INVERSE REWARD DESIGN

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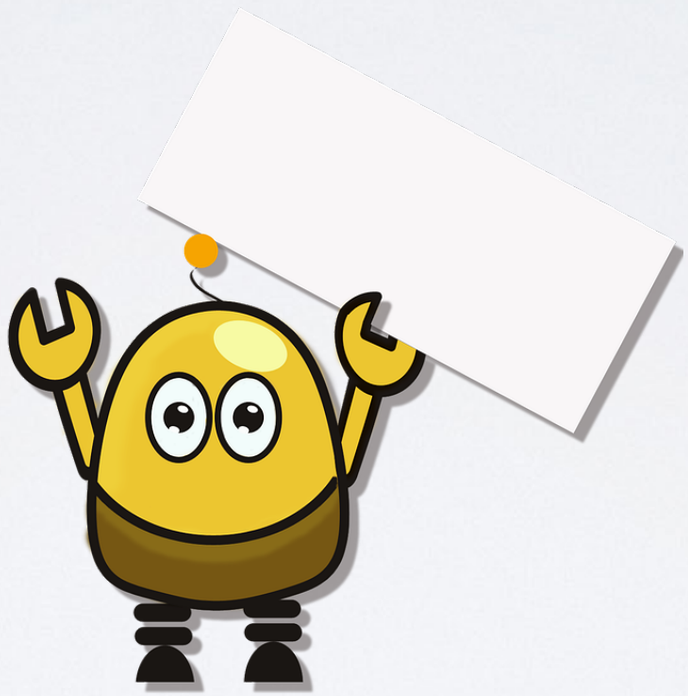

Slides by Anthony Chen

Inverse Reinforcement Learning (Review)

Inverse Reward Design (Intuition)

Inverse Reward Design (Formalism)

INVERSE REINFORCEMENT LEARNING

- Given a Markov Decision Process (MDP) with a reward function, number of ways to obtain a near-optimal or optimal policy.

- However, reward functions can be hard to specify.

- Instead, we can learn a policy by learning from the trajectories (data) generated by an expert.

    - Called inverse reinforcement learning (IRL).

DRIVING

- Many things that go into a reward: safety, comfort, etc.
- Humans learn by watching experts drive.

- In machines, we can learn from data generated by an expert.
- Don't want to exactly copy the expert; doesn't generalize.
- Instead, learn a policy that implicitly maximizes reward from expert data.

NOTATION

- MDP generally defined as a tuple: $M = \langle S, A, T, \gamma, r \rangle$
  - *S*: set of states
  - *A*: set of actions
  - *T*: transition probabilities
  - γ : discount factor
  - *r* : reward function, bounded by 1.
- A MDP without a reward function is called a **world model**, denoted by $\widetilde{M}$

- Assume a feature vector for states: $\phi(s) \in \mathbb{R}^k, \phi : S \to [0, 1]^k$
- Assume an optimal reward function: $r^* = w^* \phi(s), w^* \in \mathbb{R}^k, ||w^*||_1 \leq 1$

- A policy, π, is a mapping from states to a probability over actions.
- The value of a policy can be written as follows:

$$E[V^{\pi}(s_0)] = E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t)|\pi\right]$$

$$= E\left[\sum_{t=0}^{\infty} \gamma^t w \cdot \phi(s_t)|\pi\right]$$

$$= w \cdot E\left[\sum_{t=0}^{\infty} \gamma^t \phi(s_t)|\pi\right]$$

- We can then define the **feature expectations** to be

$$\mu(\pi) = E\left[\sum_{t=0}^{\infty} \gamma^t \phi(s_t)|\pi\right]$$

and the policy value

$$E[V^{\pi}(s_0)] = w \cdot \mu(\pi)$$

IRL FORMALISM

- Given a world model, $\widetilde{M}$, a predefined feature mapping, ϕ, and a set of trajectories $\{s_0^{(i)}, s_1^{(i)}, \dots\}_{i=1}^{m}$ generated from an expert policy, π_E.
  - Think of this expert policy as returning the optimal value.

