale, high-quality dataset of human decisions along with their eye movements while playing Atari video games.
    - We highlight the importance of attentional control in the models of decision making.

Summary

- *RQ-II: How can we improve current artificial intelligence (AI) by studying these mechanisms of the brain, so that AIs can cope with the complexity in the real world?*
- Methods for leveraging human attention in learning
  - Attention can be used as a mask to directly highlight the attended visual features (e.g., AGIL).
  - Attention can be used as an auxiliary loss function to change the features learned (e.g., CGL).
  - Attention can be used to perform semantically meaningful data augmentation (e.g., EXPAND*).

*Guan et al., arXiv 2020

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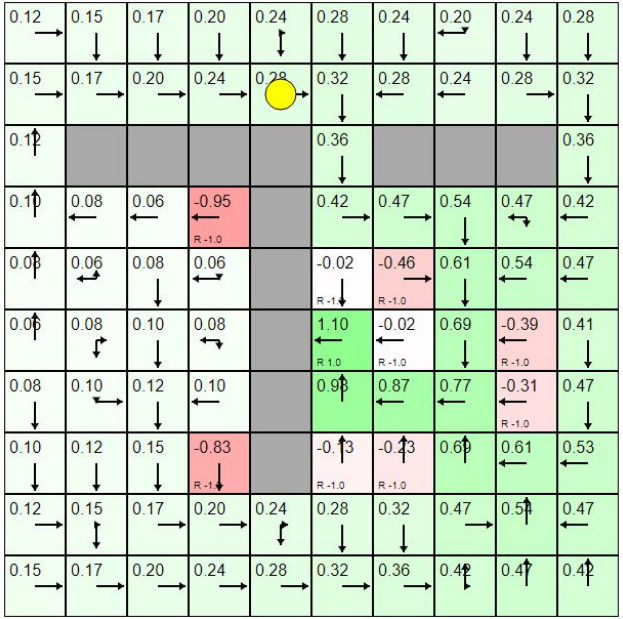
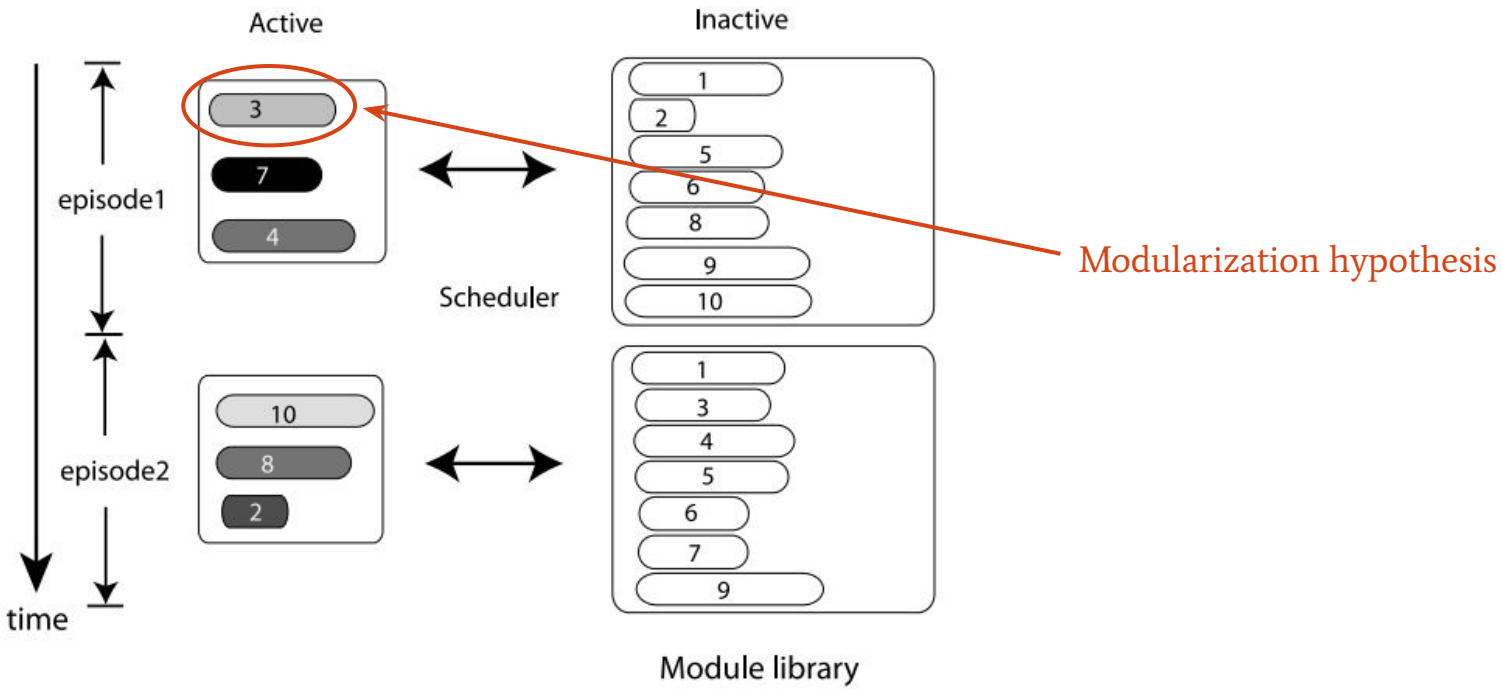
Human vs RL decisions

- Do humans make decisions like a trained RL agent in daily navigation tasks?
- Natural environments are complex and dynamic
- Humans have limited attentional resources
- We humans must have an efficient way to calculate value functions and make decisions quickly



