<CAPS>

Session 4 – Goal Specification and Reward Design

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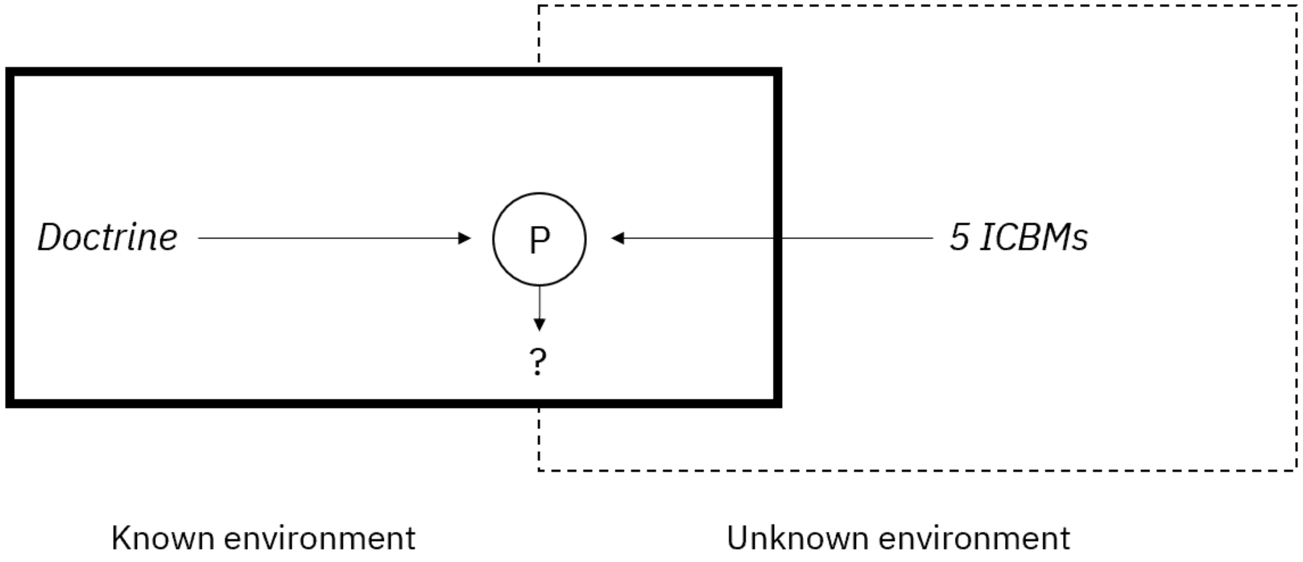
Outline

1. Recap
2. Goal Specification in the 1983 Nuclear Incident
3. Why Reward Design is Hard
4. Exercise on Rule/Reward Design
5. Two Failure Modes of Reward Design in Reinforcement Learning
6. Inverse Methods

Goal Specification in the 1983 Soviet Nuclear Incident

> September 26, 1983
> Five U.S. ICBMs surface on Soviet radar, station monitored by Stanislav Petrov
> Petrov reasons that this is a false alarm, decides not to launch counter-attack

> How can we specify Petrov's **goals**, **rewards** and **rules**?

