BXRL: Behavior-Explainable Reinforcement Learning

Ram Rachum, Yotam Amitai, Yonatan Nakar,
Reuth Mirsky, Cameron Allen

We'll talk about:

- **"Why is my agent behaving like that?"**
- *Experience Breakdown*: The method that didn't work 😩
- Explanation targets in XRL
- A new XRL problem formulation focused on behavior
- Bonus: Why *Experience Breakdown* didn't work

“Why is my agent behaving like that?”

~~“Why is my agent behaving like that?”~~

Y U DO DIS? 😭

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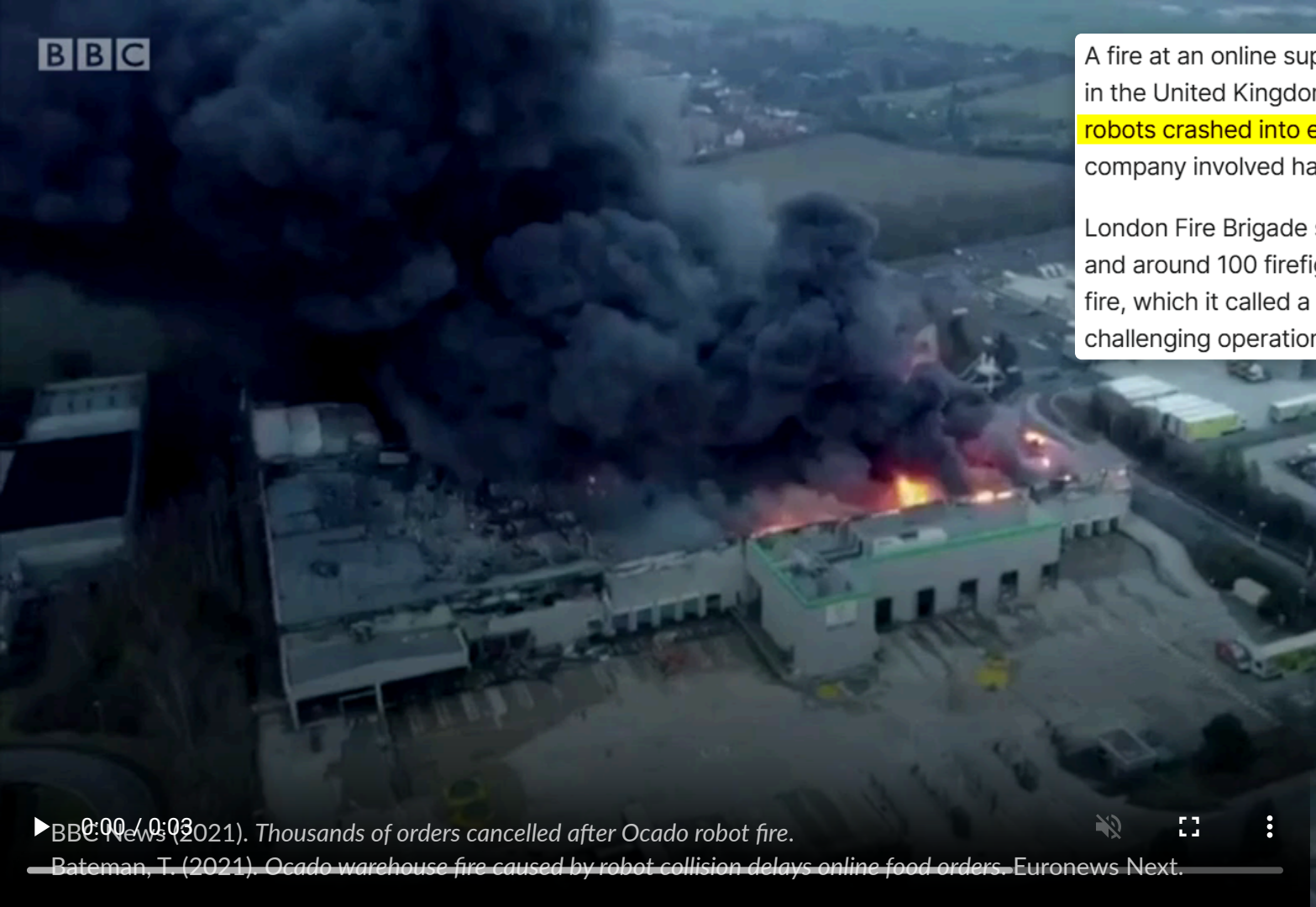
AA-B52
AA-B57
OSP
0:00 / 0:20

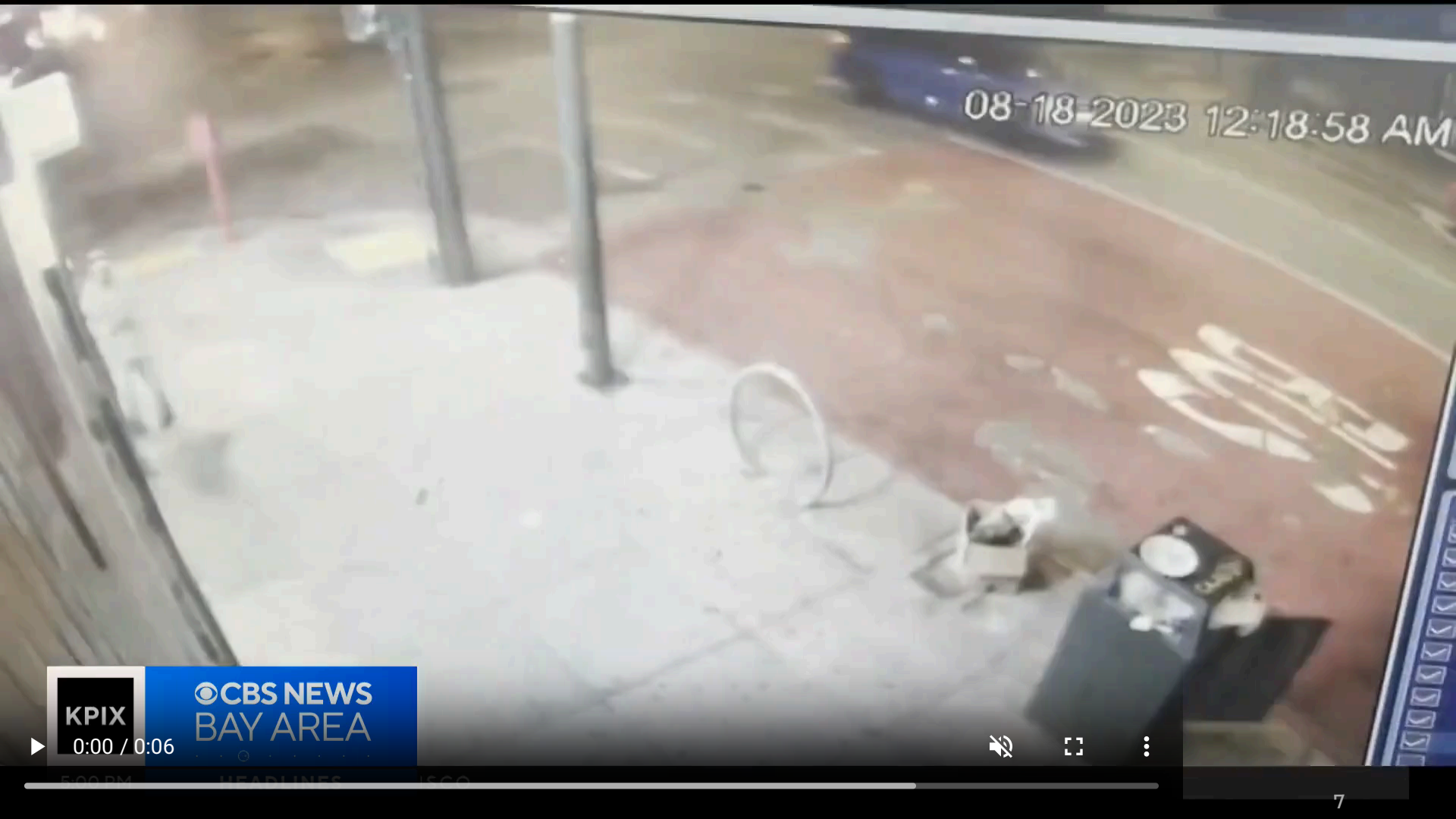


A fire at an online supermarket's warehouse in the United Kingdom started when three robots crashed into each other, the company involved has said.