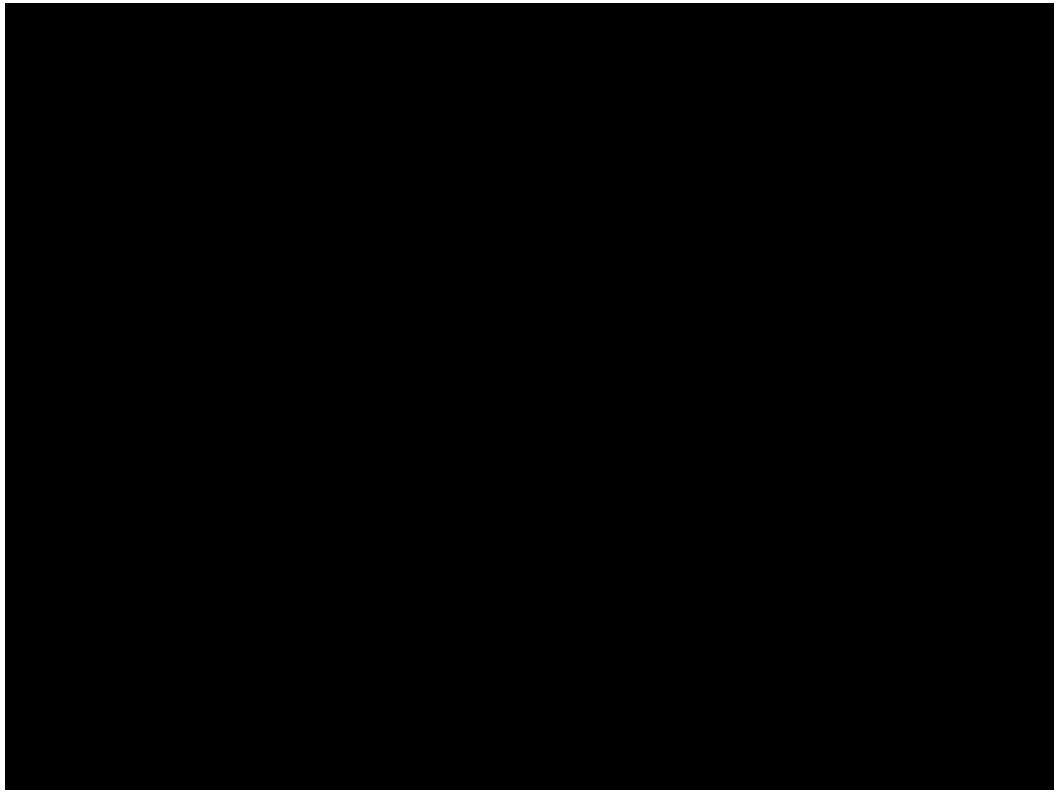
REINFORCEjs by Karpathy

Modularization hypothesis



Ballard, Brain computation as hierarchical abstraction; Ballard & Zhang, Topics in Cognitive Science 2020

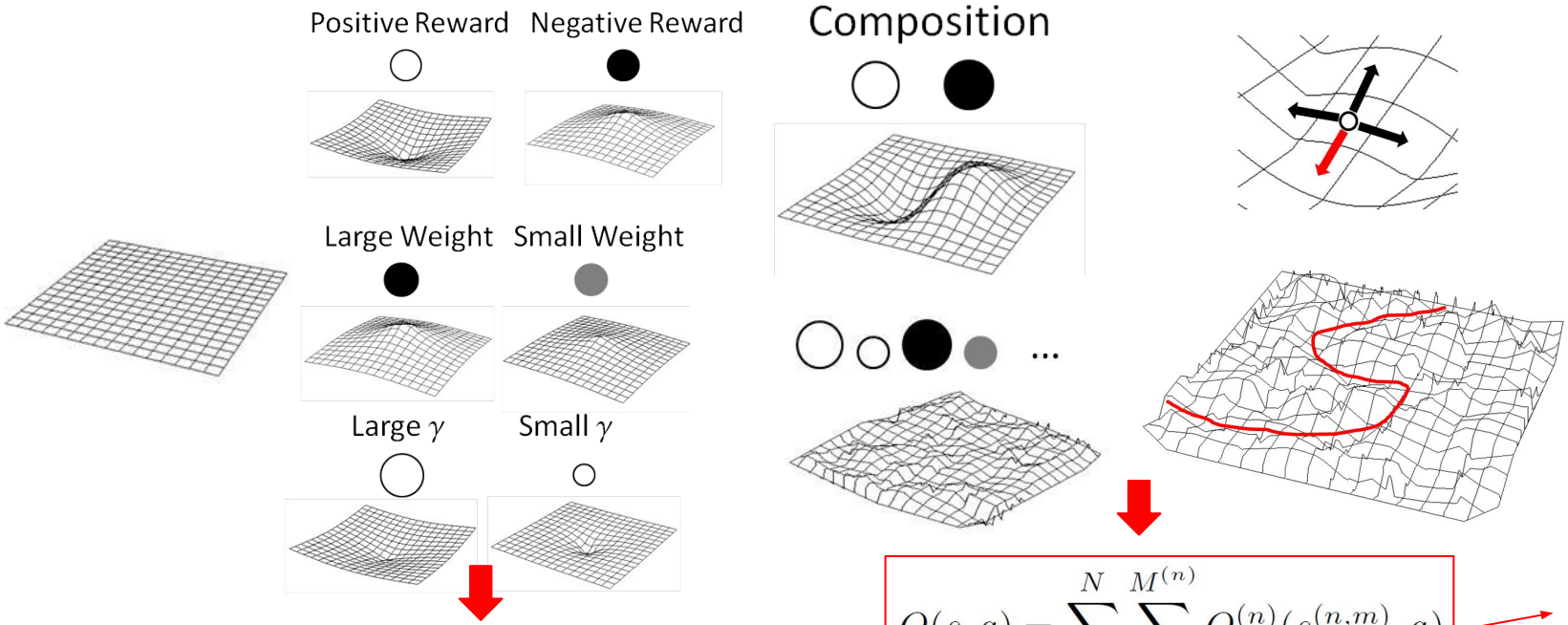
A “grid world” for humans



- A VR navigation experiment*
- Combinations of three tasks: following the path, collecting targets, and avoiding obstacles
- Room layouts differ for every trial

*Tong, Zohar, & Hayhoe, JoV 2017; Zhang et al., PLoS Comp. Bio. 2018

Modular reinforcement learning



$$Q^{(n)}(s^{(n,m)}, a) = r^{(n)}(\gamma^{(n)})^{d(s^{(n,m)},a)}$$

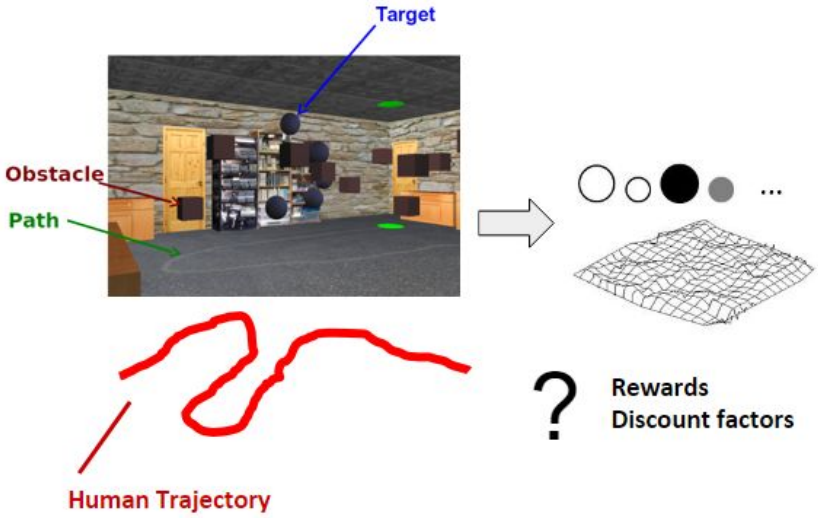
$$Q(s,a) = \sum_{n=1}^{N} \sum_{m=1}^{M^{(n)}} Q^{(n)}(s^{(n,m)}, a)$$

