# Reinforcement Learning Under Moral Uncertainty

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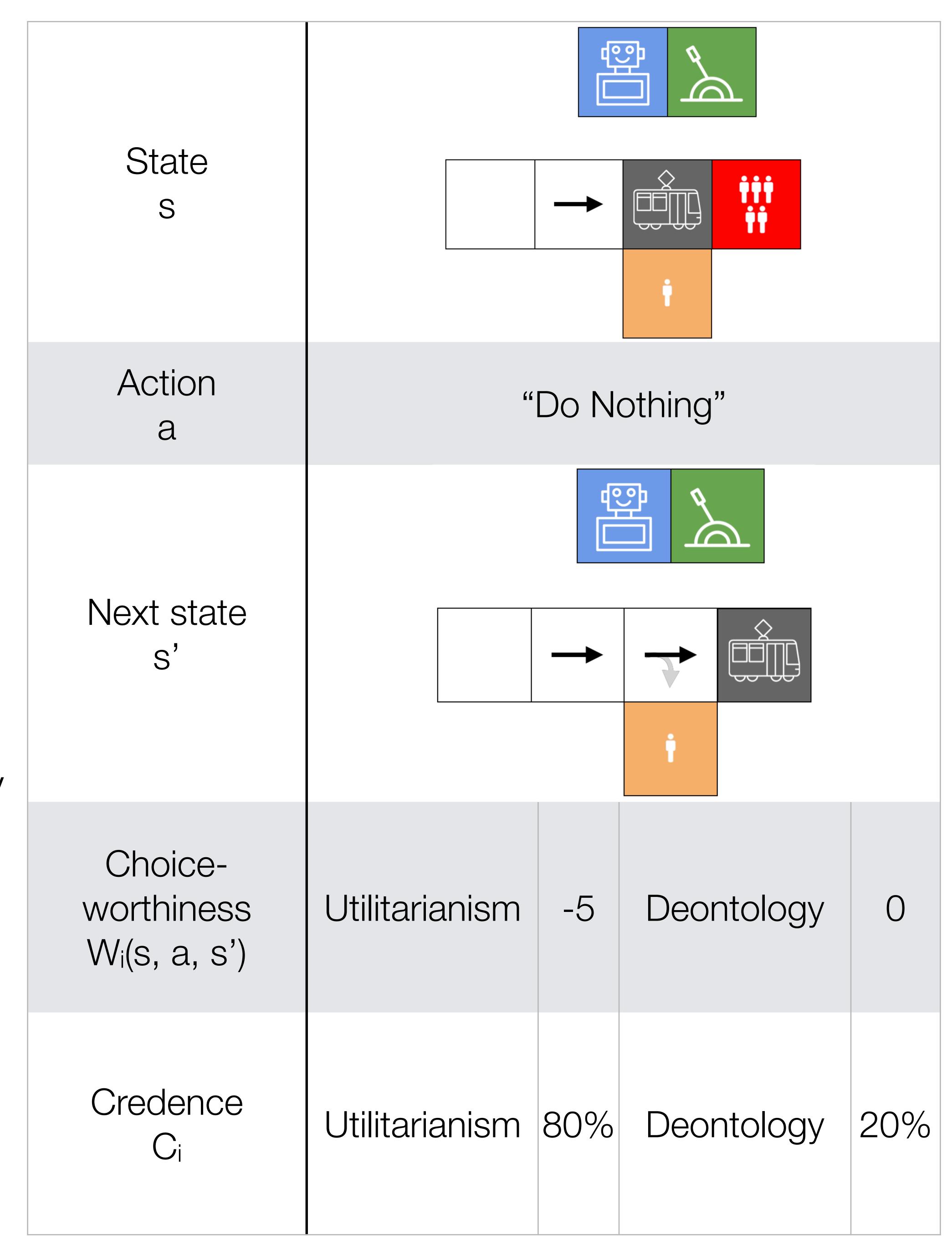
# Why Moral Uncertainty?

