Safe Reinforcement Learning

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Outline

Figure: Waymo and Tesla

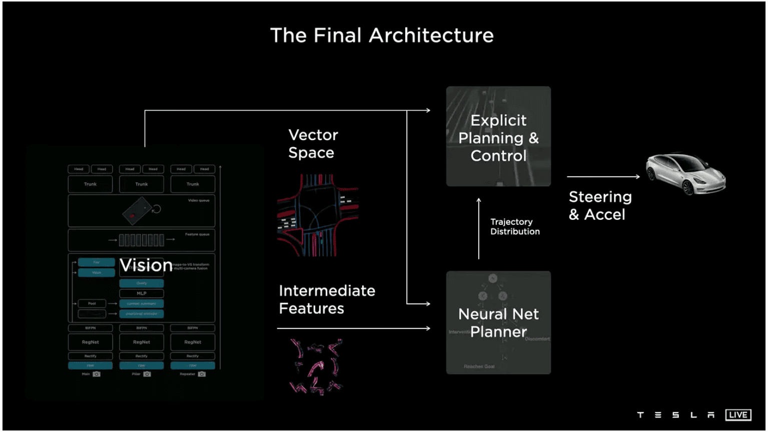


Figure: Tesla's Architecture in 2021 (source: AI Day 2021)

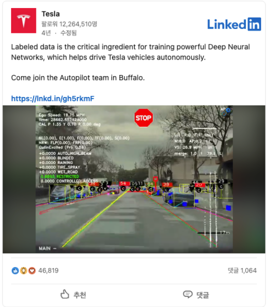
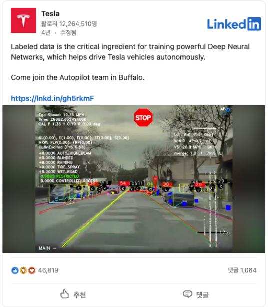


Figure: Tesla's recruitment post for data labeling positions



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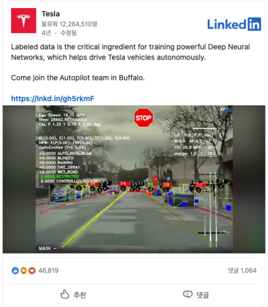
- Supervised learning requires a large amount of labeled data.

Motivation Supervised Learning



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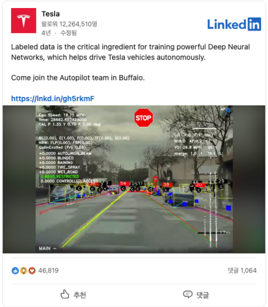


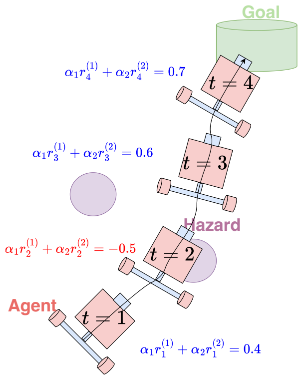
Figure: Tesla's recruitment post for data labeling positions

- 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.

Insert Reinforcement Learning example

Insert Reinforcement Learning framework

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



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My research

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

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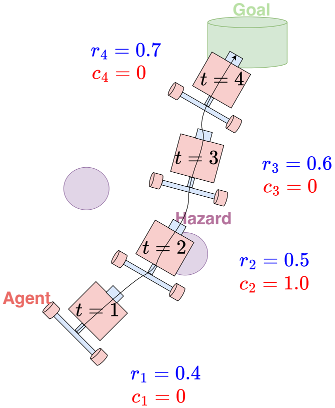

Figure: CMDP example — agent trajectory with rewards (blue) and costs (red)

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.

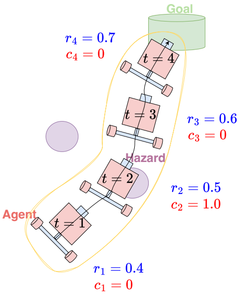
Constrained Policy Optimization Problem

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

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

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

In CMDPs, constraints are imposed on the trajectory level.



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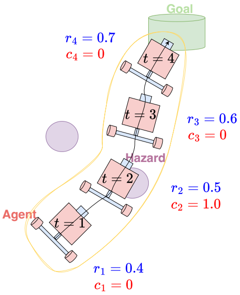

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Wouldn't imposing constraints at the state level allow for more precise constraint enforcement?

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

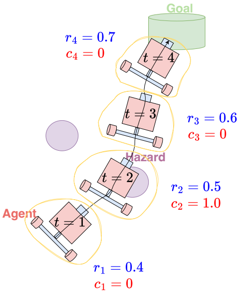

Figure: State-wise constrained MDP example — agent trajectory with rewards (blue) and costs (red)

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

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

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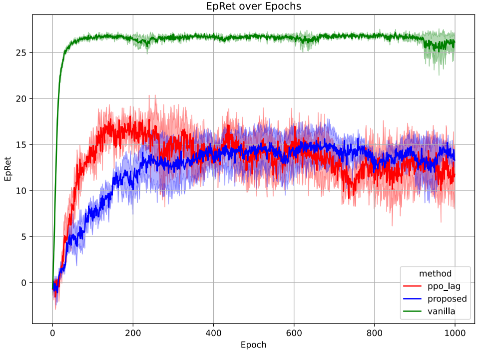
The Lagrange multiplier is replaced by a neural network's output instead of a scalar.



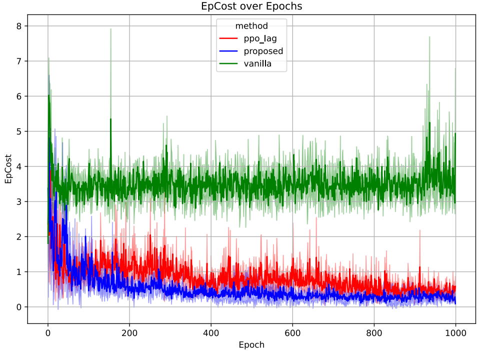


Figure: Performance comparison on Safety Gym tasks

Insert video

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  - Too strict $\rightarrow$ overly conservative policy
  - Too lenient $\rightarrow$ constraints not enforced
- Needs sufficient violations during training

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- Risk of unsafe behavior due to the Sim2Real gap
- Research direction: state-wise constrained policy learning

But there are still challenges to solve..

Future Work

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- Extension to Model-Based RL

Thank you for your attention!

References I

If you need! or remove this frame.