Composition of modules to generate behaviors

Sprague & Ballard, IJCAI 2003; Rothkopf & Ballard, Bio. Cybernetics 2013; Zhang et al., PLoS Comp. Bio. 2018

Modular inverse reinforcement learning

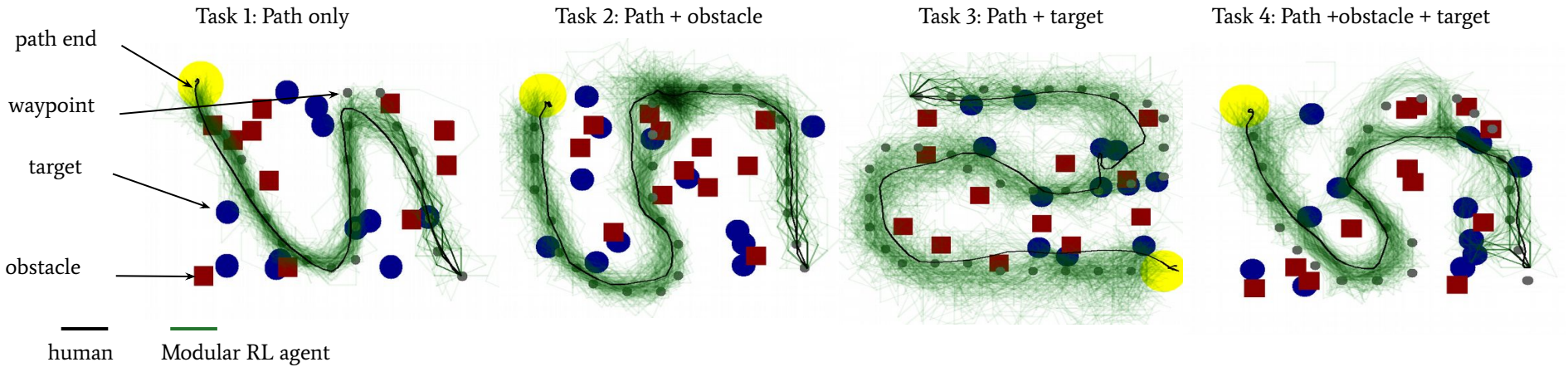
- Given: environment states, human decisions
- Estimate: human value function parameterized by module rewards and discount factors
- Maximum likelihood inference



Zhang et al., PLoS Comp. Bio. 2018

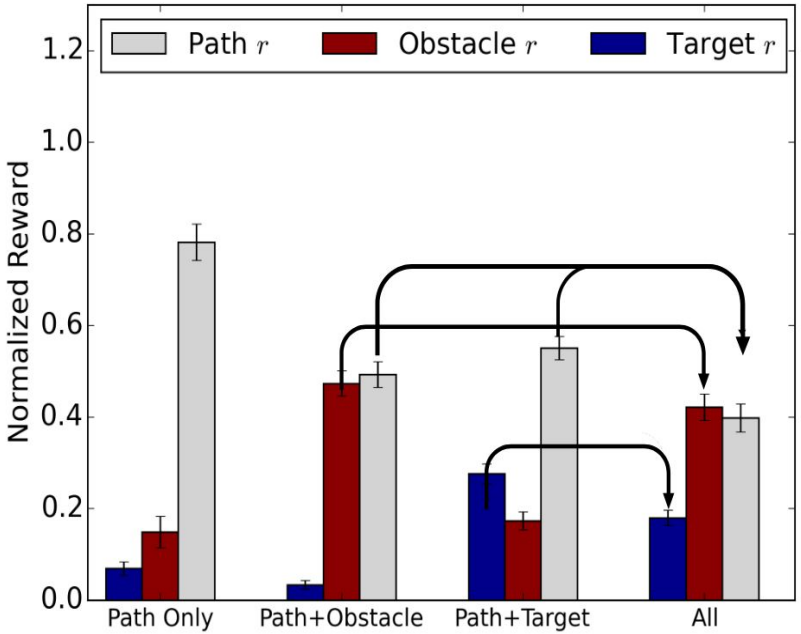
Results: Performance on hold-out data

- Average human walking direction prediction error: 25° (Bayesian IRL: 55°)
- Modular RL agents are able to navigate like humans, under all task conditions



Zhang et al., PLoS Comp. Bio. 2018

Results: Combining modules



- Evidence for the modularization hypothesis:
  - Task 4 rewards can be obtained by combining Task 2 and 3 rewards
  - Identical to rewards estimated from Task 4 human data directly
- These modules can be combined linearly

Zhang et al., PLoS Comp. Bio. 2018

Summary

- *RQ-I: How does the brain learn and make decisions to achieve behavioral goals in an information-rich environment, with limited cognitive resources?*
  - We show that modular reinforcement learning may be a useful model for human navigation behaviors.
  - Human multitasking behaviors can be decomposed into multiple modules, each maximizes its own (discounted) reward.
  - This way of calculating value function is fast and efficient, hence it is suitable for making decisions in a complex, changing environment (true for many daily scenarios)
  - This rough estimation may be used as a prior for learning a more sophisticated value function in a fixed environment.

Summary

- *RQ-II: How can we improve current artificial intelligence (AI) by studying these mechanisms of the brain, so that AIs can cope with the complexity in the real world?*
  - Modular RL has the potential to be a candidate RL algorithm for tasks with high-dimensional state space.
  - The computational model of humans also allows robots to predict human walking directions, which ensures these robots can navigate safely around humans*.