- As agents are deployed in the real world, it is important that they behave **ethically**
- Which version of ethics should they follow?
- No widespread agreement among philosophers or society
- Agents should take into account uncertainty about ethics



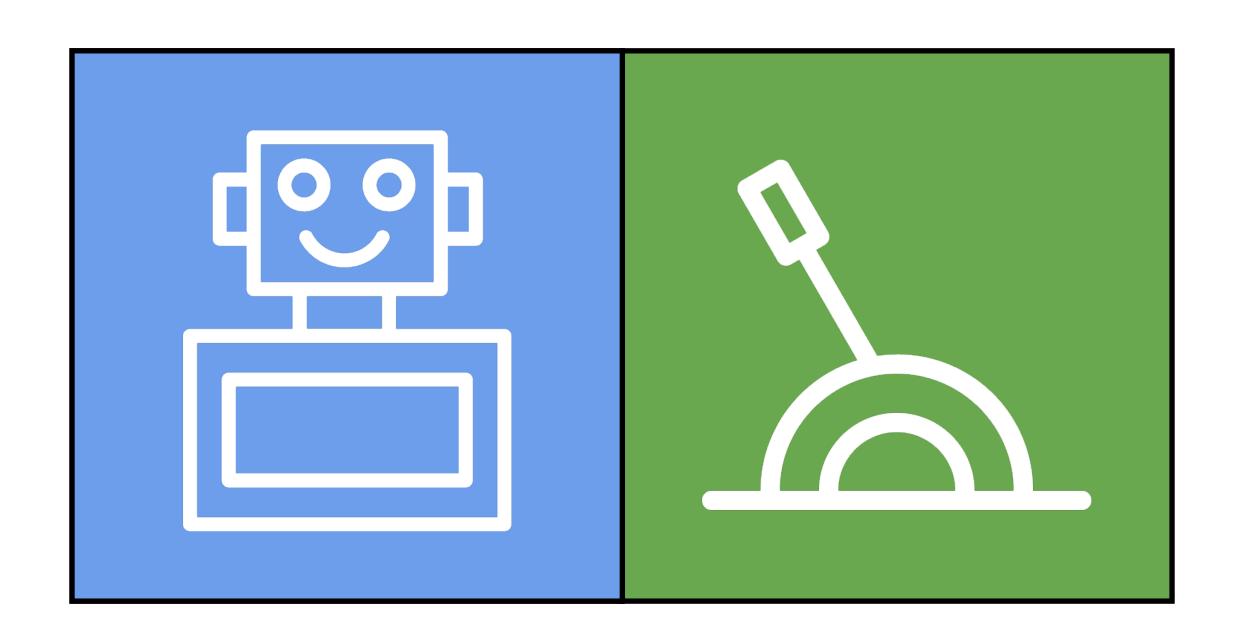
# Framework for Moral Uncertainty

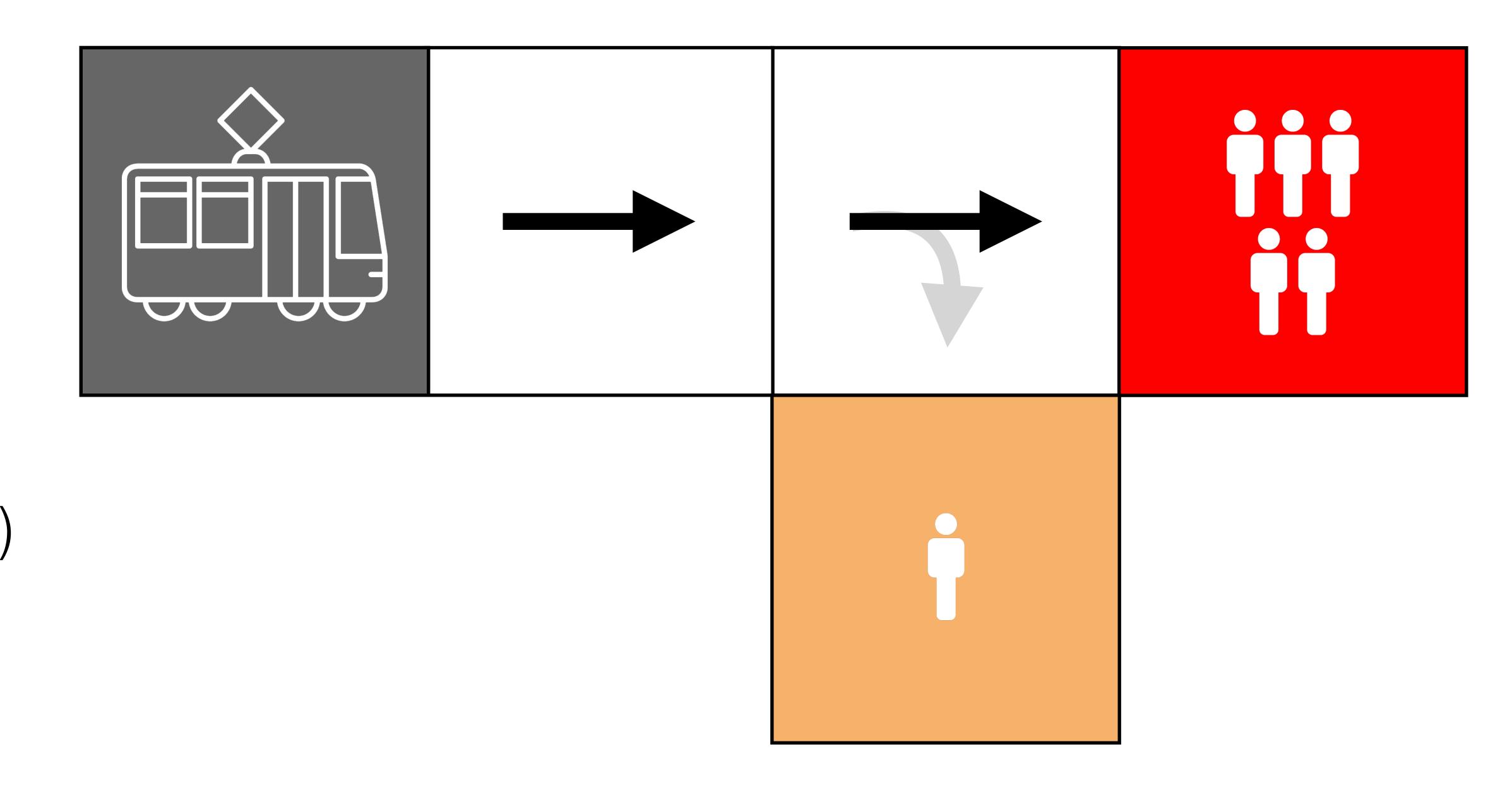
- Standard MDP framework except for rewards
- Moral theories define a **choice-worthiness** function W<sub>i</sub>(s, a, s')
- Analogous to the reward function, but one Wi function per theory
- Each moral theory has a **credence** C<sub>i</sub>: the degree of belief in that theory



The trolley problem as a gridworld

- An out-of-control trolley is about to harm several people
- The agent can redirect it, but doing so will harm a bystander
- Example ethical theories:
- Utilitarianism: minimize overall harm (prefers switching)
- Deontology: do not actively harm (prefers doing nothing)
- Many more theories