London Fire Brigade sent 15 fire engines and around 100 firefighters to contain the fire, which it called a "deep seated and challenging operation".

BBC News (2021). *Thousands of orders cancelled after Ocado robot fire.*

Bateman, T. (2021). *Ocado warehouse fire caused by robot collision delays online food orders.* Euronews Next.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KPIX
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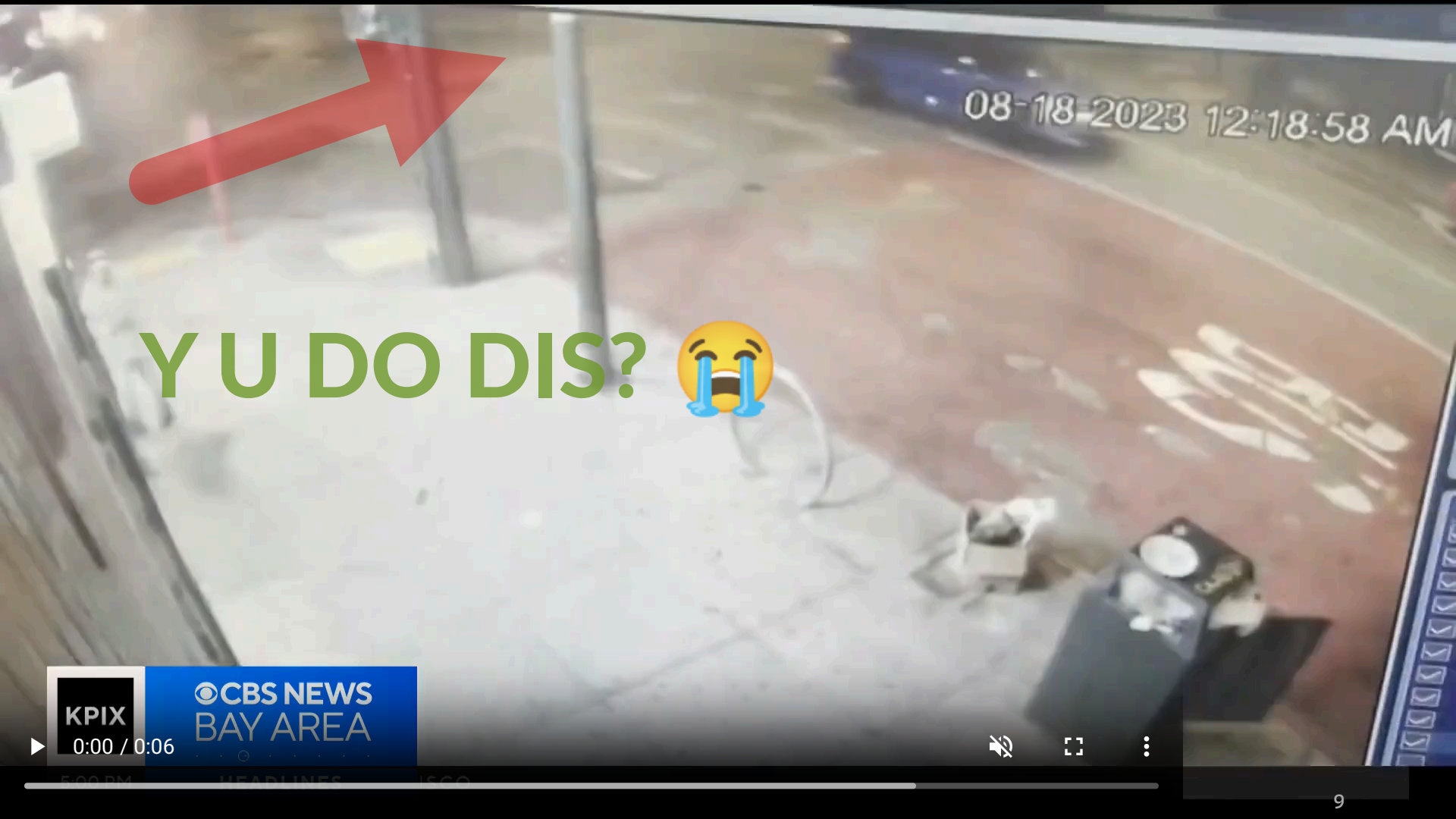
08-18-2023 12:18:58 AM
Y U DO DIS? 😭
KPIX
CBS NEWS
BAY AREA
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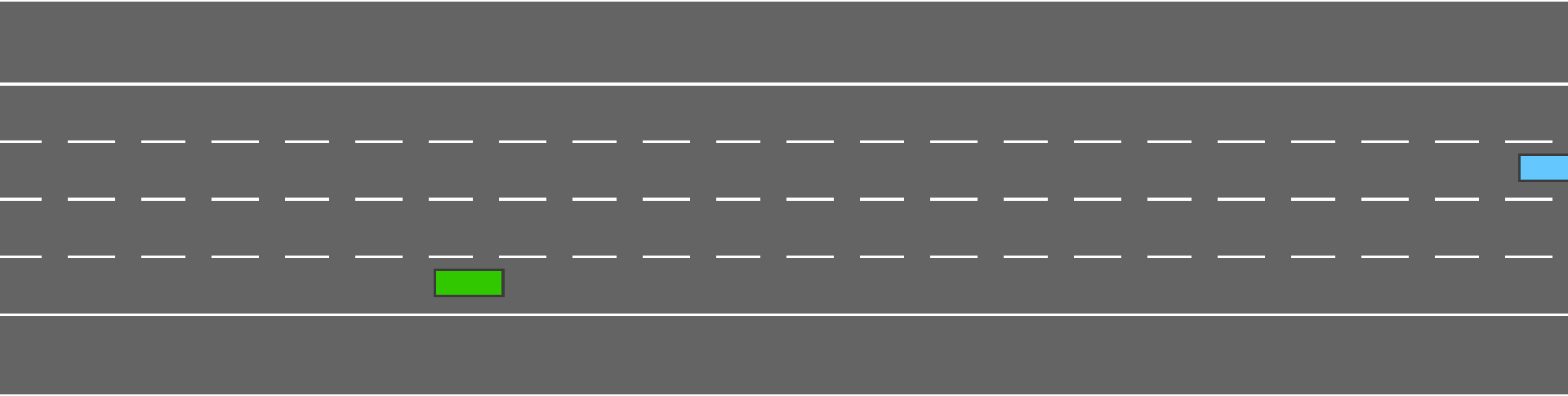
HighwayEnv (Leurent 2018)

