Safe Reinforcement Learning

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Outline

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Figure: Waymo and Tesla

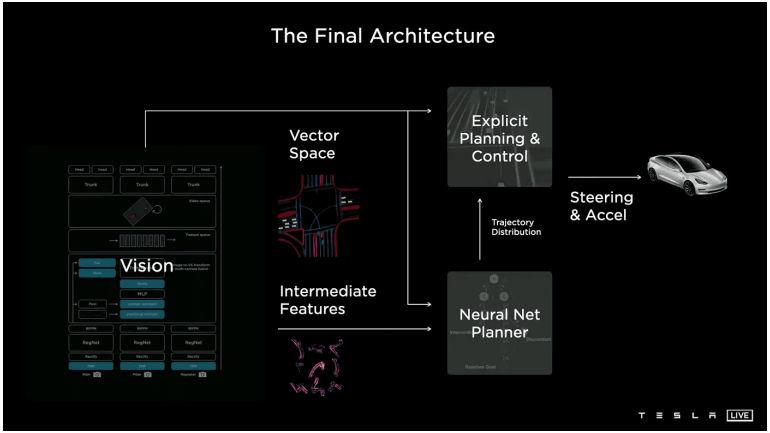


Figure: Tesla's Architecture in 2021 (source: AI Day 2021)

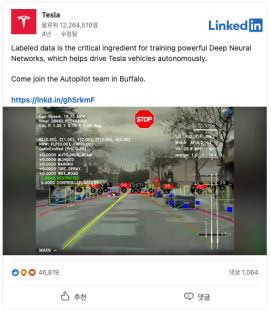
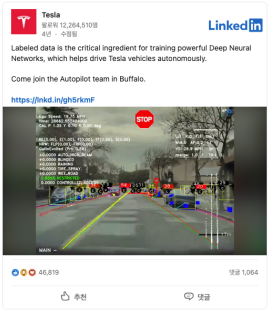


Figure: Tesla's recruitment post for data labeling positions



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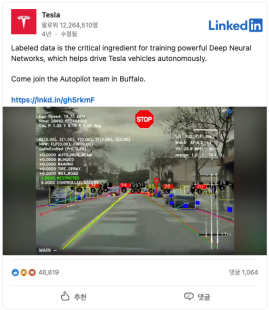
- Supervised learning requires a large amount of labeled data.



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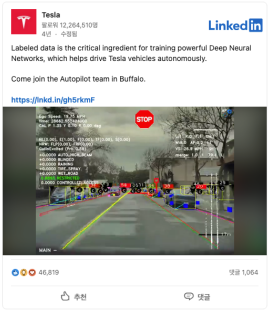

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- Supervised learning requires a large amount of labeled data.
- Since it is created by humans, it is expensive.
- The performance of supervised learning is limited by human-labeled data.

Alpha Go [1]

Deep Q-Network [2]

Proximal Policy Optimization [3]

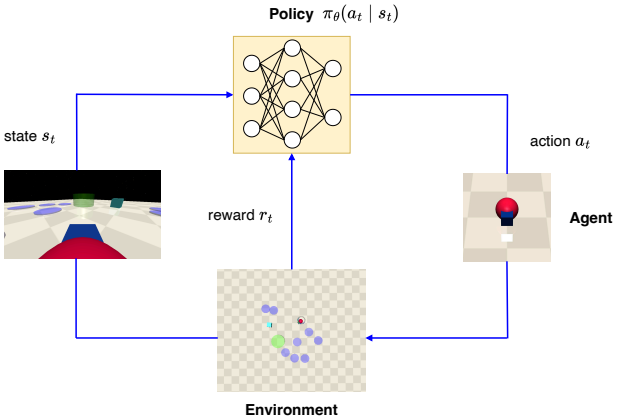

Figure: Overview of the reinforcement learning framework

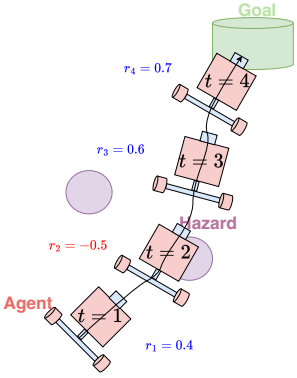

Figure: Illustration of sequential decision making: the agent receives a reward after each action.

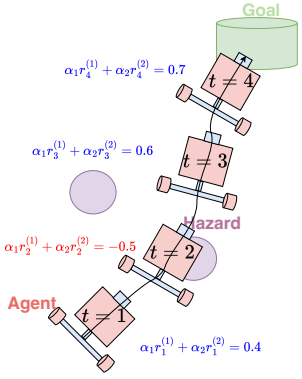

Figure: Illustration of reward engineering: shaping the reward signal to guide the agent's learning process.