*Junges et al., QEST 2017

Roadmap

1. Attentional control

    1.1 Modeling human visual attention

    1.2 Comparing human attention with machine attention

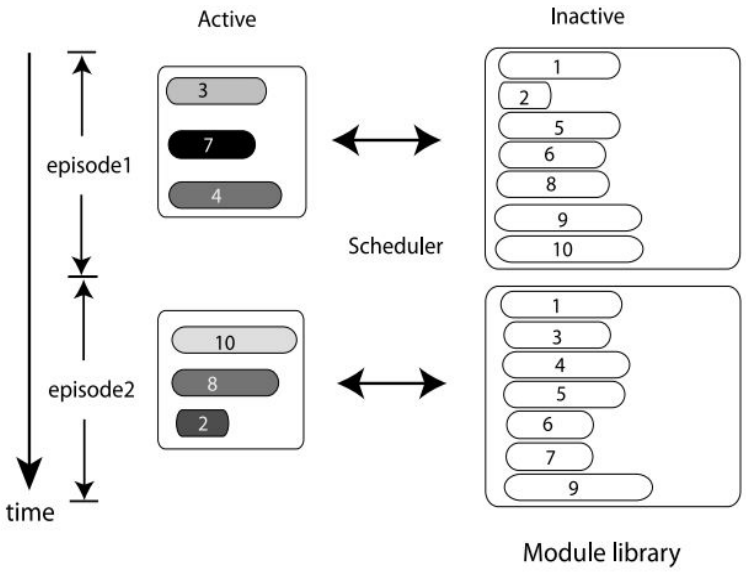
    1.3 Human attention guided learning

2. Modularization hypothesis

3. A theory of their neural basis

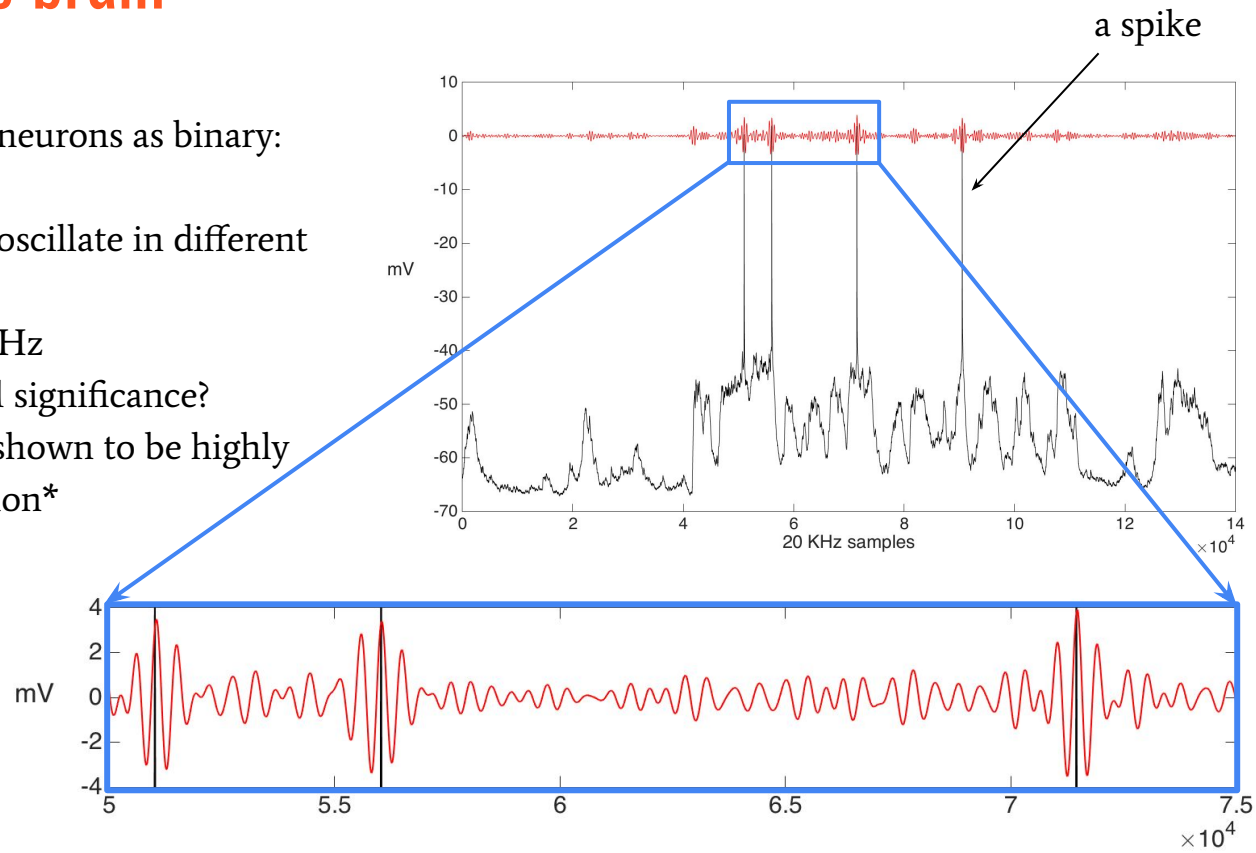
How does the brain implement all these?

- Modularization implies multiple, coexisting neural processes in the brain
- Attentional control implies a neural mechanism that manages resources (neurons) for these processes
- A theoretical model: Gamma Spike Multiplexing (GSM)



Oscillations in the brain

- We normally think of neurons as binary: spike/no spike
- Membrane potentials oscillate in different frequency bands
  - Gamma: 30 - 80Hz
- Is there any functional significance?
- Gamma activities are shown to be highly correlated with attention*
- Why?

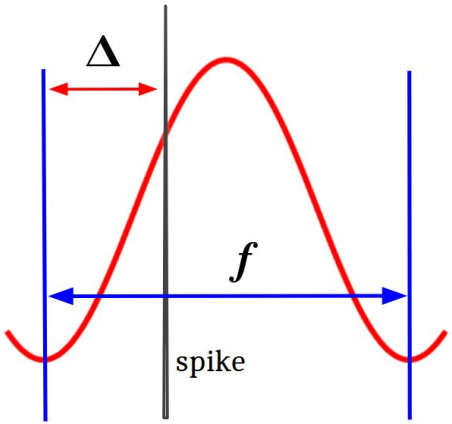


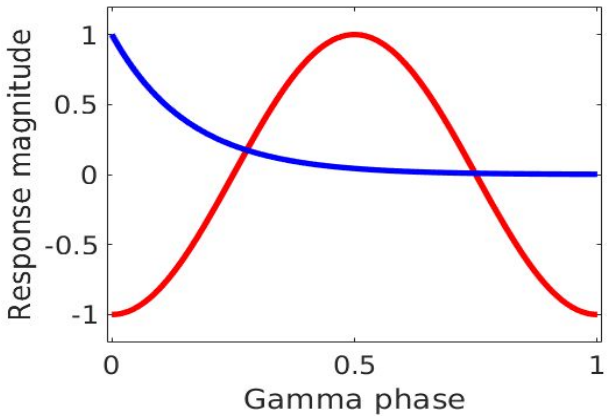
Data collection: Thanks to
Luc Gentet
Neuroscience Laboratory, Lyon
Quentin Perrenoud
Yale School of Medicine