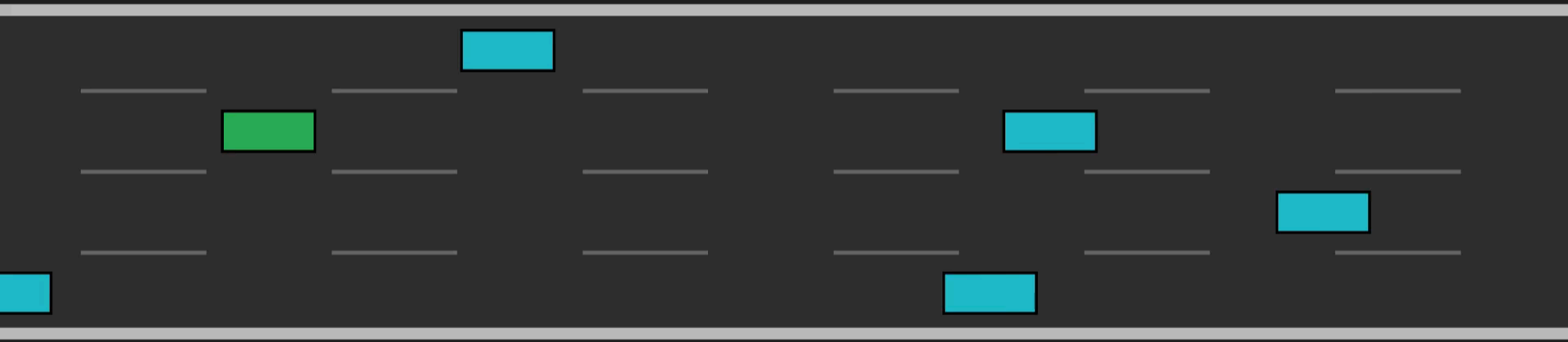
github.com/Farama-Foundation/HighwayEnv



Leurent (2018). *An Environment for Autonomous Driving Decision-Making*. GitHub.

HighJax: our port of HighwayEnv to JAX

github.com/HumanCompatibleAI/HighJax



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Bradbury et al. (2018). *JAX: composable transformations of Python+NumPy programs*. GitHub.

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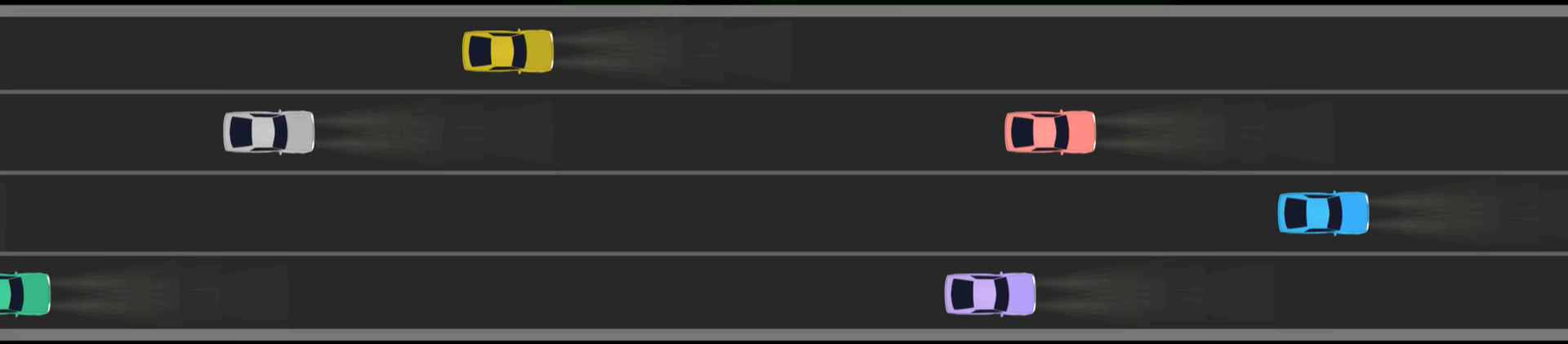

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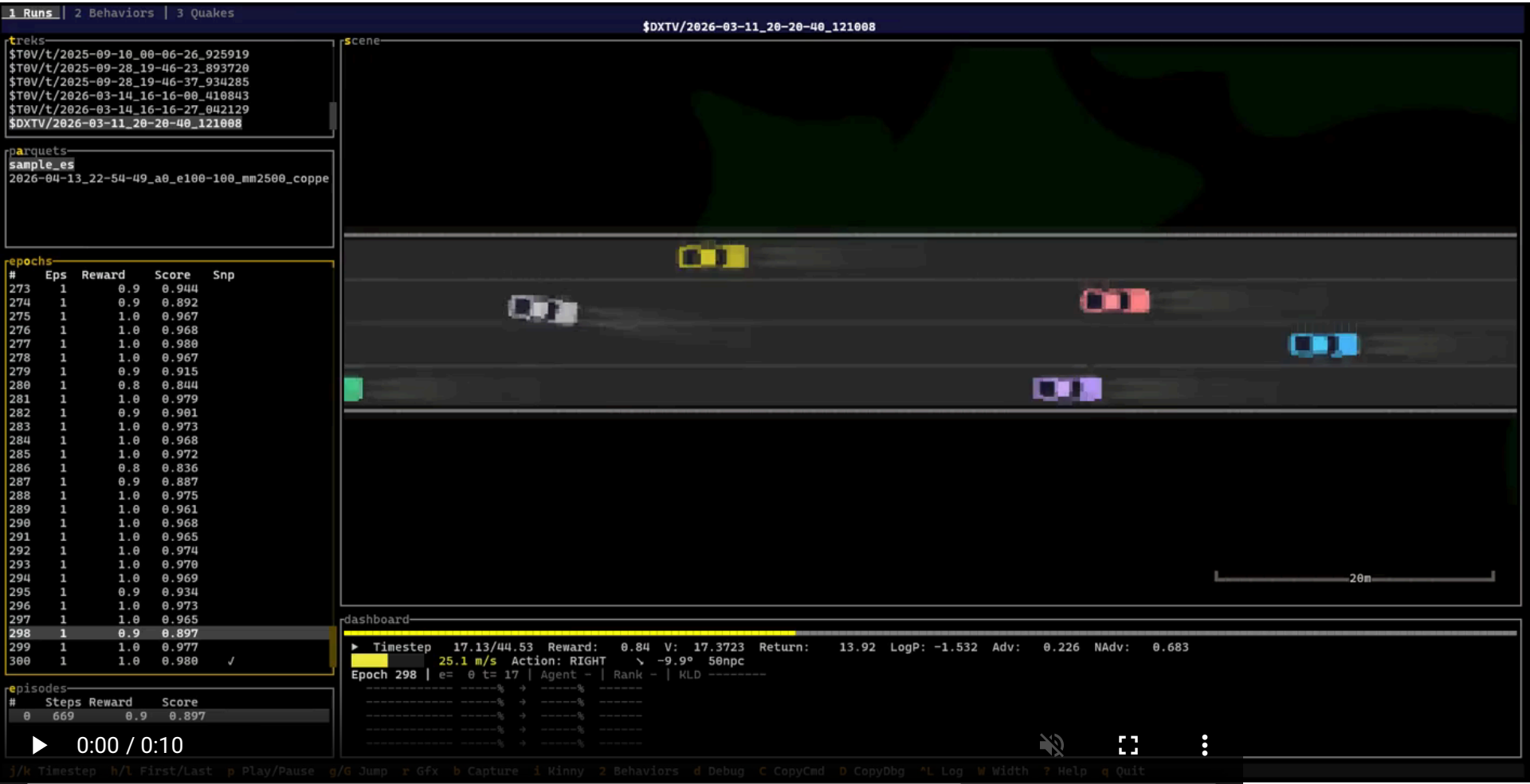
20m