- Policy parameterized by θ, denoted as $\pi_\theta(a|s)$
- Goal: find the optimal policy π^*_θ that maximizes the expected cumulative reward

$$\theta^* = \arg\max_\theta J(\theta)$$
$$J(\theta) = \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} r_t\right] \tag{1}$$

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My research

Challenges 2 & 3: learning safe policies without relying on reward engineering

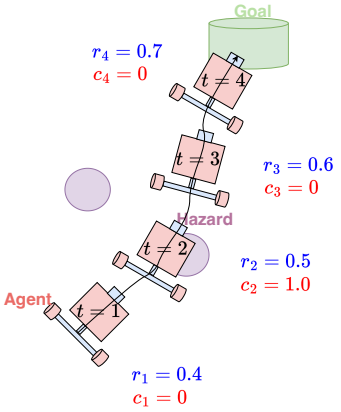

Figure: Constrained RL example — agent trajectory with rewards (blue) and costs (red)

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Constrained Policy Optimization Problem

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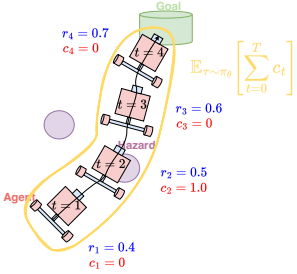
- Find a policy that maximizes rewards while satisfying constraints.
- Directly solving constrained optimization is difficult.
- By applying Lagrangian relaxation, we can convert it to an unconstrained problem.

$$\theta^* = \arg\max_{\theta} \mathcal{L}(\theta, \lambda)$$
$$\mathcal{L}(\theta, \lambda) = \mathbb{E}_{\tau \sim \pi_\theta}\left[\sum_{t=0}^{T} r_t\right] - \lambda\left(\mathbb{E}_{\tau \sim \pi_\theta}\left[\sum_{t=0}^{T} c_t\right] - d\right) \tag{3}$$

$$\lambda \leftarrow \left[\lambda + \beta\left(\hat{J}_c - d\right)\right]_+ \tag{4}$$

Penalty (λ) increases when constraints are violated $\rightarrow$ policy is encouraged to satisfy them.

In CMDPs [4], constraints are imposed on the trajectory level.



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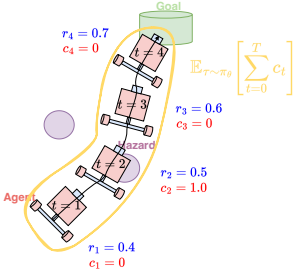

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Wouldn't imposing constraints at the state level allow for more precise constraint enforcement?

In state-wise constrained MDPs, constraints are imposed on each state.

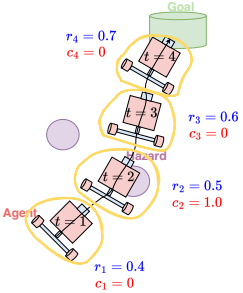

Figure: State-wise constrained MDP example — agent trajectory with rewards (blue) and costs (red)

$$\pi^* = \arg\max_{\pi_\theta} J(\theta)$$
$$J(\theta) = \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} r_t\right] \text{ subject to } \mathbb{E}_{\tau\sim\pi_\theta}[c(s,a)] \leq w, \quad \forall s \in S \tag{5}$$

$$\lambda(s) \leftarrow \lambda(s) + \beta(\hat{J}_c - w) \tag{6}$$

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The Lagrange multiplier is replaced by a neural network's output instead of a scalar.

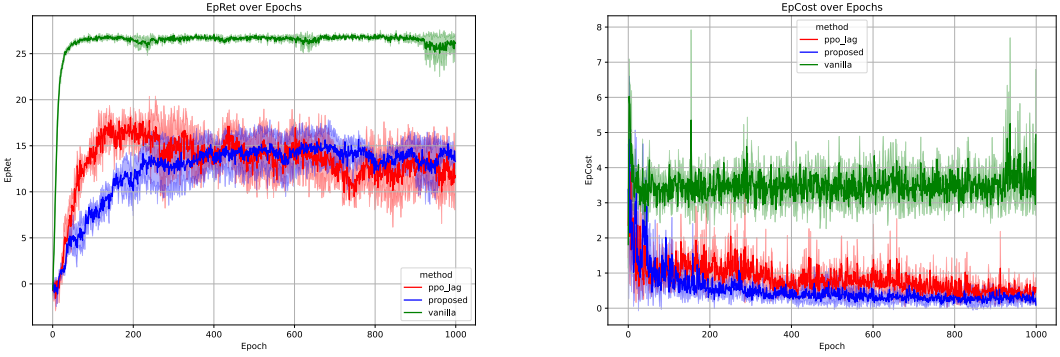

Figure: Performance comparison on Safety Gym tasks

PPO **PPO Lagrangian** **Proposed Method**

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- Sensitivity to Lagrange multiplier (init., learning rate)

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  - Too strict → overly conservative policy
  - Too lenient → constraints not enforced
- Needs sufficient violations during training

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But there are still challenges to solve..

- Extension to Model-Based RL

Thank you for your attention!

References I

[1] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. Van Den Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot *et al.*, "Mastering the game of go with deep neural networks and tree search," *nature*, vol. 529, no. 7587, pp. 484–489, 2016.

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[4] E. Altman, *Constrained Markov decision processes*. Routledge, 2021.