*Bauer, M. et al. J. Neuroscience 2006; Jensen, Kaiser, & Lachaux, Trends in Neurosciences 2007

Gamma frequency phase coding model

- Neurons uses somatic gamma oscillation as a timing reference
- Phase code allows a single spike to represent an analog value instead of {0,1} using the delay Δ

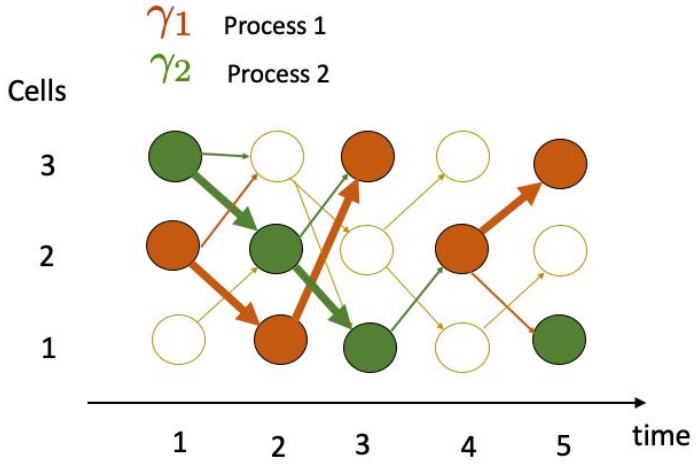




Ballard & Jehee, Frontiers in Computational Neuroscience 2011; Zhang & Ballard, Neural Computation 2020

How is this useful?

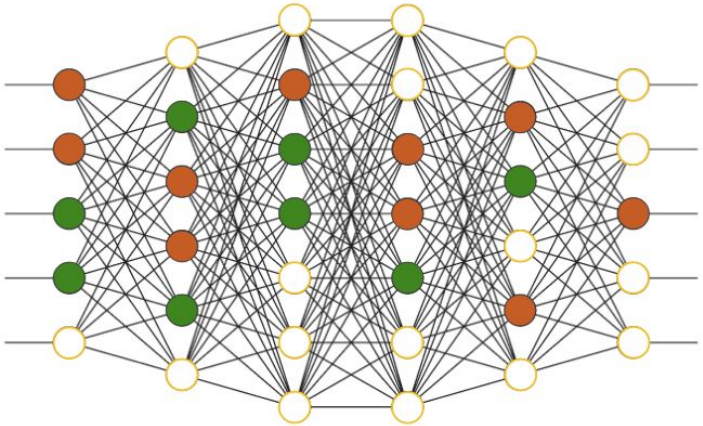
- Multiple neurons can synchronize their gamma oscillations so they are effectively “on the same clock”
- Thus neurons can decode the value represented by the incoming spikes from their cohort members
- Each neural process has a dedicated gamma frequency
- A neuron can participate in different processes by changing its frequency



Zhang & Ballard, Neural Computation 2020

Neural multiplexing model

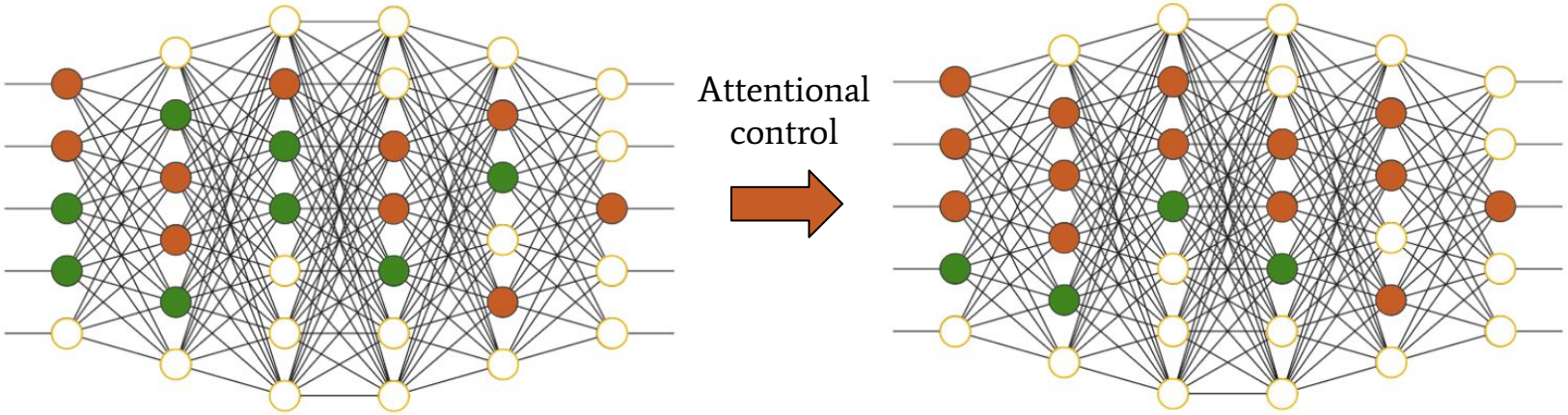
- GSM dynamically partitions a large network into multiple sub-networks/modules
- “Radio” network
  - “Communicate through coherence”*
  - Neurons oscillate together, wire together



*Fries, Neuron 2015

Reinterpret attention

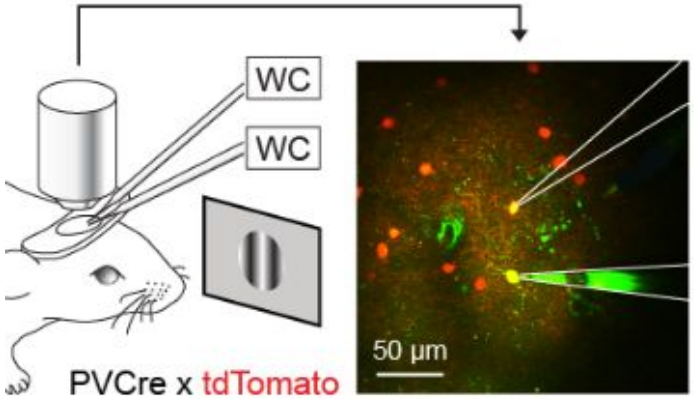
- Attentional control allocates more neurons to participate in a process
  - By synchronizing these neurons to the gamma frequency associated with the attended process
  - Could lead to better precision in computation (the “neural gain” factor*)



*Eldar, Cohen, & Niv, Nature Neuroscience 2013; Zhang & Ballard, Neural Computation 2020

Ongoing and future work

- The GSM model is being tested using mouse patch-clamp data*.
- In the long run, we hope to be able to identify active neural processes (modules) from brain oscillations.