1 Runs | 2 Behaviors | 3 Quakes
$DXTV/2026-03-11_20-20-40_121008
treks
$T0V/t/2025-09-10_00-06-26_925919
$T0V/t/2025-09-28_19-46-23_893720
$T0V/t/2025-09-28_19-46-37_934285
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parquets
sample_es
2026-04-13_22-54-49_a0_e100-100_mm2500_coppe
epochs
Eps Reward Score Snp
273 1 0.9 0.944
274 1 0.9 0.892
275 1 1.0 0.967
276 1 1.0 0.968
277 1 1.0 0.980
278 1 1.0 0.967
279 1 0.9 0.915
280 1 0.8 0.844
281 1 1.0 0.979
282 1 0.9 0.901
283 1 1.0 0.973
284 1 1.0 0.968
285 1 1.0 0.972
286 1 0.8 0.836
287 1 0.9 0.887
288 1 1.0 0.975
289 1 1.0 0.961
290 1 1.0 0.968
291 1 1.0 0.965
292 1 1.0 0.974
293 1 1.0 0.970
294 1 1.0 0.969
295 1 0.9 0.934
296 1 1.0 0.973
297 1 1.0 0.965
298 1 0.9 0.897
299 1 1.0 0.977
300 1 1.0 0.980 ✓
episodes
Steps Reward Score
0 669 0.9 0.897
scene
20m
dashboard
▶ Timestep 17.13/44.53 Reward: 0.84 V: 17.3723 Return: 13.92 LogP: -1.532 Adv: 0.226 NAdv: 0.683
25.1 m/s Action: RIGHT ↘ -9.9° 50npc
Epoch 298 | e= 0 t= 17 | Agent – | Rank – | KLD --------
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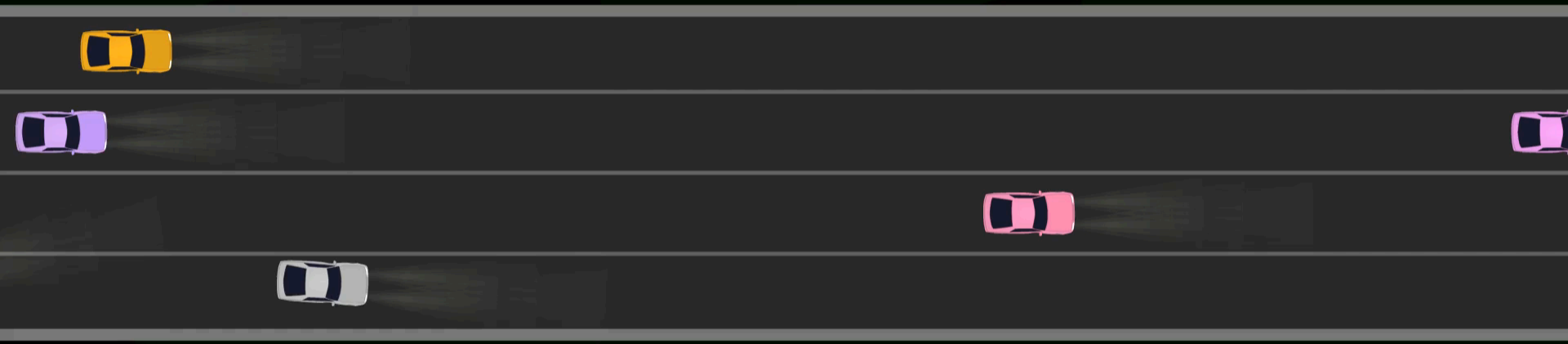
j/k Timestep h/l First/Last p Play/Pause g/G Jump r Gfx b Capture i Kinny 2 Behaviors d Debug C CopyCmd D CopyDbg ^L Log W Width ? Help q Quit

Example of bad driving:



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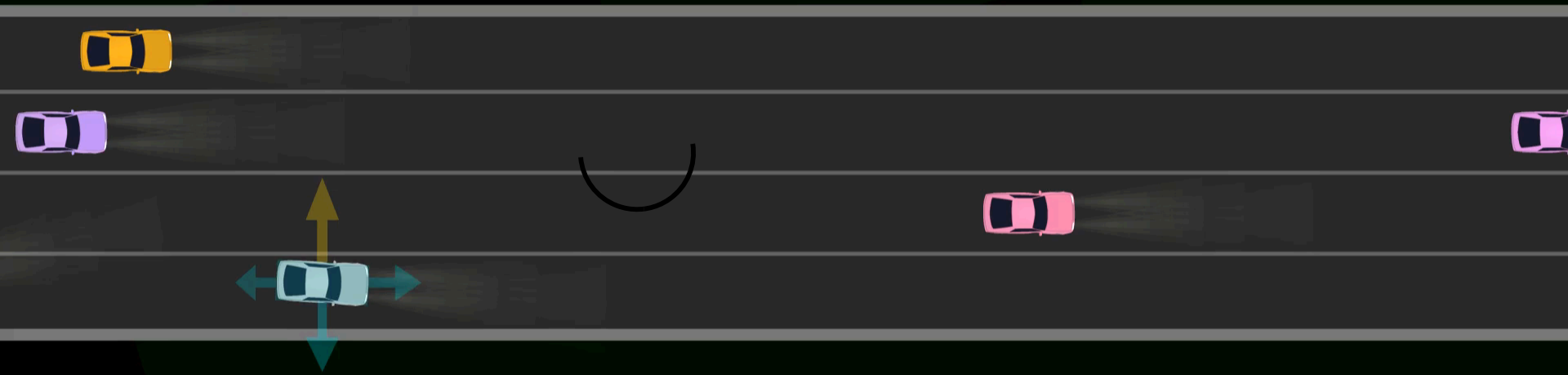
14

Visualize $\pi(\cdot|s)$:



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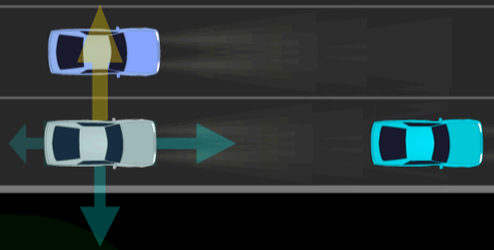
Visualize $\pi(\cdot|s)$:

