A preference-based approach to machine ethics for automated planning

PhD. Thesis Defense - Martin Jedwabny

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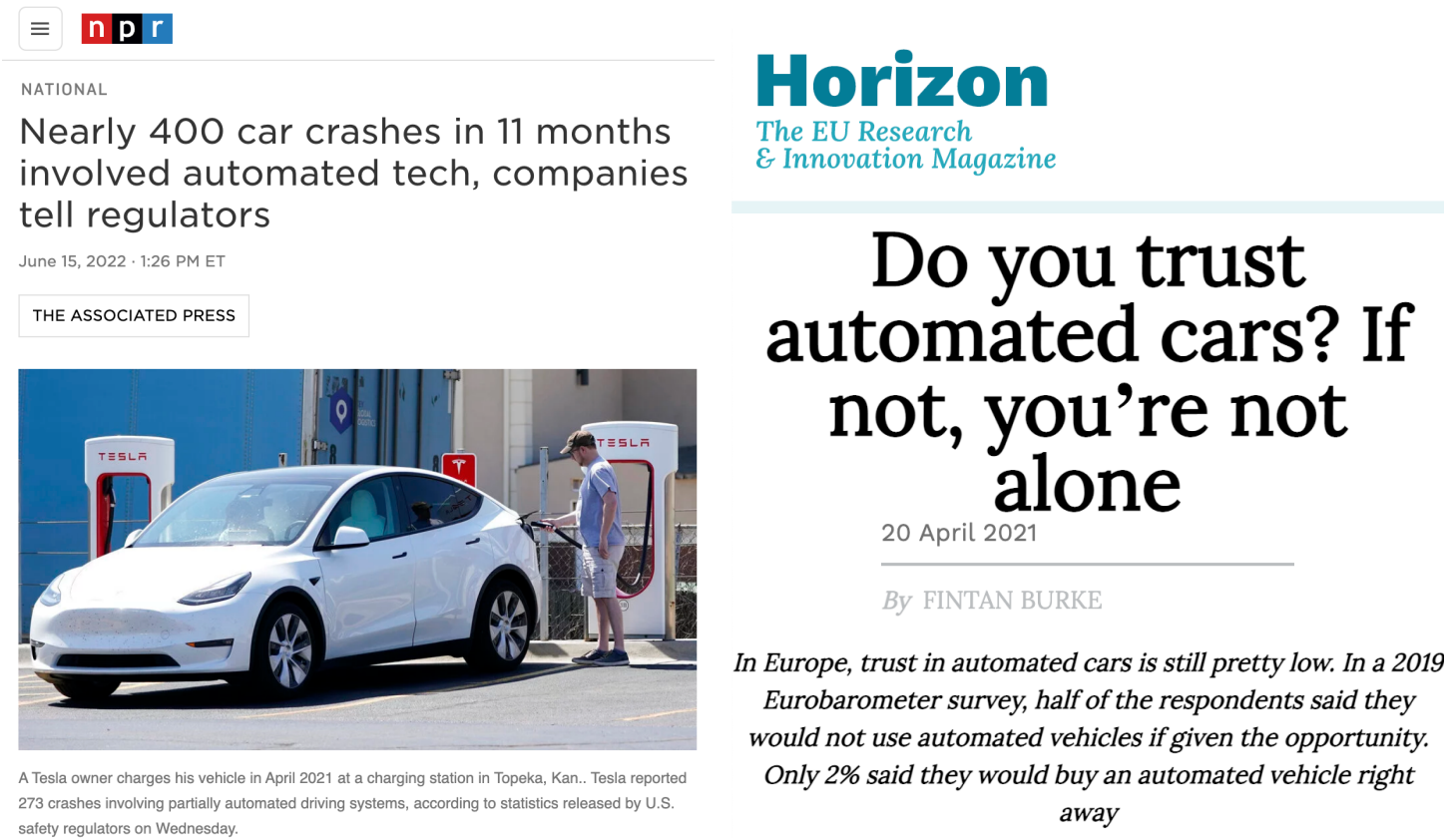
Introduction