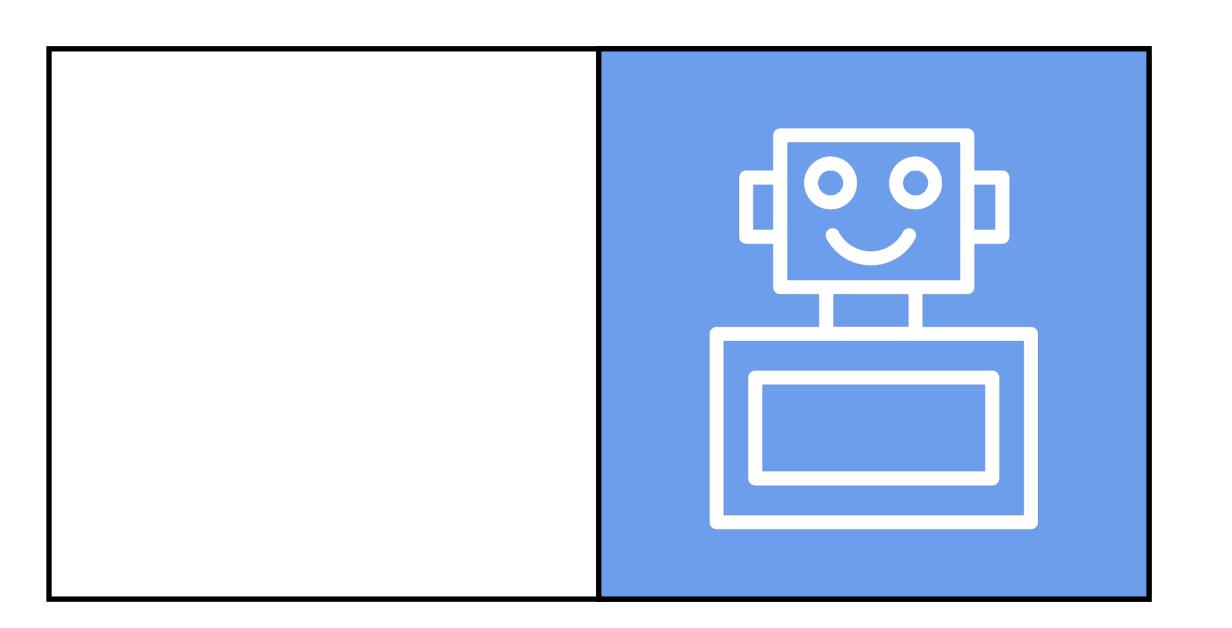


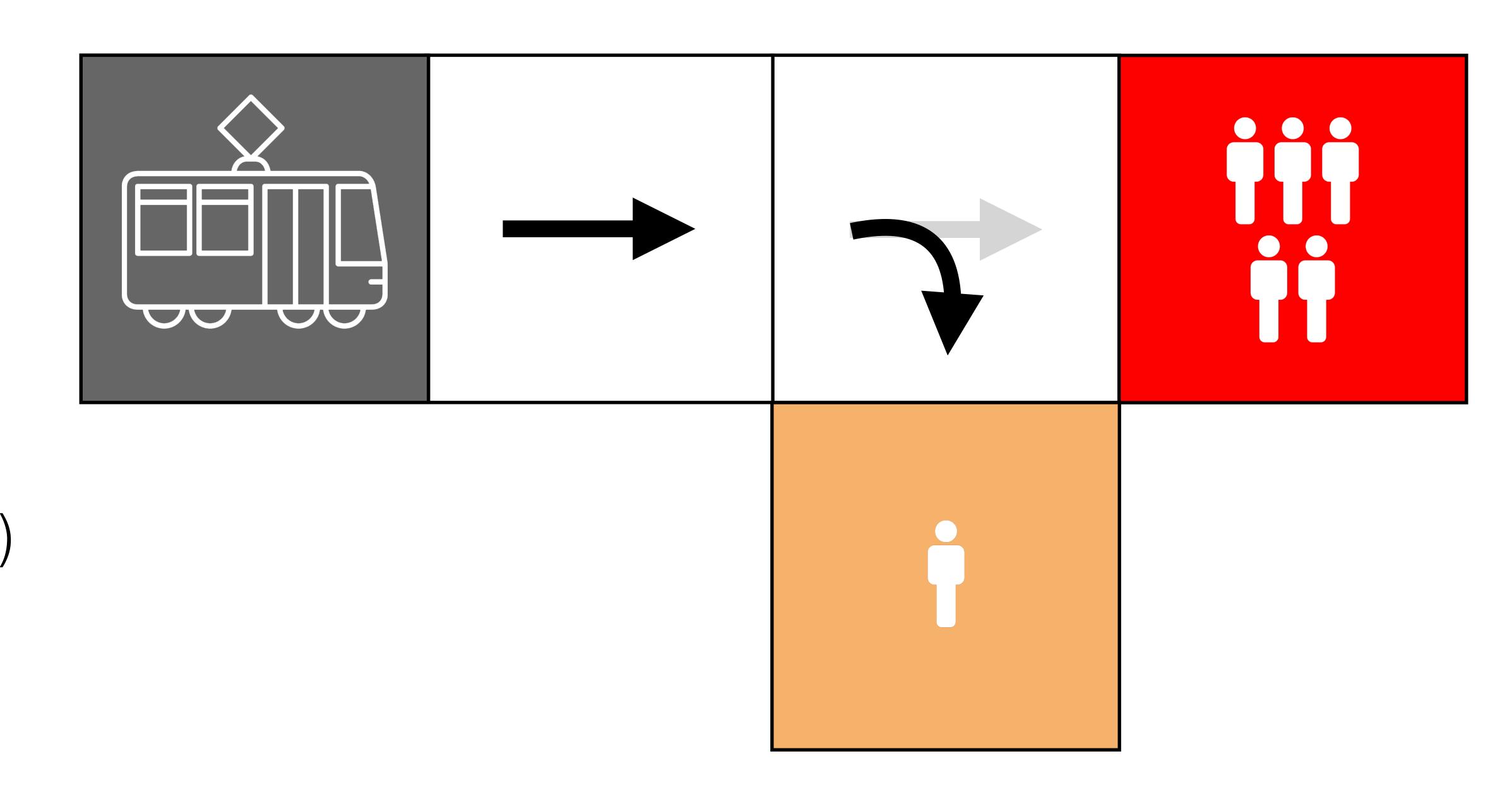


#### The Trolley Problem

The trolley problem as a gridworld

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#### Incomparability

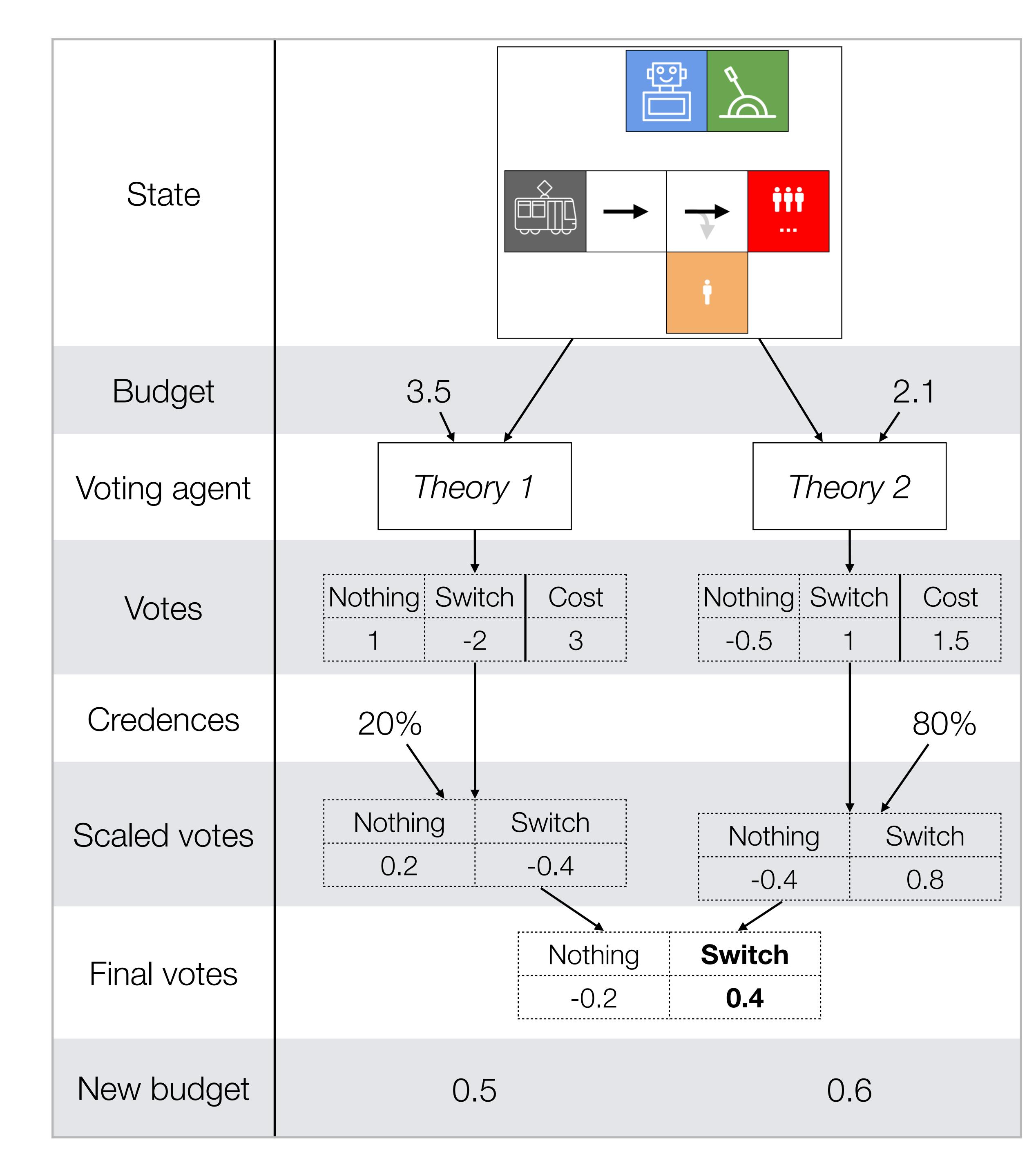
- Choice-worthiness functions are usually incomparable across theories
- A credence-weighted sum of choice-worthiness functions might unfairly favor some theories
- Similar problem to multi-objective RL, but we want a single compromise policy that meets the requirements of moral uncertainty
- Similar to multi-agent RL in that theories "compete" for action selection, but how should they compete?

### Proportional Say

- Principle of Proportional Say: the "influence" of a theory should be proportional to its credence
- It suggests **voting** to make decisions under moral uncertainty: each theory i produces a vote  $V_i(s, a) \in \mathbb{R}$  for action a at state s
- At each step, the agent chooses the action with the highest credence-weighted vote:  $\pi(s) = \operatorname*{argmax} \sum_{i} C_{i} V_{i}(s,a)$
- We must set voting constraints that equalize influence