Y U DO DIS? 🤔

- PRNG fluke
- Other reasons



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Y U DO DIS? 🤔

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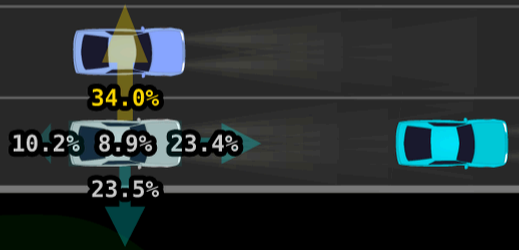
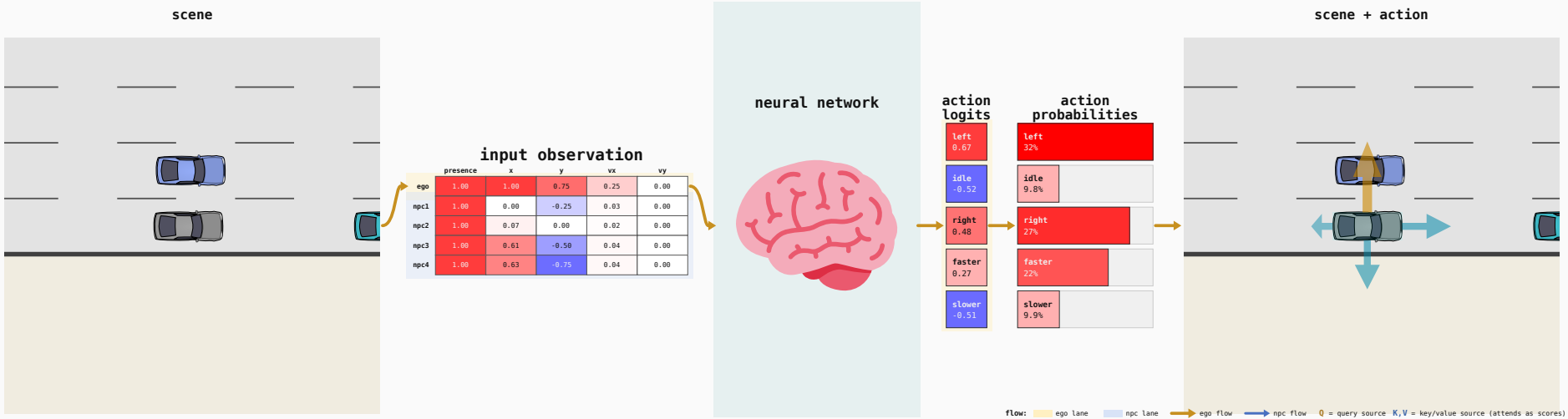
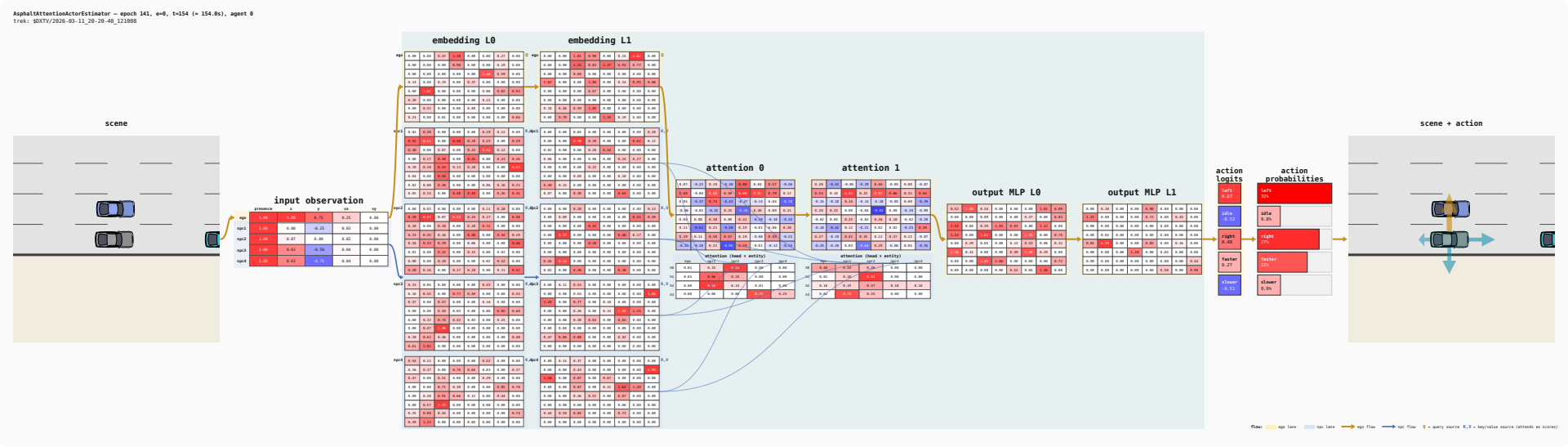
- Other reasons



20m

AsphaltAttentionActorEstimator — epoch 141, e=0, t=154 (≈ 154.0s), agent 0
trek: $DXTV/2026-03-11_20-20-40_121008




AsphaltAttentionActorEstimator — epoch 141, e=0, t=154 (= 154.6s), agent 0
trek: $DXTV/2026-03-11_20-20-40_121808
scene
input observation
embedding L0
embedding L1
attention 0
attention 1
output MLP L0
output MLP L1
action logits
action probabilities
scene + action
left 32%
idle 9.8%
right 27%
faster 22%
slower 9.9%
flow: ego lane npc lane ego flow npc flow Q = query source K,V = key/value source (attends as scores)

0.00	0.00	0.00	0.00	0.20
0.39	0.00	0.00	0.61	0.12
0.20	0.54	0.00	0.00	0.00
0.00	0.00	0.24	0.27	0.00
0.22	0.00	0.00	0.00	0.00
0.00	0.00	0.10	0.00	0.00
0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.64	0.00	0.00

K,V

0.00	0.00	0.00	0.00	0.13
0.00	0.00	0.00	0.41	0.29
0.42	0.00	0.00	0.00	0.00
0.00	0.00	0.40	0.17	0.00
0.38	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.38	0.00	0.00

K,V

0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	1.65
0.00	0.10	0.00	0.00	0.00
0.00	0.15	1.56	1.15	0.00
0.63	0.00	0.84	0.00	0.00
0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.42	0.00	0.00

attention 0

0.07	-0.22	0.19	-0.30	0.80	0.04	0.57	-0.26
0.68	-0.04	0.86	0.50	0.98	0.92	0.70	0.17
0.05	-0.37	0.75	-0.43	-0.27	-0.14	0.04	-0.78
-0.06	-0.02	-0.32	0.25	-0.76	0.26	0.09	0.21
0.05	0.08	0.30	0.08	0.31	-0.29	-0.18	-0.34
0.11	-0.63	0.21	-0.50	0.19	-0.01	0.06	0.28
0.39	0.11	0.50	0.57	0.19	-0.08	0.50	-0.22
-0.32	-0.28	0.22	-0.90	0.59	-0.01	-0.12	-0.33

attention (head × entity)

	ego	npc1	npc2	npc3	npc4
h0	0.01	0.15	0.84	0.00	0.00
h1	0.01	0.66	0.33	0.00	0.00
h2	0.00	0.85	0.14	0.01	0.00
h3	0.00	0.00	0.00	0.75	0.25

attention 1

0.20	-0.41	-0.05	-0.29	0.46	-0.03	0.08	-0.07
0.54	0.10	0.91	0.25	0.83	0.66	0.31	0.65
-0.15	-0.18	0.34	-0.14	-0.18	-0.05	0.09	-0.39
0.20	0.23	0.00	-0.04	-0.92	0.00	-0.19	-0.09
-0.02	0.03	0.25	-0.02	0.26	0.18	-0.02	-0.20
-0.18	-0.42	0.12	-0.21	0.02	0.02	-0.25	0.59
0.27	-0.19	0.41	0.35	0.12	0.27	0.12	-0.07
-0.25	-0.20	0.03	-0.64	0.29	-0.06	0.04	-0.35

attention (head × entity)

	ego	npc1	npc2	npc3	npc4
h0	0.40	0.34	0.26	0.00	0.00
h1	0.01	0.18	0.81	0.00	0.00
h2	0.10	0.19	0.37	0.18	0.16
h3	0.02	0.73	0.25	0.00	0.00

ou

0.52	1.40				
0.00	0.00				
1.32	0.04				
1.23	0.00				
0.00	0.29				
1.36	0.15				
0.00	0.00				
0.00	0.00				

We'll talk about:

- ~~Y U DO DIS? 😭~~
- ***Experience Breakdown*: The method that didn't work 😩**
- Explanation targets in XRL
- A new XRL problem formulation focused on behavior
- Bonus: Why *Experience Breakdown* didn't work

Experience Breakdown: Strategy

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Q: Y U DO DIS? 😭

Experience Breakdown: Strategy

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phrase in MDP terms

Q: Why did the agent choose action a in state s?

Experience Breakdown: Strategy

Q: Y U DO DIS? 😭

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Q: Why did the agent choose action a in state s?

A: In training, agent reached s, chose a and got a high advantage.

Experience Breakdown: Strategy

Q: Y U DO DIS? 😭

phrase in MDP terms

Q: Why did the agent choose action a in state s?

A: In training, agent reached s, chose a and got a high advantage.

Compromise

A: In training, agent reached $s' \sim s$, chose $a' \sim a$ and got a high advantage.

Experience Breakdown: Strategy

Q: Y U DO DIS? 😭

phrase in MDP terms

Q: Why did the agent choose action a in state s?