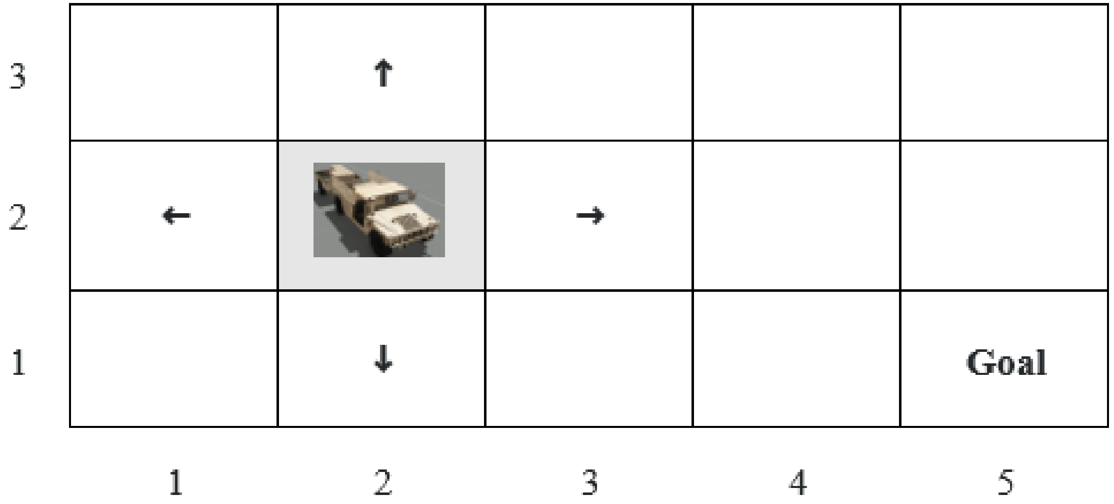


Why Reward Design is Hard

- **Premise**
  - Human designs scalar reward signal that is generated by the environment
  - Reward signal should lead the agent to converge to the designer‘s *desired* outcome
  - Design process often trial-and-error search
- **Challenges**
  - Goal might be difficult to translate into reward signal
  - Agents might find undesirable ways to make the environment deliver reward
  - Good reward signal might be rare in the environment (plateau problem); subgoal decomposition might not lead to convergence to desired outcome
- **Do we know all the properties of the environment? Do we know our own preferences?**

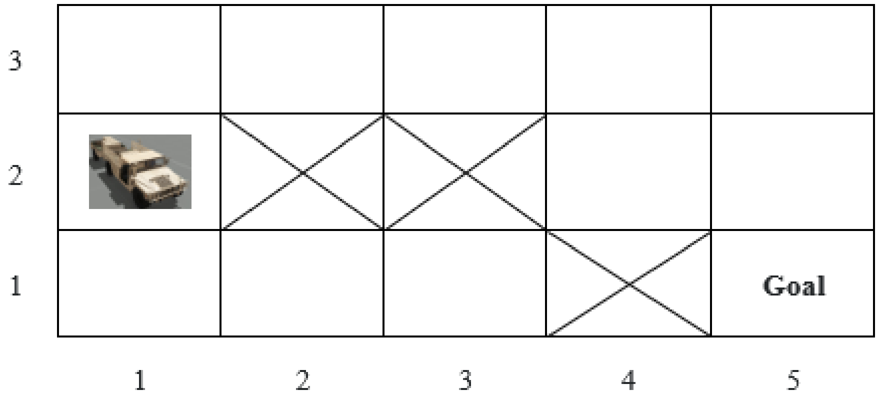
Exercise on Rule + Reward Design for ASV

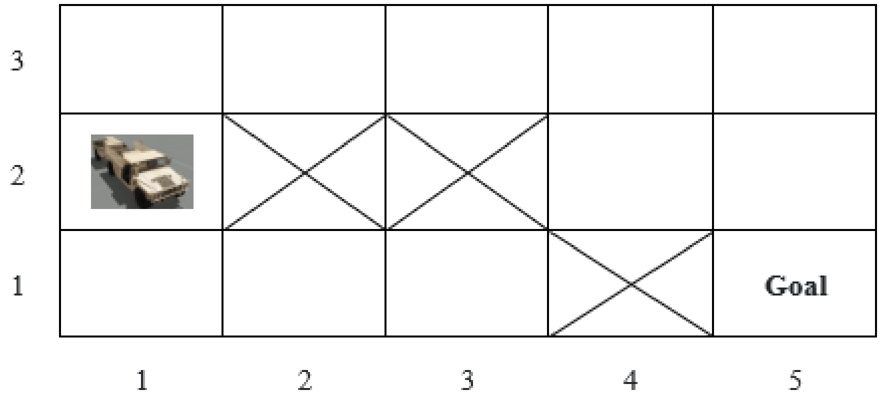
> Your task is to find the optimal path to reach the goal and specify a decision rule / reward architecture that allows the ASV to optimally reach the goal