*Perrenoud et al., PLoS Comp. Bio. 2018

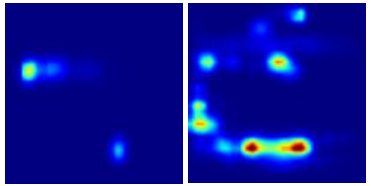
Summary

- *RQ-I: How does the brain learn and make decisions to achieve behavioral goals in an information-rich environment, with limited cognitive resources?*
  - GSM model provides a possible explanation for how modularization and attentional control are implemented, although many details are yet to be resolved.
  - The proposed GSM model allows the brain to
    - Code information efficiently using spike timing
    - Perform multiple computations in parallel
    - Select processes to be activated.

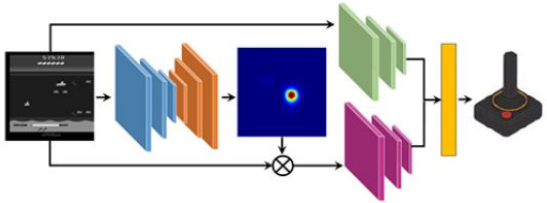
Conclusions

Gaze Prediction

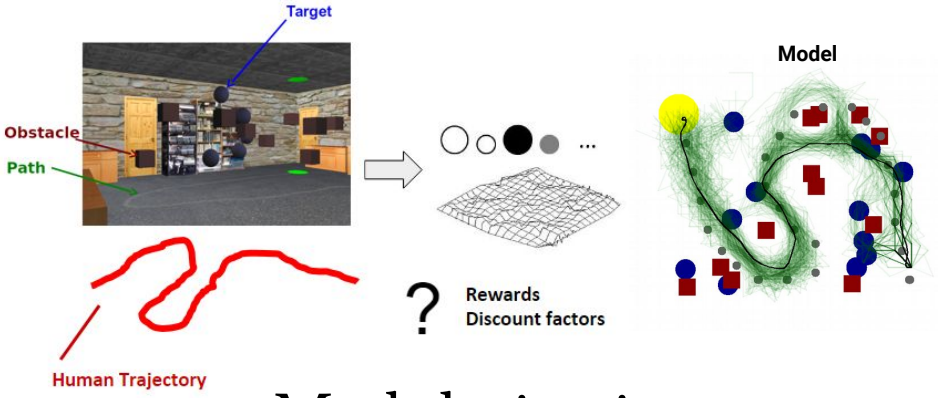
Human vs. RL Attention



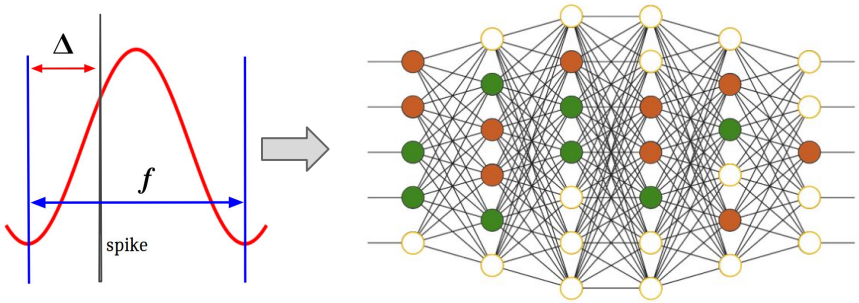
Attention-Guided Learning



Attentional Control



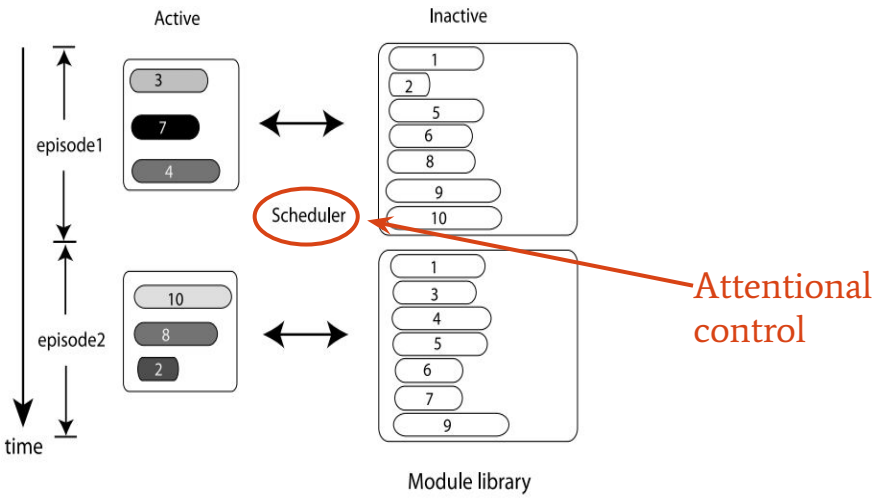
Modularization



Neural Basis

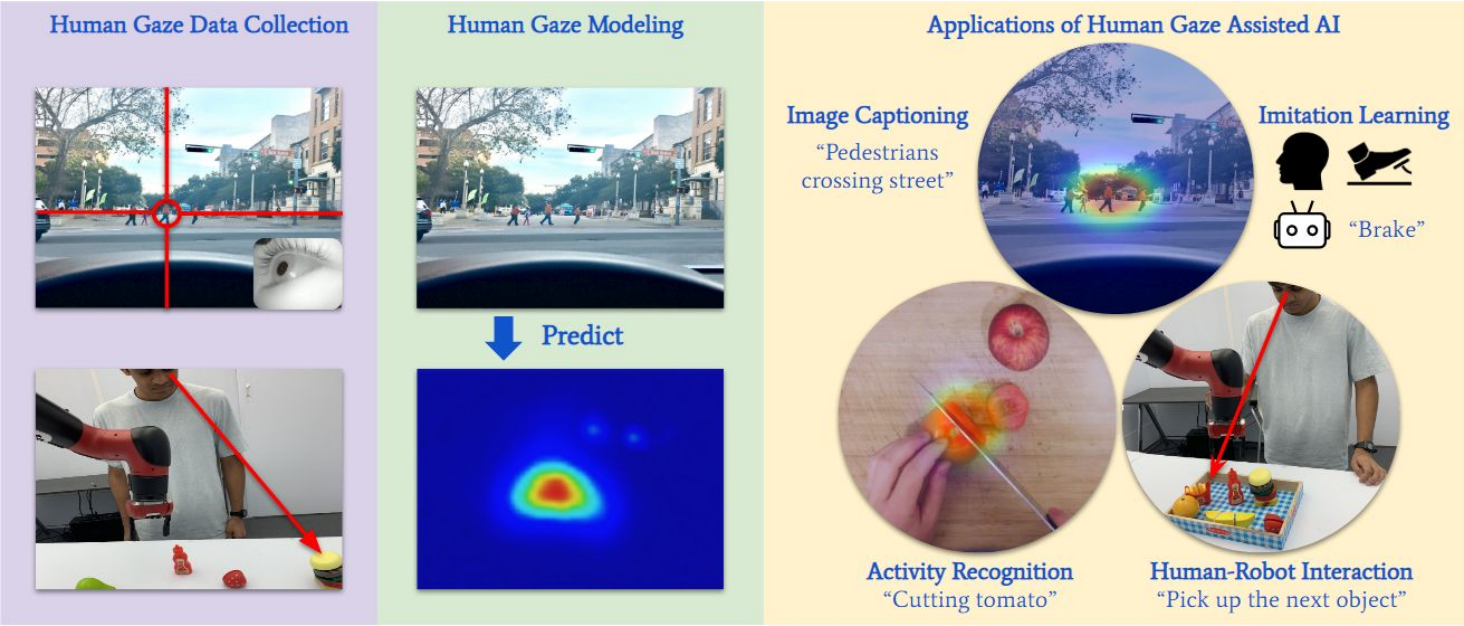
Contributions

- This work emphasizes the role of attentional control in the previous modular behavior model.
- Incorporating attention information into decision modeling leads to improved results, indicating that attention was a missing piece in between perception and decision.



Contributions

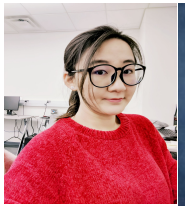
- A new learning paradigm for human-in-the-loop machine learning: learning attention from humans

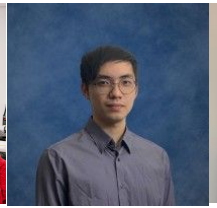


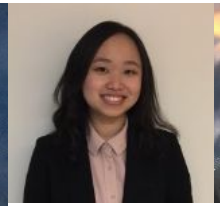
Zhang et al., IJCAI Survey 2019; 2020

Thank you all!

National Institutes of Health


Yuchen Cui

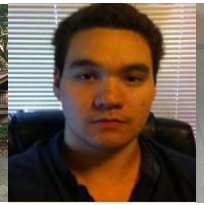

Lin Guan

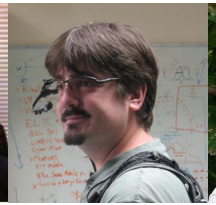

Suna Guo


Zhuode Liu

Bo Liu


Yuezhang Liu


Karl Muller

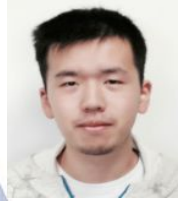

Matthew Tong


Calen Walshe


Jake Whritner


Akanksha Saran


Luxin Zhang


Shun Zhang


Yifeng Zhu


Dana Ballard


Luc Gentet


Mary Hayhoe


Constantin Rothkopf


Peter Stone

The University of Texas at Austin
Graduate School

Thank you all for your attention!
Questions?

Reference

1. Johnson, L., Sullivan, B., Hayhoe, M., & Ballard, D. (2014). Predicting human visuomotor behaviour in a driving task. Philosophical Transactions of the Royal Society B: Biological Sciences, 369(1636), 20130044.