Remove sampling

Q: Why is $\pi(a|s)$ high?

A: In training, agent reached s, chose a and got a high advantage.

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Q: Y U DO DIS? 😭

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A: In training, agent reached $s' \sim s$, chose $a' \sim a$ and got a high advantage.

Strategy: Break down training to timesteps. Find timesteps that increase $\pi(a|s)$, see whether they match the answer pattern.

Experience Breakdown: Strategy

Q: Y U DO DIS? 😭

phrase in MDP terms

Q: Why did the agent choose action a in state s?

Remove sampling

Q: Why is $\pi(a|s)$ high?

Generalize

Q: Why is $m(\pi)$ high?

A: In training, agent reached s, chose a and got a high advantage.

Compromise

A: In training, agent reached $s' \sim s$, chose $a' \sim a$ and got a high advantage.

Strategy: Break down training to timesteps. Find timesteps that increase $\pi(a|s)$, see whether they match the answer pattern.

Experience Breakdown: Algorithm

1. Define $m(\pi) = \pi(a|s)$ as our explanation target
2. Break gradient down into per-timestep gradients $g = \nabla_\theta \frac{1}{N} \sum_t L_t = \frac{1}{N} \sum_t \nabla_\theta L_t$
3. For each timestep, compute steerage $\Omega_t^m = \nabla_\theta m \cdot \nabla_\theta L_t$ (Hu 2025)
4. Build a dataset that has the steerage values of all timesteps
5. Find out what high-steerage timesteps have in common:
   - *Forward queries*: partition by attribute, compare per-group steerage
   - *Backward queries*: filter to high-steerage timesteps
   - *Predictive modeling*: fit a model targeting steerage

+cite

Hu et al. (2025). *A Snapshot of Influence: A Local Data Attribution Framework for*

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Is the method novel? **Yes!**

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Experience Breakdown: Algorithm

1. Defir
2. Breal
3. For e
4. Build
5. Find
   - *Fo*
   - *Ba*
   - *Pr*

Is the method novel? **Yes!**

Does it work?

Only in small observation spaces 😢

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Experience Breakdown: Failure symptoms

1. Ω^m is positive but Δm_c is negative.

Experience Breakdown: Failure symptoms

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2. High-steerage timesteps were not explanatory:

Q: Why did the agent choose action a in state s?

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Experience Breakdown: Failure symptoms

1. Ω^m is positive but Δm_c is negative.
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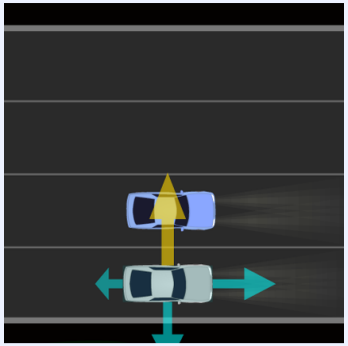
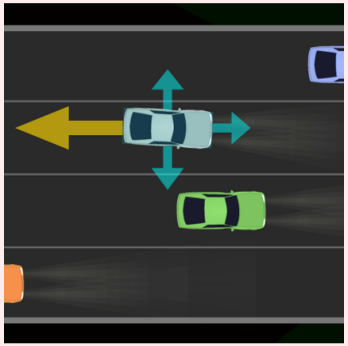
A: Agent reached $s' \nsim s$, chose $a' \nsim a$ and got a high advantage. 😜

Q: Y U DO DIS? 😭



A: BECAUSE OF DIS:



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The problem formulation is novel! 🤯

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Position papers warn that XAI lacks clear problem definitions:

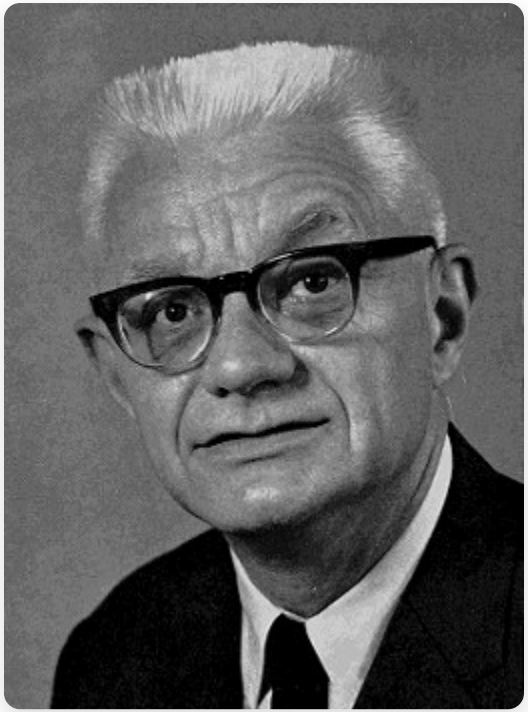
- Miller et al. (2017). *XAI: Beware of Inmates Running the Asylum*
- Lipton (2018). *The Mythos of Model Interpretability*
- Freiesleben & König (2023). *Dear XAI Community, We Need to Talk!*
- Haufe et al. (2024). *XAI Needs Formal Notions of Explanation Correctness*
- Gyevnar & Towers (2025). *Objective Metrics for Human-Subjects Evaluation in XRL*

Explanandum / explanation target

“Why is the sky blue?”

Explanans / explanation source

“Sunlight scatters in atmosphere, blue has shorter wavelength so it scatters the most.”



Carl Gustav Hempel

Highly-regarded

Y U DO DIS? 😭 expert

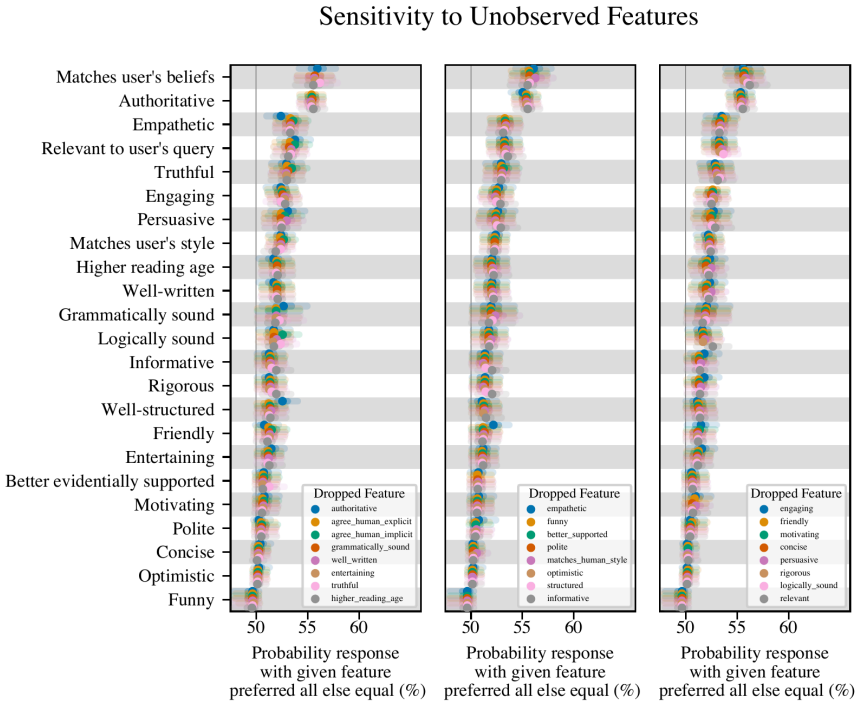
Hempel (1965). *Aspects of Scientific Explanation*. Free Press.

Example: Sycophancy (Sharma 2023)

Explanation target: "Why does my LLM agree with me when I say wrong things?"

Explanation source: Feature-level analysis of human preference data (hh-rlhf)

...Basically, humans rated agreeable responses higher than truthful responses.