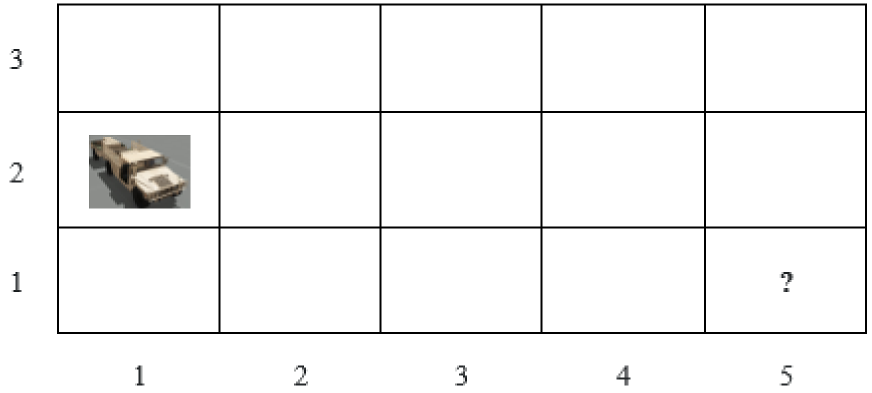
> ASV can move into **four directions**, right (→), left (←), up (↑), down (↓); one move at each time step
> ASV can only sense its current state and **cannot see into an adjacent state**, unless it enters that state
> Designer has perfect information about the world, e.g., she can see into all of the 15 states of the world However, **her knowledge of the world is restricted to what is explicitly specified**