2. Ballard, D. H. (2015). Brain computation as hierarchical abstraction. MIT Press.
3. Tong, M. H., Zohar, O., & Hayhoe, M. M. (2017). Control of gaze while walking: task structure, reward, and uncertainty. Journal of vision, 17(1), 28-28.
4. Rothkopf, C. A., & Ballard, D. H. (2013). Modular inverse reinforcement learning for visuomotor behavior. Biological cybernetics, 107(4), 477-490.
5. Sprague, N., & Ballard, D. (2003). Multiple-goal reinforcement learning with modular sarsa (0). IJCAI.
6. Perry, J. S., & Geisler, W. S. (2002, May). Gaze-contingent real-time simulation of arbitrary visual fields. In Human vision and electronic imaging VII (Vol. 4662, pp. 57-69). International Society for Optics and Photonics.
7. Greydanus, S., Koul, A., Dodge, J., & Fern, A. (2017). Visualizing and understanding atari agents. ICML.
8. Bauer, M., Oostenveld, R., Peeters, M., & Fries, P. (2006). Tactile spatial attention enhances gamma-band activity in somatosensory cortex and reduces low-frequency activity in parieto-occipital areas. Journal of Neuroscience, 26(2), 490-501.
9. Jensen, O., Kaiser, J., & Lachaux, J. P. (2007). Human gamma-frequency oscillations associated with attention and memory. Trends in neurosciences, 30(7), 317-324.
10. Ballard, D., & Jehee, J. (2011). Dual roles for spike signaling in cortical neural populations. Frontiers in computational neuroscience, 5, 22.
11. Fries, P. (2015). Rhythms for cognition: communication through coherence. Neuron, 88(1), 220-235.
12. Eldar, E., Cohen, J. D., & Niv, Y. (2013). The effects of neural gain on attention and learning. Nature neuroscience, 16(8), 1146.
13. Yu, C., & Smith, L. B. (2012). Embodied attention and word learning by toddlers. Cognition, 125(2), 244-262.
14. Warnell, G., Waytowich, N., Lawhern, V., & Stone, P. (2018, April). Deep tamer: Interactive agent shaping in high-dimensional state spaces. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 32, No. 1).
15. Knox, W. B., & Stone, P. (2009, September). Interactively shaping agents via human reinforcement: The TAMER framework. In Proceedings of the fifth international conference on Knowledge capture (pp. 9-16).
16. de Haan, P., Jayaraman, D., & Levine, S. (2019). Causal confusion in imitation learning. arXiv preprint arXiv:1905.11979.