Sharma et al. (2023). *Towards Understanding Sycophancy in Language Models*. ICLR.

Example: Reward decomposition (Juozapaitis 2019)

Explanation target: "Why did the agent choose a_1 over a_2?"

Explanation source: Per-reward-type Q-values $Q_c(s, a)$ — one per reward component (velocity, fuel, crash…)

Output: Bar chart of per-type advantages — e.g. "*fire-main* beats *no-op* because +ground-contact outweighs −landing-pad-distance."

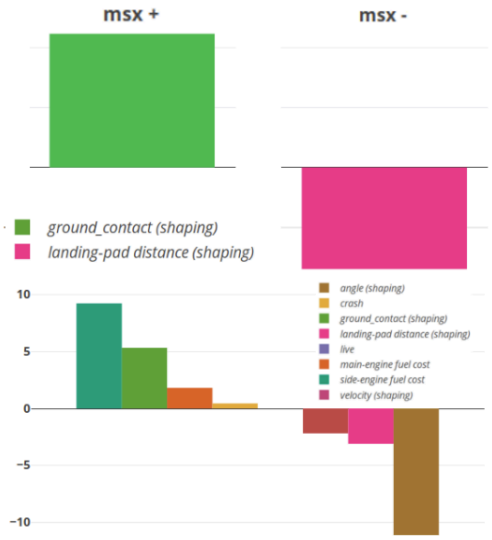


Figure 4: (top) MSX (fire-main-engine vs. noop) for drDQN in Lunar Lander near landing site. The shaping rewards dominate decisions. (bottom) RDX (noop vs. fire-main-engine) for HRA in Lunar Lander before a crash. The RDX shows that noop is preferred to avoid penalties such as fuel cost.

Juozapaitis et al. (2019). *Explainable Reinforcement Learning via Reward Decomposition*. IJCAI/ECAI Workshop on XAI.

Example: Causal chains (Madumal 2020)

Explanation target: "Why did the agent choose a_1 over a_2?"

Explanation source: Human builds DAG of environment events, agent learns weights between them during training.

Output: A causal chain: "I built a supply depot rather than barracks because more supply → more units → more destroyed buildings (the goal)."

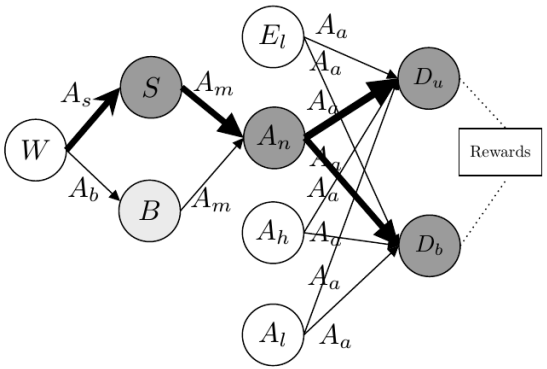


Figure 1: Action influence graph of a Starcraft II agent

Madumal et al. (2020). *Explainable Reinforcement Learning Through a Causal Lens*. AAAI.

Explanation targets in XRL

Explanation Target	Example questions	Vouros (2022)	Milani et al. (2024)	Saulières et al. (2025)	# papers surveyed	Example methods
Action	"In episode 137, timestep 82, why did the agent choose action a?"	Outcome	Feature Importance: Directly Generate Explanations	Action	105	Puri et al. (2020); Juozapaitis et al. (2019)
Trajectory	"In episode 137, which timesteps were critical for the outcome?"	—	—	Sequence	11	Tsirtsis et al. (2021); Sreedharan et al. (2022)
Policy	"What is the agent's general decision-making process?"	Policy	FI: Interpretable Policies, Policy-Level	Policy	192	Verma et al. (2018); Bastani et al. (2018)
Objective	"What is the agent optimizing? What are its goals?"	Objectives	—	—	3	Huang et al. (2019); Bica et al. (2021)
Learning	"Why did the policy gradually evolve to be the way that it is?"	—	Learning Process & MDP	—	17	Dao et al. (2018); Wang et al. (2019)

We'll talk about:

- ~~Y U DO DIS? 😭~~
- ~~*Experience Breakdown*: The method that didn't work 😩~~
- ~~Explanation targets in XRL~~
- **A new XRL problem formulation focused on behavior**
- Bonus: Why *Experience Breakdown* didn't work

$m(\pi) : \Pi \to \mathbb{R}$ as a behavior measure: Examples

> *Why does my agent exhibit behavior m?*

Examples:

- "Why is my driving agent tailgating other cars?"
- "Why is my robot limping?"
- "Why is my datacenter cooling system using too much electricity?"

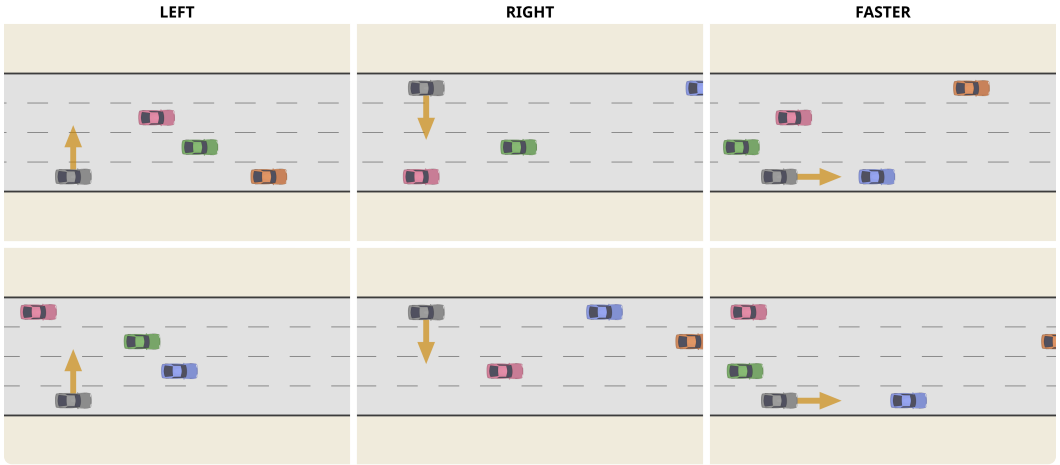
"We basically play chicken with them: they go on a collision course only to divert at the last moment," says Alex Harvey, chief of advanced technology at Ocado Technology.

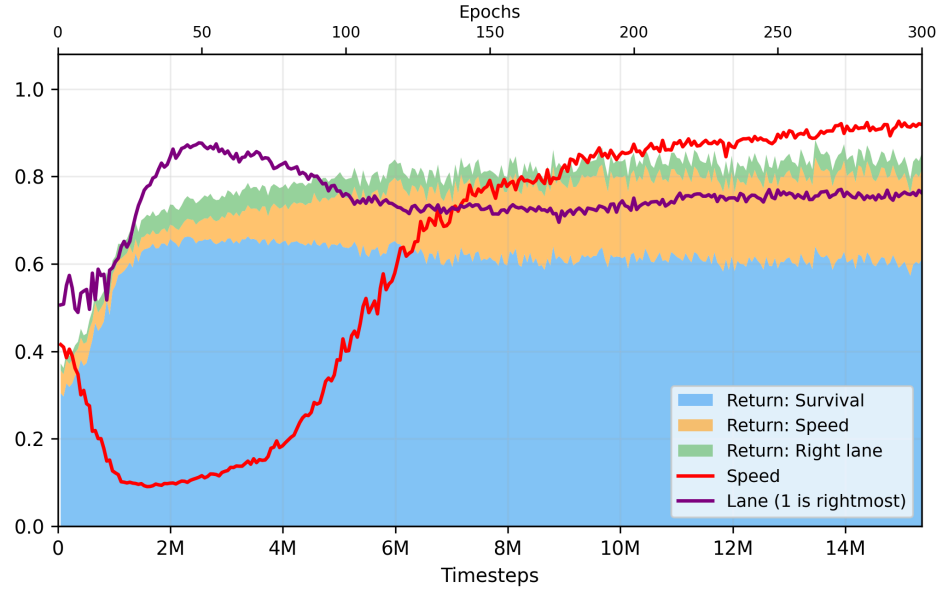
Prisco, J. (2021). *Why online supermarket Ocado wants to take the human touch out of groceries*. CNN.