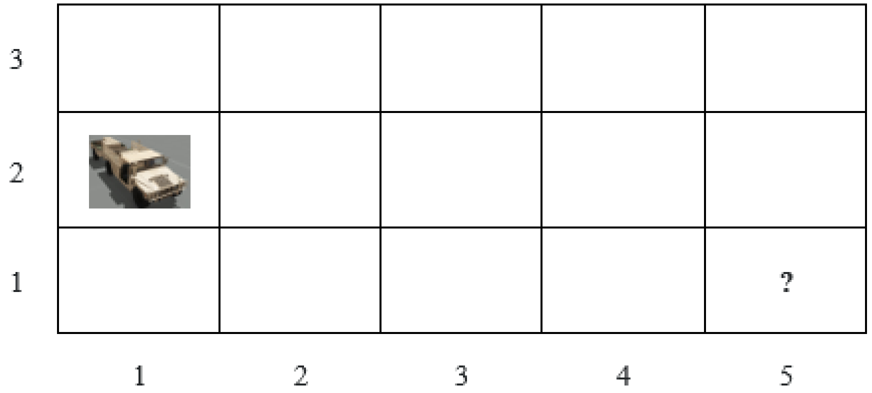
Pathfinding with Obstacles



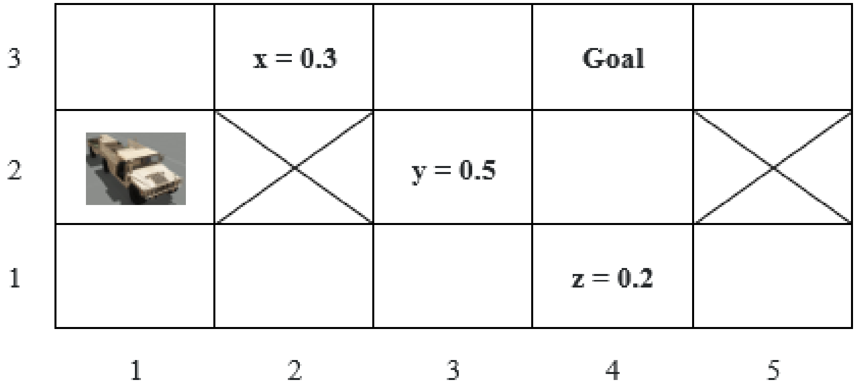


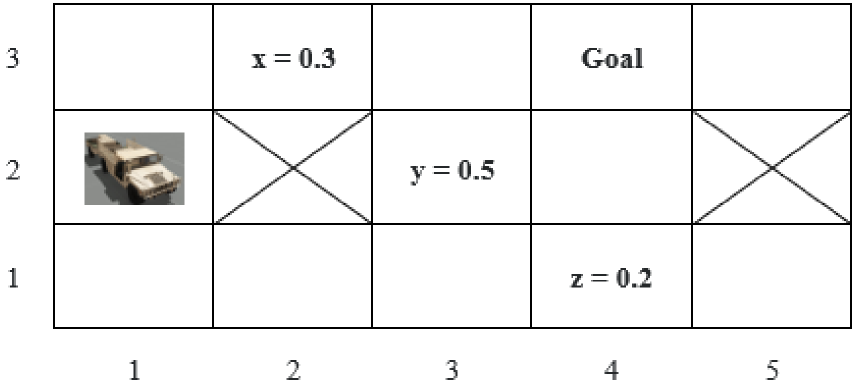
Unknown Goal



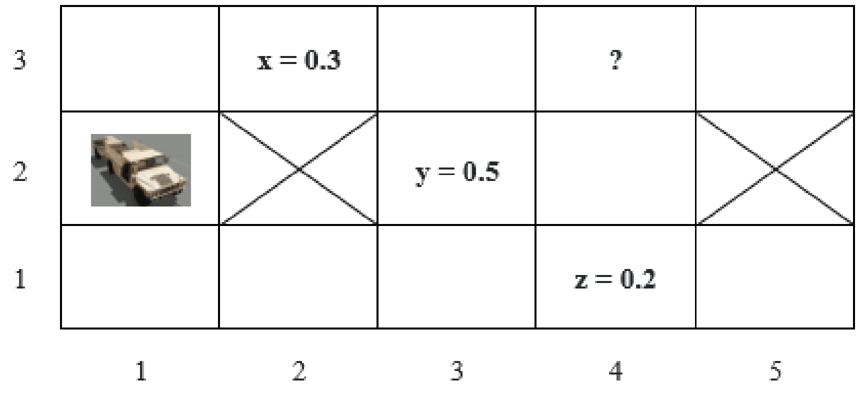


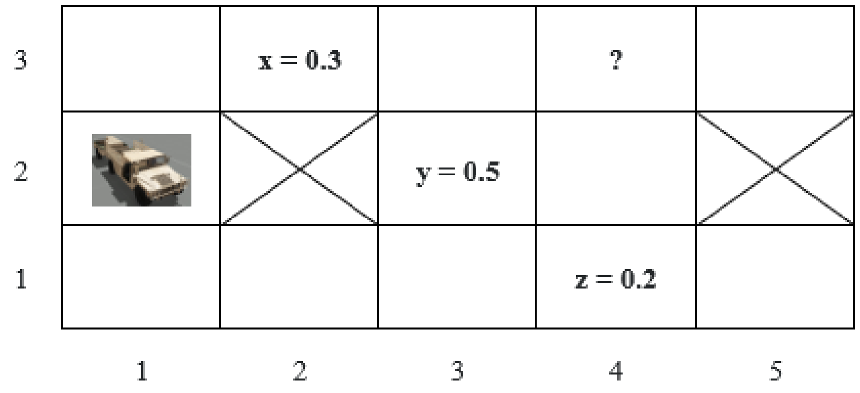
Known Probabilistic Fire and Known Goal





Known Probabilistic Fire and Unknown Goal





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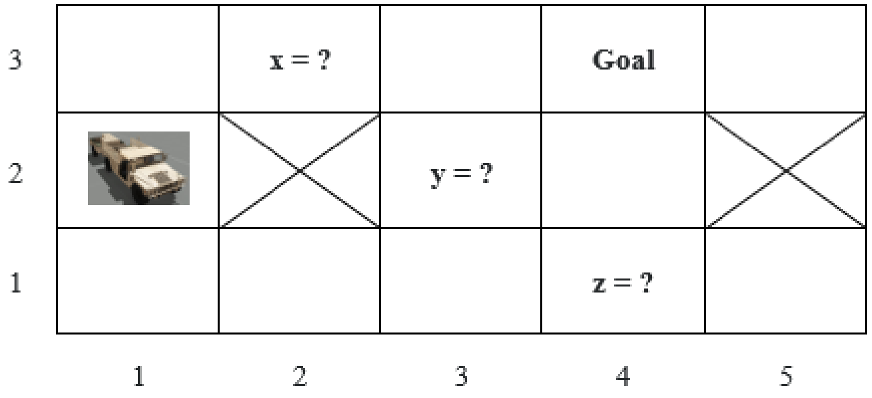