Reference

1. Zhang, Ruohan. "Action selection in modular reinforcement learning." Master Thesis, 2014.
2. Zhang, Ruohan, Zhao Song, and Dana Ballard. "Global policy construction in modular reinforcement learning." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 29, no. 1. 2015.
3. Zhang, Ruohan, Yue Yu, Mahmoud El Chamie, Behçet Açikmese, and Dana H. Ballard. "Decision-Making Policies for Heterogeneous Autonomous Multi-Agent Systems with Safety Constraints." In IJCAI, pp. 546-553. 2016.
4. Zhang, Ruohan, and Zhao Song. "Maximum Sustainable Yield Problem for Robot Foraging and Construction System." In IJCAI, pp. 2725-2731. 2016.
5. Genter, Katie, Patrick MacAlpine, Jacob Menashe, Josiah Hannah, Elad Liebman, Sanmit Narvekar, Ruohan Zhang, and Peter Stone. "UT Austin Villa: project-driven research in AI and robotics." IEEE Intelligent Systems 31, no. 2 (2016): 94-101.
6. Yen, Ian EH, Xiangru Huang, Kai Zhong, Ruohan Zhang, Pradeep Ravikumar, and Inderjit S. Dhillon. "Dual decomposed learning with Factorwise Oracles for structural SVMs of large output domain." Advances in neural information processing systems 29 (2016): 5030.
7. Zeng, Xiaoyu, and Ruohan Zhang. "Participatory art museum: collecting and modeling crowd opinions." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 31, no. 1. 2017.
8. Huang, Xiangru, Ian En-Hsu Yen, Ruohan Zhang, Qixing Huang, Pradeep Ravikumar, and Inderjit Dhillon. "Greedy direction method of multiplier for MAP inference of large output domain." In Artificial Intelligence and Statistics, pp. 1550-1559. PMLR, 2017.
9. Menashe, Jacob, Josh Kelle, Katie Genter, Josiah Hanna, Elad Liebman, Sanmit Narvekar, Ruohan Zhang, and Peter Stone. "Fast and precise black and white ball detection for robocup soccer." In Robot world cup, pp. 45-58. Springer, Cham, 2017.
10. Zhang, Ruohan, Zhuode Liu, Mary M. Hayhoe, and Dana H. Ballard. "Attention guided deep imitation learning." Cognitive Computational Neuroscience (2017).
11. Zhang, Ruohan, Shun Zhang, Matthew H. Tong, Mary M. Hayhoe, and Dana H. Ballard. "Modeling Sensorimotor Behavior through Modular Inverse Reinforcement Learning with Discount Factors." Journal of Vision 17, no. 10 (2017): 1267-1267.
12. Ballard, Dana H., and Ruohan Zhang. "Cortical spike multiplexing using gamma frequency latencies." bioRxiv (2018): 313320.
13. Junges, Sebastian, Nils Jansen, Joost-Pieter Katoen, Ufuk Topcu, Ruohan Zhang, and Mary Hayhoe. "Model Checking for Safe Navigation Among Humans." In International Conference on Quantitative Evaluation of Systems, pp. 207-222. Springer, Cham, 2018.
14. Zhang, Luxin, Ruohan Zhang, Zhuode Liu, Mary Hayhoe, and Dana Ballard. "Learning attention model from human for visuomotor tasks." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 32, no. 1. 2018.

Reference

1. Zhang, Ruohan, Zhuode Liu, Luxin Zhang, Jake A. Whritner, Karl S. Muller, Mary M. Hayhoe, and Dana H. Ballard. "Agil: Learning attention from human for visuomotor tasks." In Proceedings of the european conference on computer vision (eccv), pp. 663-679. 2018.
2. Zhang, Ruohan, Jake Whritner, Zhuode Liu, Luxin Zhang, Karl Muller, Mary Hayhoe, and Dana Ballard. "Modelling complex perception-action choices." Journal of Vision 18, no. 10 (2018): 533-533.
3. Zhang, Ruohan, Shun Zhang, Matthew H. Tong, Yuchen Cui, Constantin A. Rothkopf, Dana H. Ballard, and Mary M. Hayhoe. "Modeling sensory-motor decisions in natural behavior." PLoS computational biology 14, no. 10 (2018): e1006518.
4. Yuezhang, Liu, Ruohan Zhang, and Dana H. Ballard. "An initial attempt of combining visual selective attention with deep reinforcement learning." arXiv preprint arXiv:1811.04407 (2018).
5. Zhang, Ruohan. "Attention guided imitation learning and reinforcement learning." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, no. 01, pp. 9906-9907. 2019.
6. Zhang, Ruohan, Faraz Torabi, Lin Guan, Dana H. Ballard, and Peter Stone. "Leveraging human guidance for deep reinforcement learning tasks." In IJCAI, (2019).
7. Ballard, Dana H., and Ruohan Zhang. "The hierarchical evolution in human vision modeling." Topics in Cognitive Science (2020).
8. Zhang, R., A. Saran, B. Liu, Y. Zhu, S. Guo, S. Niekum, D. Ballard, and M. Hayhoe. "Human Gaze Assisted Artificial Intelligence: A Review." In IJCAI: Proceedings of the Conference, vol. 2020, pp. 4951-4958. 2020.
9. Ballard, Dana, Ruohan Zhang, and Luc Gentet. "Cortical Spikes use Analog Sparse Coding." bioRxiv (2020).
10. Saran, Akanksha, Ruohan Zhang, Elaine Schaertl Short, and Scott Niekum. "Efficiently Guiding Imitation Learning Algorithms with Human Gaze." arXiv preprint arXiv:2002.12500 (2020).
11. Zhang, Ruohan, Calen Walshe, Zhuode Liu, Lin Guan, Karl Muller, Jake Whritner, Luxin Zhang, Mary Hayhoe, and Dana Ballard. "Atari-head: Atari human eye-tracking and demonstration dataset." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 04, pp. 6811-6820. 2020.
12. Guan, Lin, Mudit Verma, Sihang Guo, Ruohan Zhang, and Subbarao Kambhampati. "Explanation Augmented Feedback in Human-in-the-Loop Reinforcement Learning." arXiv preprint arXiv:2006.14804
13. Zhang, Ruohan, and Dana H. Ballard. "Parallel neural multiprocessing with gamma frequency latencies." Neural Computation 32, no. 9 (2020): 1635-1663.
14. Guo, Sihang, Bharath Masetty, Ruohan Zhang, Dana Ballard, and Mary Hayhoe. "Modeling human multitasking behavior in video games through modular reinforcement learning." Journal of Vision 20, no. 11 (2020): 1552-1552.
15. Zhang, Ruohan, Bo Liu, Yifeng Zhu, Sihang Guo, Mary Hayhoe, Dana Ballard, and Peter Stone. "Human versus Machine Attention in Deep Reinforcement Learning Tasks." arXiv preprint arXiv:2010.15942 (2020).