Development of explainable reinforcement learning approaches for safe autonomous driving

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Agenda

- Autonomous driving at a glance
- The need for explainability of Al in autonomous driving
- Reinforcement learning for autonomous driving
- Explainable reinforcement learning for autonomous driving
- Ongoing work
- Conclusions







Autonomous driving at a glance

- Decision making in autonomous driving (AD):









Autonomous driving at a glance

- Five levels of state-of-the-art AD as defined by the SAE International (SAE International, 2018):
- Level 0: No Driving Automation
- Level 1: Driver Assistance
 Adaptive cruise control
- Level 2: Partial Driving Automation

 Advanced Driving Assistance Systems (ADAS)
- Level 3: Conditional Driving Automation
 v Object/Obstacle detection
- Level 4: High Driving Automation
 Near-full automation, in a geofenced area (Alphabet's Waymo)
- Level 5: Full Driving Automation

 Everything is automated, no human supervision is required







- Three primary reasons of the need for explainability of Al in AD (Atakishiyev et al., 2021):
- Psychological lens: Traffic accidents and the safety concerns with the presence of autonomous vehicles.

Tesla sedan hits parked police vehicle in Laguna Beach, California, in 2018



CBC, 2020







- Sociotechnical lens: Design, development, and deployment of autonomous vehicles should be human-centered by
 - 1. reflecting the users' needs,
 - 2. take their prior opinions and expectations into account.



Mercedes-Benz Group Media, 2017







- **Philosophical lens:** Explainable AI (XAI) decisions can provide descriptive information about the causality of real-time actions.
- Also, General Data Protection Regulation (GDPR):
 "Right of explanation" for end users



Atakishiyev et al., 2021







Canonical example: "The Molly problem"

A young girl called Molly is crossing the road alone and is hit by an unoccupied self-driving vehicle. There are no eye-witnesses. What should happen next?

https://www.itu.int/en/ITU-T/focusgroups/ai4ad/Pages/MollyProblem.aspx







Thus, XAI for autonomous driving is a compendium of AI-driven approaches

- 1) ensuring an acceptable level of safety in a vehicle's real-time decisions,
- 2) providing explanations and transparency on an automated car's decisions in critical traffic scenarios, and

3) obeying all traffic rules established by the regulators."







Reinforcement learning for autonomous driving

- Supervised learning methods are not effective in AD, except scene understanding.
- Decisions are temporal and sequential.
- Thus, the goal becomes to solve sequential decision-making problems: We need reinforcement learning (RL).



Atakishiyev et al., 2021







Given that we necessitate

- Sequential decision making
- Explainability

We need to develop explainable RL (XRL) methods for autonomous driving.







How? Three potential approaches:

- Textual explanations: Describing an agent's decisions linguistically in a natural language



Example of textual descriptions + explanations: Ours: "The car is driving forward + because there are no other cars in its lane"

Kim et al., 2018. ECCV







How?

- Visual explanations: Providing saliency maps (heatmaps) that topographically highlight areas which are crucial for an agent's decision.











How?

- Policy-level explanations: Developing interpretable RL policies, such as by summarizing transitions.









Developing an end-to-end explainable RL framework on the CARLA simulator that powers safe actions for a car and provides justifications on these actions

CARLA: Open-source simulator for autonomous driving research



Video clip from: Zhang, 2021



https://carla.org/





1. Investigating model-free vs model-based approaches in terms of explainability

- Model-free RL lacks explainability of learning
- Model-based RL has a planning component, which can be explainable







2. Investigating safety-explainability dilemma: Does explainability affect the safety performance of an RL algorithm negatively?

- Implementing model-free approaches, such as DQN, DDPG, PPO, and SAC
- Implementing model-based RL approaches such as Dyna
- Make a comparative analysis between model-free and model-based approaches in terms of safety







3. Once having safest decision-making RL algorithm(s) for a car, developing explanations on top of them using

- Visual techniques: Developing interpretable saliency maps that provide visual rationales behind temporal actions
- Natural language: We propose to use visual question-answering (VQA) for this purpose
- Interpretable policies: Possibly by summarizing transitions







VQA: How can it be used for explanatory purposes in autonomous driving?

- 1. Why (Causal) questions:
 - Q: <u>Why</u> was the lane changed to the right?
 - A: <u>Because</u> the current lane narrows down ahead.



Chen 2022, CVPR







VQA: How can it be used for explanatory purposes in autonomous driving?

- 2. Descriptive questions:
 - Q: How many cars are around? A: Two.



https://www.autoweek.com/news/technology/a3549 2454/levels-of-autonomous-driving-explained/







VQA: How can it be used for explanatory purposes in autonomous driving?

- **3. Temporal questions:**
 - Q: What was the speed <u>before</u> the emergency brake? A: 50 km/h.



https://www.euroncap.com/en/vehicle-safety/the-ratings-explained/safety-assist/aeb-car-to-car/







Conclusions

- We aim to develop a safe and end-to-end explainable reinforcement learning framework for autonomous vehicles.
- The proposed framework combines reinforcement learning, computer vision, and natural language processing methods for explainable decisions.
- With safe and transparent AI, we can move a step closer to publicly approved and environmentally friendly intelligent vehicles in the near future.







Thank you very much for your attention!