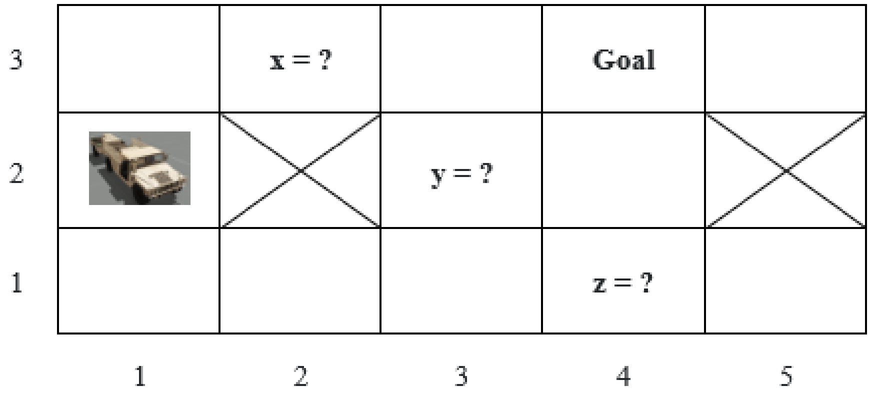

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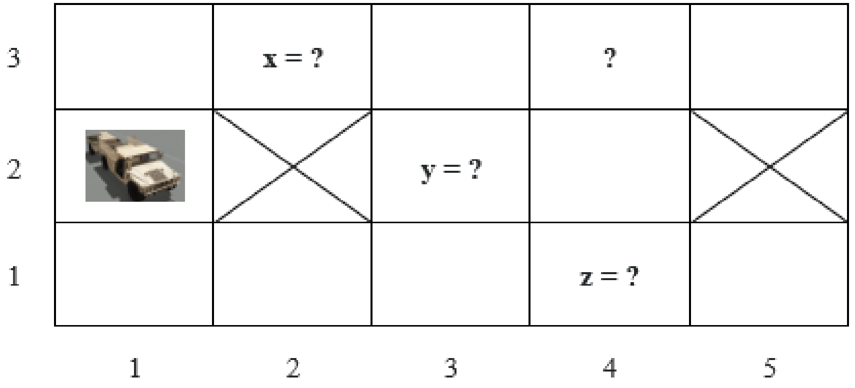
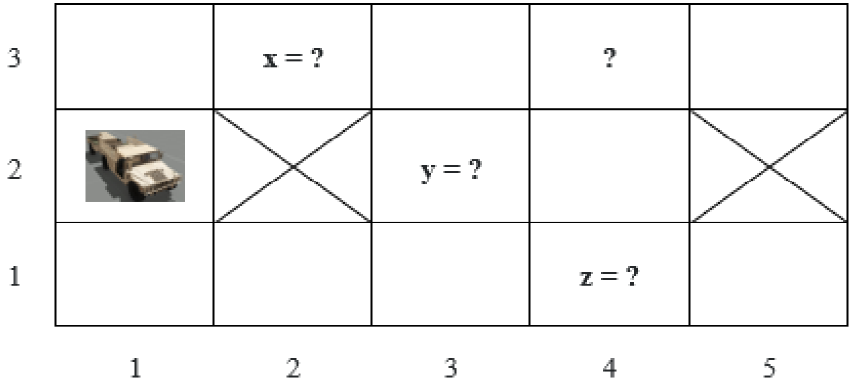