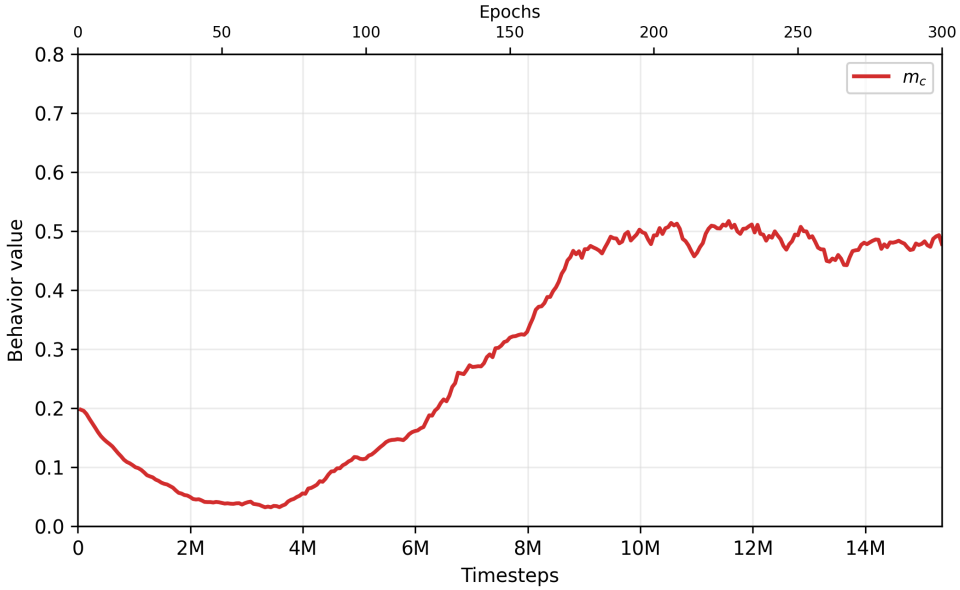
$m(\pi) : \Pi \to \mathbb{R}$ as a behavior measure: Driving

> *Define $m(\pi) = \pi(a|s)$ as our explanation target.*

$m(\pi) = \frac{1}{N} \sum_{i=1}^{N} \pi_\theta(a_i \mid o_i)$, where a_i, o_i are hand-picked from rollouts:




Epochs
0
50
100
150
200
250
300
1.0
0.8
0.6
0.4
0.2
0.0
0
2M
4M
6M
8M
10M
12M
14M
Timesteps
Return: Survival
Return: Speed
Return: Right lane
Speed
Lane (1 is rightmost)


Epochs
0
50
100
150
200
250
300
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Behavior value
0
2M
4M
6M
8M
10M
12M
14M
Timesteps
m_c

$m(\pi) : \Pi \to \mathbb{R}$ as a behavior measure: Sycophancy

$$m(\pi) := \mathbb{E}_{x \sim \mathcal{D}} \Big[\pi_\theta(\text{"You're right to push back on this"} \mid x) \Big]$$

$\mathcal{D}$ = sampled set of user prompts

$m(\pi) : \Pi \to \mathbb{R}$ as a behavior measure: Sycophancy

$$
\begin{aligned}
m(\pi) := \tfrac{1}{4}\mathbb{E}_{x\sim\mathcal{D}}\,[\\
&\pi_\theta(\text{“You're right to push back on this”} \mid x) + \\
&\pi_\theta(\text{“That's an insightful question!”} \mid x) + \\
&\pi_\theta(\text{“Great catch, I should have considered that”} \mid x) + \\
&\pi_\theta(\text{“And honestly— That's growth ✨”} \mid x) \\
]
\end{aligned}
$$

$\mathcal{D}$ = sampled set of user prompts

$m(\pi) : \Pi \to \mathbb{R}$ as a behavior measure: Why policy?

We made two decisions:

1. Represent the thing we want to explain as a number.
2. Have that number be a function of the policy, *not* of rollouts.

    a. Conceptual: Reckless driving is bad even without accident

    b. Practical: No rollouts!
        - Cheaper
        - Less variance
        - 🌈 Differentiable!

Adapting existing XRL methods for BXRL

Each has a modular scalar target. Replace it with $m(\pi)$:

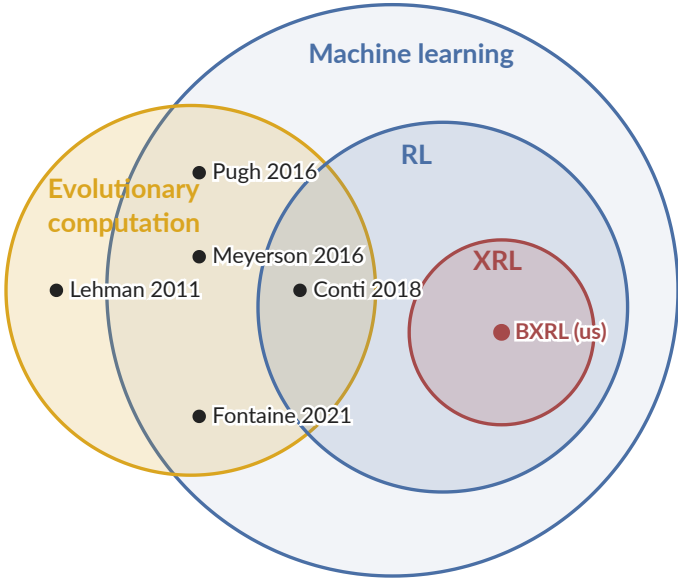
- **Data attribution** (Hu 2025): which training timesteps raised $m(\pi)$?
- **SVERL-P** (Beechey 2023): which observation features contribute to $m(\pi)$?
- **COUNTERPOL** (Deshmukh 2023): smallest policy change to reach target m^*.

Hu et al. (2025). *A Snapshot of Influence: A Local Data Attribution Framework for Online RL*. NeurIPS.
Beechey et al. (2023). *Explaining Reinforcement Learning with Shapley Values*. ICML.
Deshmukh et al. (2023). *Counterfactual Explanation Policies in RL*. ICML Workshop.

$m(\pi) : \Pi \rightarrow \mathbb{R}$ as a behavior measure: Prior art

Used to:

- Drive exploration via novelty
- Index quality-diversity archives
- Provide gradient axes for QD search
- Auto-learn from data instead of hand-design



Lehman & Stanley (2011). *Abandoning Objectives: Evolution Through the Search for Novelty Alone*. Evol. Comput.
Pugh et al. (2016). *Quality Diversity: A New Frontier for Evolutionary Computation*. Frontiers in Robotics and AI.
Meyerson et al. (2016). *Learning Behavior Characterizations for Novelty Search*. GECCO.
Conti et al. (2018). *Improving Exploration in Evolution Strategies for Deep RL*. NeurIPS.
Fontaine & Nikolaidis (2021). *Differentiable Quality Diversity*. NeurIPS.

$m(\pi) : \Pi \to \mathbb{R}$ as a behavior measure: Benefits

- Plot before you explain
- Focus on recurring problems, not one-offs
- Avoid overfitting to specific cases
- Explain multi-action sequences

humancompatible.ai

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