- Let μ_E be the expert feature expectation and $\hat{\mu}_E$ be the estimated expert feature expectation.

$$\hat{\mu}_E = \frac{1}{m} \sum_{i=1}^{m} \sum_{t=0}^{\infty} \gamma^t \phi\left(s_t^{(i)}\right)$$

- We can find a policy that implicitly maximizes the expert's ***unknown*** reward function via the following optimization:

$$\hat{\pi} = \min_{\pi} ||\mu(\pi) - \hat{\mu}_E||_2$$

Inverse Reinforcement Learning
(Review)

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(Intuition)

Inverse Reward Design
(Formalism)

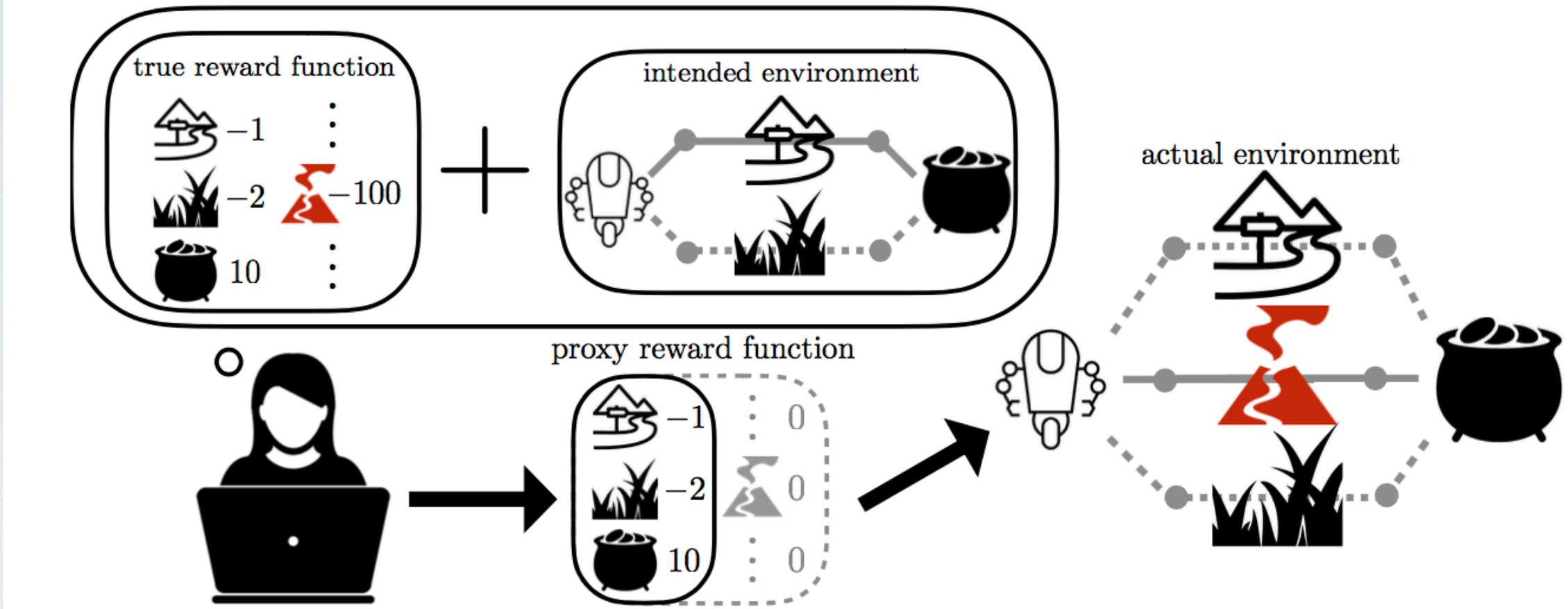
INTUITION

- When a human designs a reward function (known as a proxy reward function), they try and capture as much about the world as possible.

- However, we can't possibly capture all scenarios, leading to **negative side effects** when encountering new states.

- Machines should thus take our reward function as an **guess** at what the true reward function is and assign **uncertainty estimates** to the rewards generated by our reward function.

Image taken from paper



KEY IDEAS

- Proxy reward functions are likely to be true in the context they were defined. Assign high confidence to rewards generated in this case.