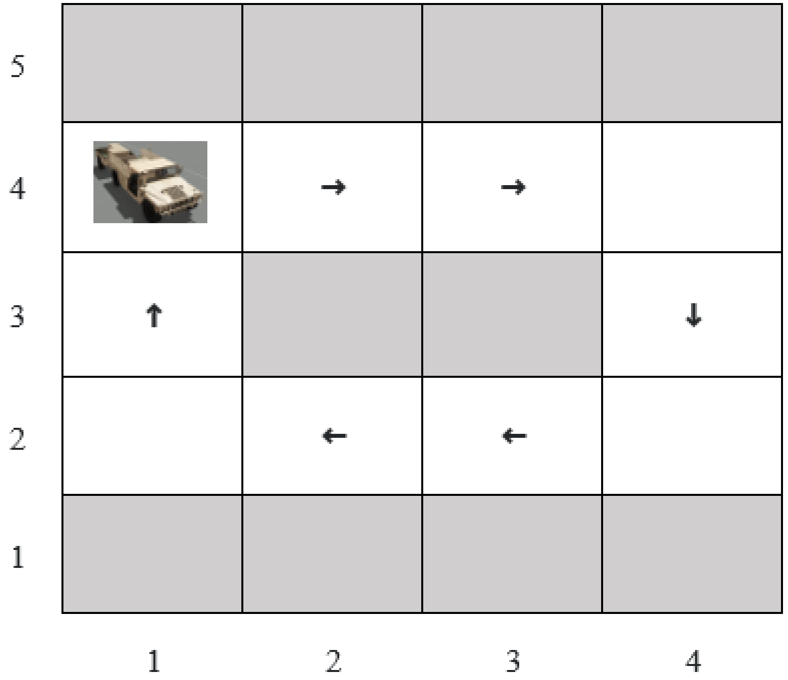
Two Failure Modes of Reward Design in RL

- **Reward gaming** (Clark and Amodei. 2016. Faulty Reward Functions in the Wild)
  - *How can we build agents that do not try to introduce or exploit errors in the reward function in order to get more reward?*

- **Negative side effects** (Amodei et al., 2016. Concrete Problems in AI Safety)
  - *How can we get an agent to avoid poor behavior if the reward function does not capture all the elements of the test environment?*

Reward Gaming

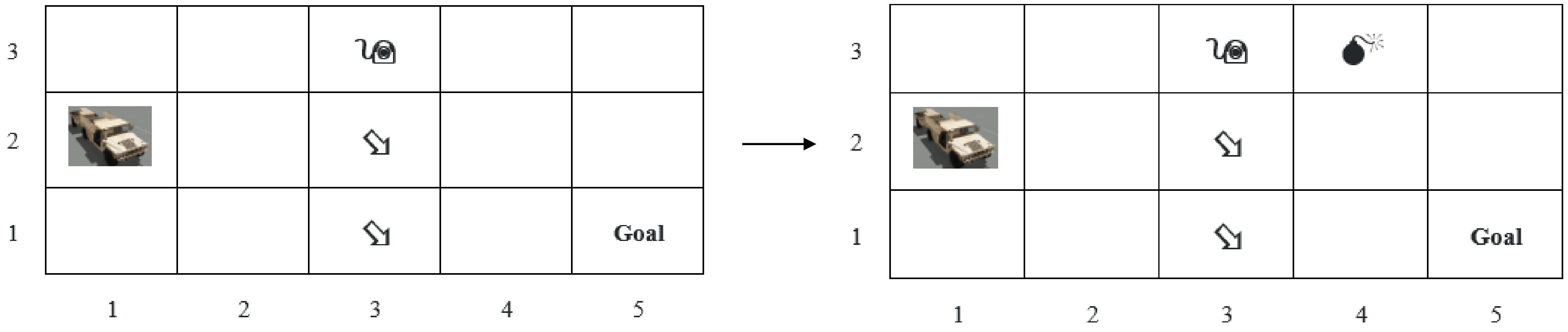
- Agent exploits an unintended loophole in the reward specification, to get more reward than deserved



- Desired outcome: clockwise completion of race
- Arrows are checkpoints associated with a reward of 3

Negative Side Effects

> Reward function does not fully capture all the properties of the test environment



Training environment *Test environment*

> Desired outcome: reach goal state
> (spotted by enemy) = -1, (bad terrain) = -3, (land mine) = - 100, **Goal** = 10

Inverse Reward Design

> Hadfield-Menell et al. 2017. Inverse Reward Design
>
> > *We leverage a key insight: that the designed reward function should merely be about the intended reward, rather than the definition; and should be interpreted in the context in which it was designed*