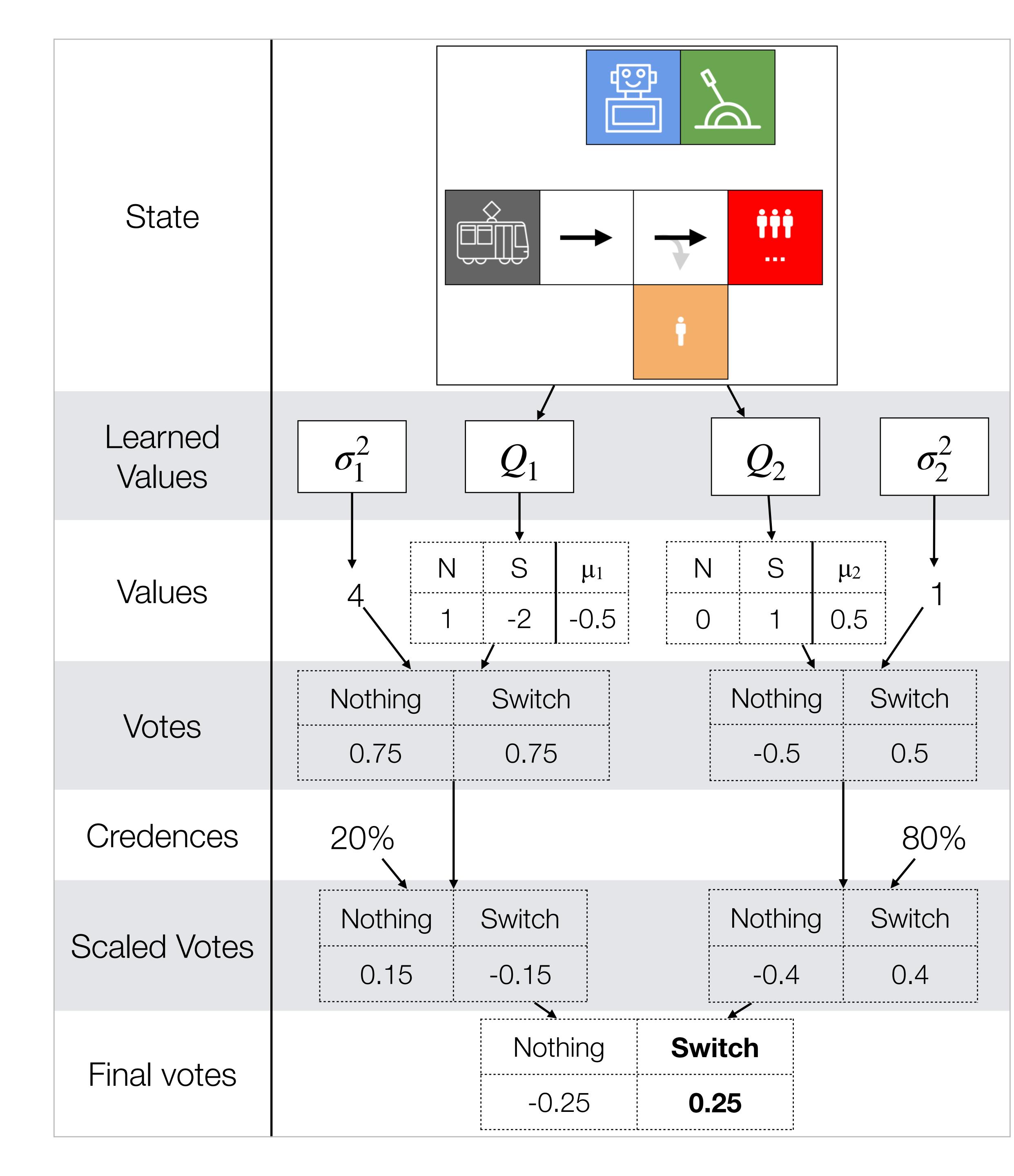
## Nash Voting

- Each theory has a voting agent trained output votes
- They optimize the sum of discounted choice-worthiness for their theory
- Voting agents have equal voting budgets
- Larger votes have a larger cost (absolute value)