- Proxy reward functions can be very wrong in contexts not defined in. Assign high uncertainty to rewards generated in this case.

- Our agent should try and avoid high uncertainty scenarios.

- Formally speaking, inverse reward design tries to capture the true reward function given a proxy reward function.

INVERSE RL V.S. RD

- IRL and IRD both tackle the problem of **value alignment**: the problem of communicating to an agent an good reward.

- Inverse Reinforcement Learning: Hard to design a reward function. Instead given trajectories from expert.

- Inverse Reward Design: More tractable to design reward function. Reward function designed by "expert" but not necessarily complete.

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BAYESIAN MODELING OF IRD

- In the IRD formalism, we are given a world model, $\widetilde{M}$, and a proxy reward function, $\widetilde{r} = \widetilde{w} \cdot \phi(\xi)$
  - ξ represents a trajectory

- Our goal is to recover the optimal reward function $r^* = w^* \cdot \phi(\xi)$ by recovering the optimal set of weights.

- Let $\pi(\xi|\widetilde{r}, \widetilde{M})$ be the probability of a trajectory under a world model and a proxy reward function.

- We can represent a posterior distribution over the optimal reward function via:

$$P(w^*|\widetilde{w}, \widetilde{M}) = P(\widetilde{w}|w^*, \widetilde{M}) \cdot P(w^*)$$

- Remember, we want to assume that our proxy reward function results in near optimal in the situations in which it was defined.

- We can model the likelihood as follows:

$$P(\widetilde{w}|w^*, \widetilde{M}) \propto exp\Big(\beta \cdot \mathbb{E}\Big[{w^*}^T \phi(\xi)|\xi \sim \pi(\xi|\widetilde{w}, \widetilde{M})\Big]\Big)$$

- This says that in the trajectories generated by our proxy reward function, the reward yielded is optimal with respect to the optimal reward function.

- The posterior can then be written as

$$P(w = w^*|\widetilde{w}, \widetilde{M}) \propto \frac{\exp\left(\beta \cdot w^T \widetilde{\mu}\right)}{\widetilde{Z}(w)} P(w)$$

where $\widetilde{Z}(w) = \int_{\widetilde{w}} \exp\left(\beta w^T \widetilde{\mu}\right) d\widetilde{w}$ is a normalizing constant. Need to approximate.

RISK-AVERSE POLICY

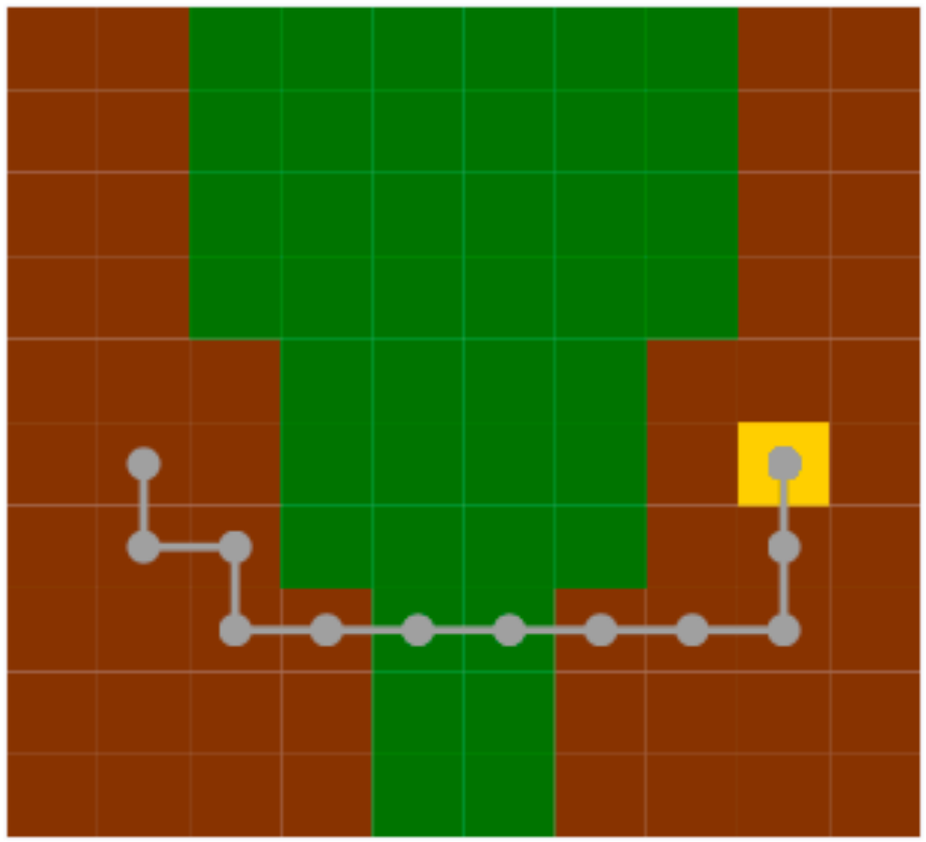
- We can obtain a risk averse policy in the following way:

1. Sample a set of weights $\{\widetilde{w}_i\}$ from our posterior distribution

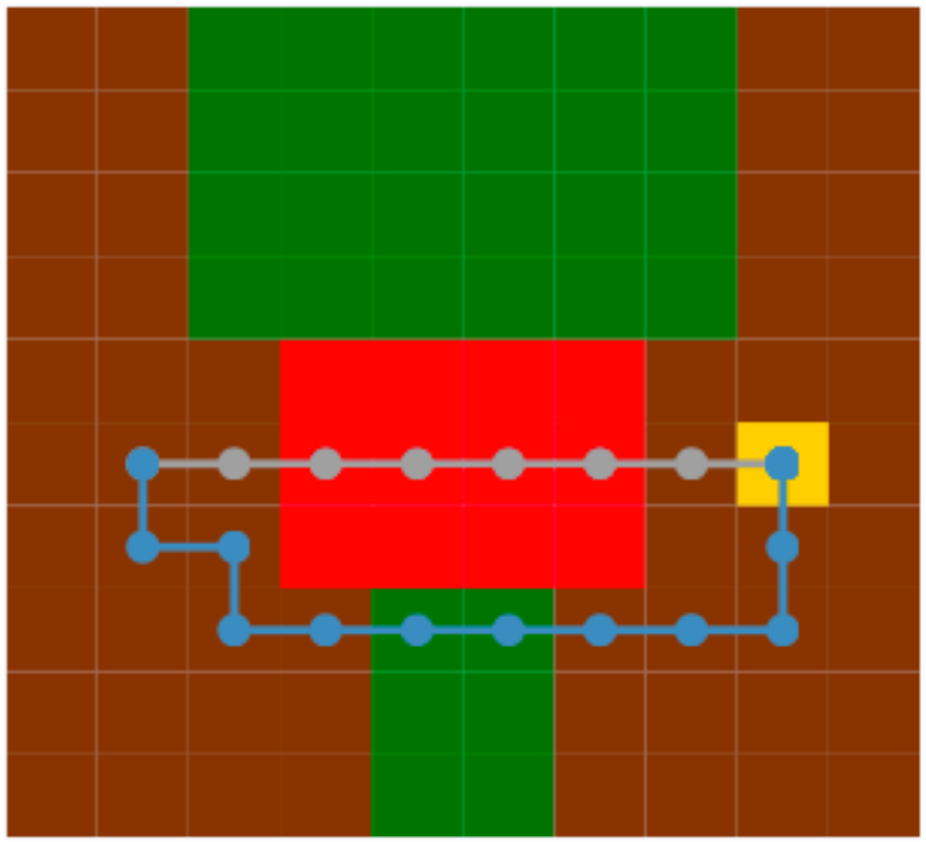
2. Given those weights, pick a trajectory that maximizes the reward in the worst case:

$$\xi^* = \arg\max_{\xi} \min_{w \in w_i} w^T \phi(\xi)$$

EVALUATION: LAVALAND

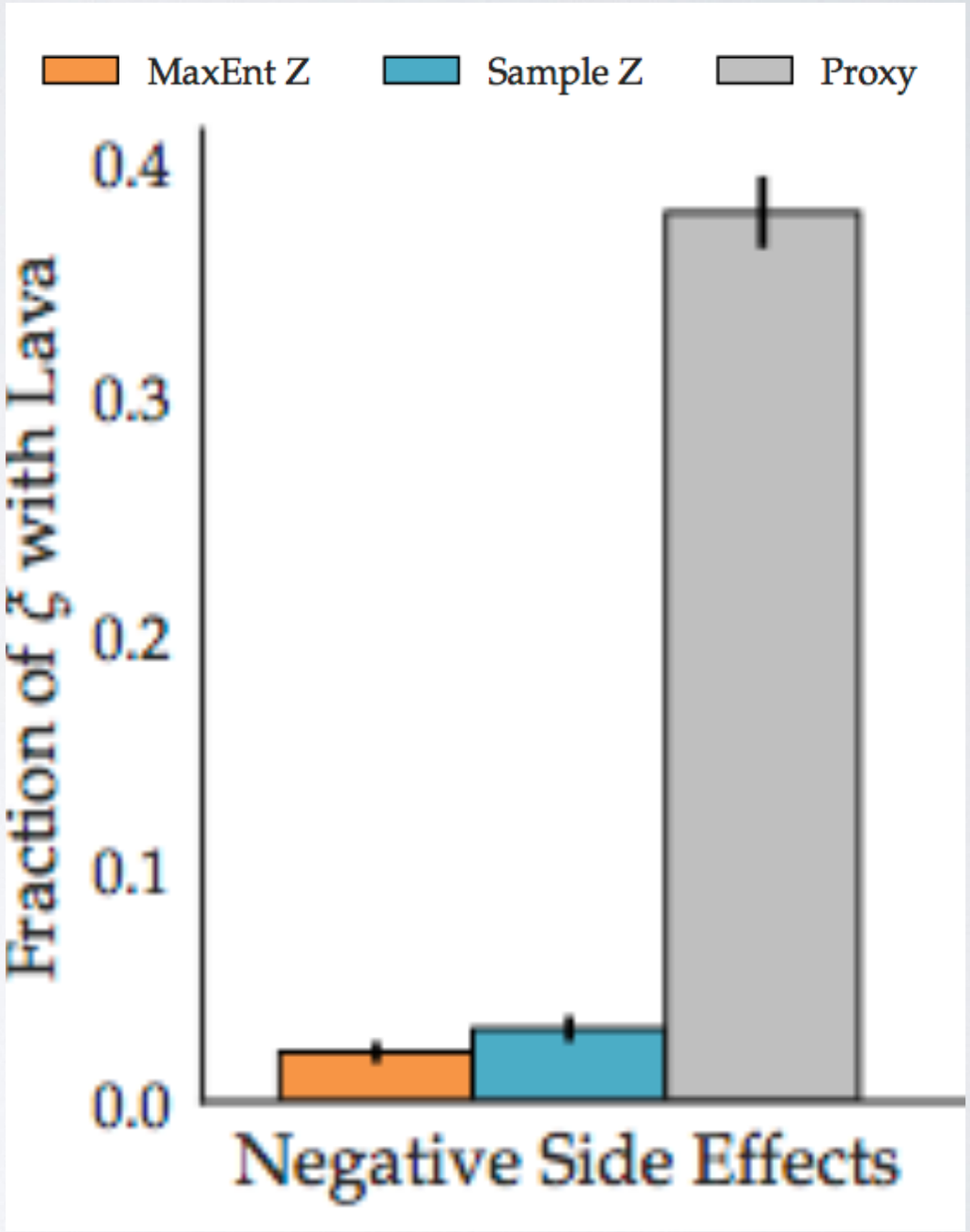


Training



Testing

- Maps initialized at random.
- **Testing**: 5% lava, 66.5% dirt, 28.5% grass
- **Features**: 3 dimensional
- **Proxy reward**: generated random uniformly.
- **Metric**: % of trajectories during test time with lava.



CONCLUSIONS

- In this work, the authors present a method that accounts for uncertainty in the reward function.

- They propose a Bayesian framework to model this uncertainty

- They show empirically on toy examples that their framework can avoid catastrophic events in the face of high uncertainty.