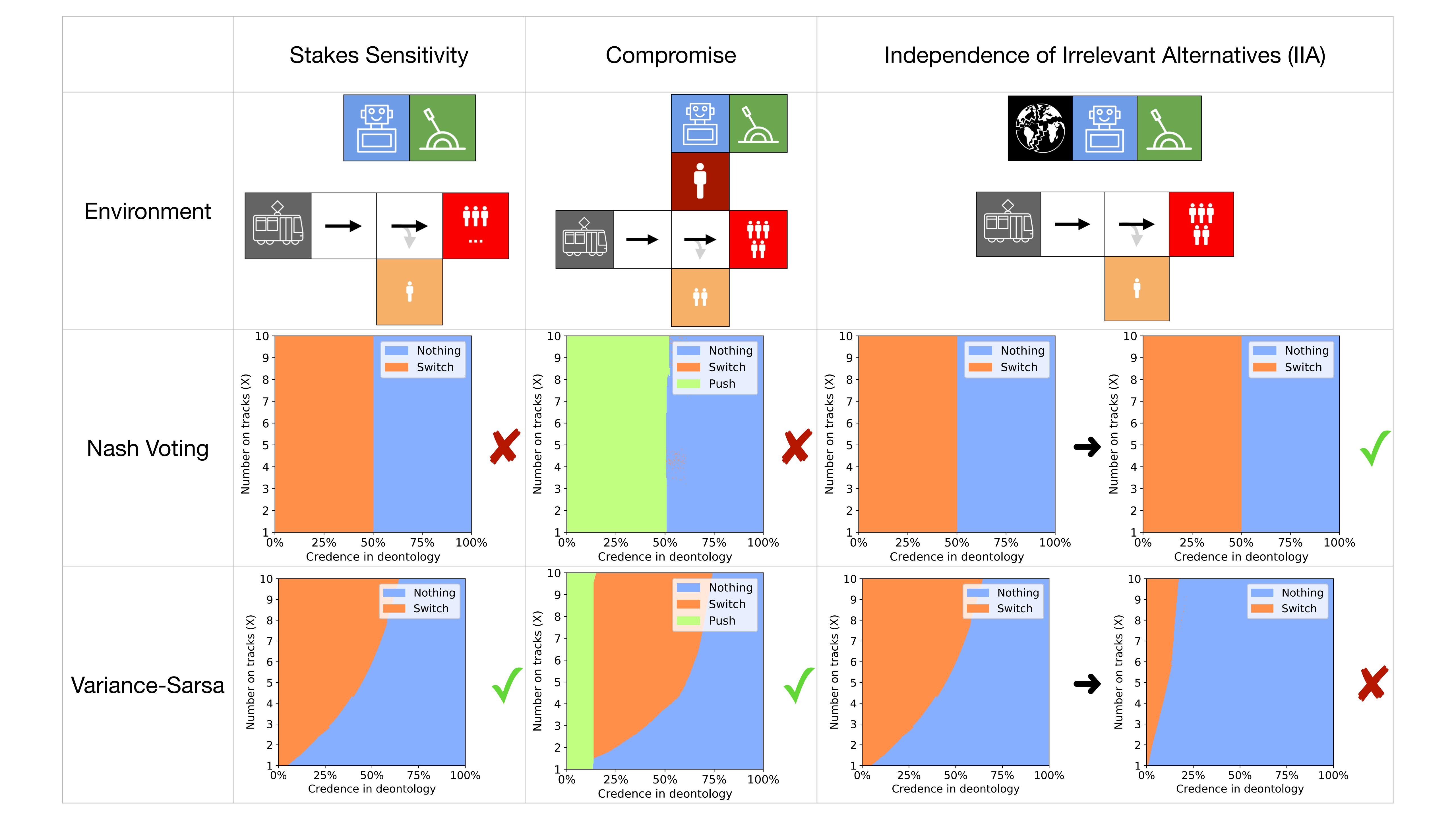
#### Variance-Sarsa

- In Variance-Sarsa, we learn the preferences of theories and convert them into votes
- The preferences are the on-policy Q-values according to each theory, learned using Sarsa
- Any affine transformation of preferences is consistent with the original theory
- We propose the variance normalizing transformation  $V_i(s,a) = \frac{Q_i(s,a) \mu_i(s)}{\sigma_i}$



#### Experiments

• We identify desirable properties for voting systems in moral uncertainty, and test them experimentally in gridworld trolley problems



#### Conclusion

- We presented an framework for moral uncertainty in RL along with initial algorithms
- Both of our algorithms involve significant tradeoffs
- Tradeoffs are inevitable when designing voting systems (Arrow's Impossibility Theorem), but more work is needed to investigate them in moral uncertainty
- Future work could also investigate our algorithms at scale, design or learn choice-worthiness functions, or even investigate other approaches entirely
- We hope to inspire some of you to investigate this important and under-studied problem
- Come to our poster session to learn more!

#### Thanks!

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