Introduction

Recent years of progress in computer science have resulted in the *widespread use of AI*, **but** the introduction of automated agents in certain domains has stirred much **public concern**:



NATIONAL

Nearly 400 car crashes in 11 months involved automated tech, companies tell regulators

June 15, 2022 · 1:26 PM ET

THE ASSOCIATED PRESS

A Tesla owner charges his vehicle in April 2021 at a charging station in Topeka, Kan.. Tesla reported 273 crashes involving partially automated driving systems, according to statistics released by U.S. safety regulators on Wednesday.

Horizon
The EU Research & Innovation Magazine

Do you trust automated cars? If not, you're not alone

20 April 2021

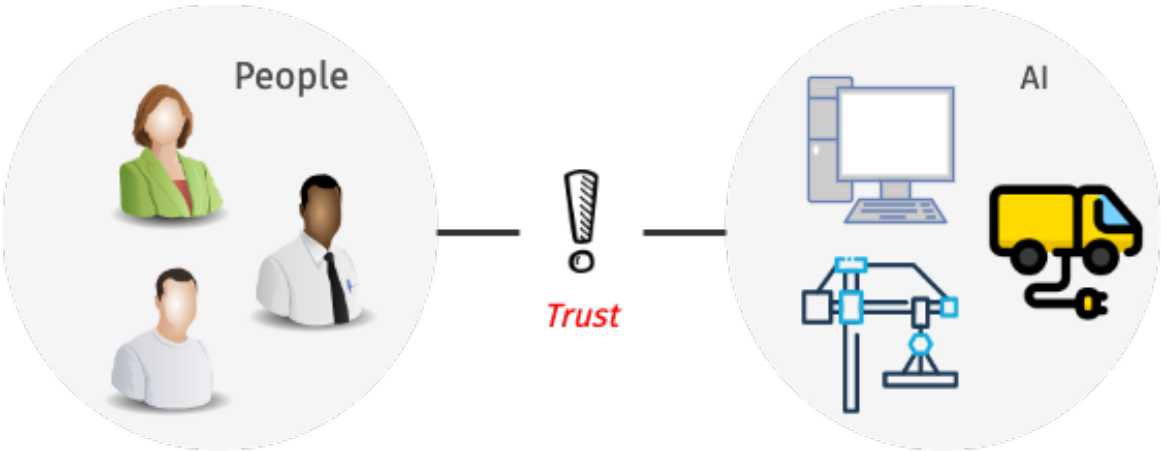
By FINTAN BURKE

In Europe, trust in automated cars is still pretty low. In a 2019 Eurobarometer survey, half of the respondents said they would not use automated vehicles if given the opportunity. Only 2% said they would buy an automated vehicle right away

Figure 1: News articles from [NPR Website, 2022] and [Horizon Magazine Website, 2021]

Introduction

How can we develop systems we can **trust**?



Two ways research has identified for developing trustworthy AI:

- Ethically-aligned agents [Shahriari and Shahriari, 2017], and
- Explainable AI (XAI) [Arrieta et al., 2020].

Introduction

- **Machine ethics** [Anderson and Anderson, 2007] is the subfield of artificial intelligence (AI) that studies the *automation of ethical reasoning*.

- **However**, determining which decision is the *most ethical* can be a very hard problem:

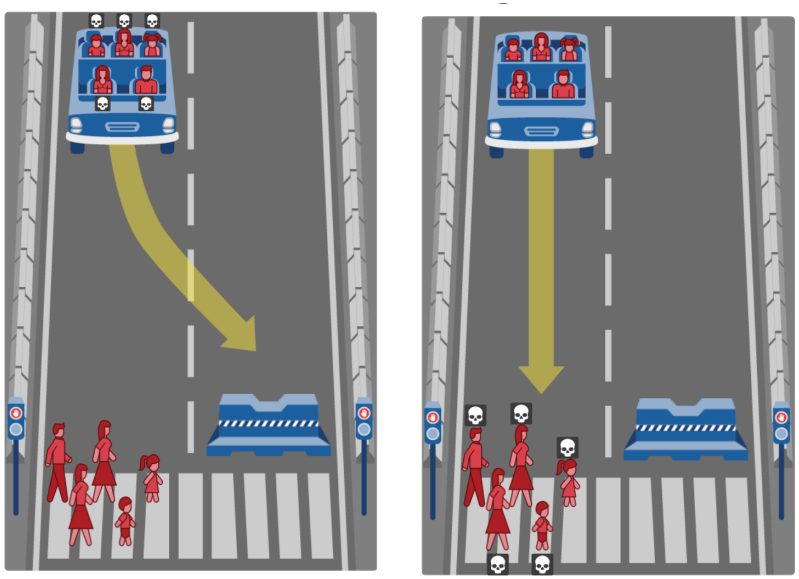


Figure 2: Moral Machine [Awad et al., 2018] example case.

Introduction

- **However**, determining which decision is the *most ethical* can be a very hard problem:

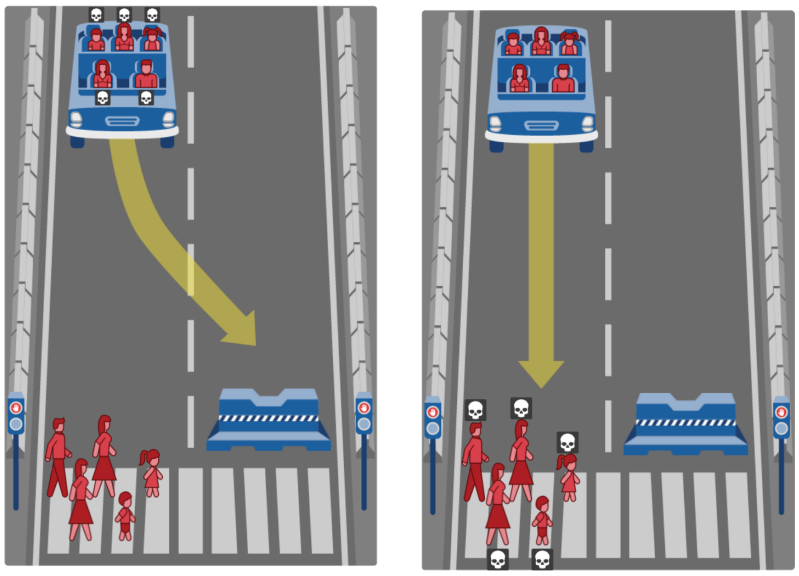


Figure 3: Moral Machine [Awad et al., 2018] example case.

- Permissibility?
- Utilities?
- Causality?

Introduction

Machine ethics *implementations* can be **classified** [Moor, 2006] into:

1. Top-down: **explicitly model** the rightness of action,

2. Bottom-up: **learn** what is ethical from human behavior,

3. Hybrid: a **mix**, i.e: learning following a high-level symbolic theory.

Introduction

⚠ **Problem 1 (top-down)**: too **restrictive** and adaptations require the opinion of **experts**.

⚠ **Problem 2 (bottom-up)**: lack of **transparency** and **explainability**.

⚠ **Problem 3 (hybrid)**: most do not handle either reasoning **many steps** in advance, or **noisy datasets**.

Introduction

★ **Research question**: how can an automated agent

1. **Assess** actions according to many **ethical theories** under the same framework,

2. In a context that allows reasoning **many steps** in advance,

3. And **align** its behavior to societal opinions of ethics, i.e: right and wrong?

Introduction

★ **Research question**: how can an automated agent

1. **Assess** actions according to many **ethical theories** under the same framework,

   ⇒ **Symbolic model of ethics**.

2. In a context that allows reasoning **many steps** in advance,

   ⇒ **Planning**.

3. And **align** its behavior to societal opinions of ethics, i.e: right and wrong?

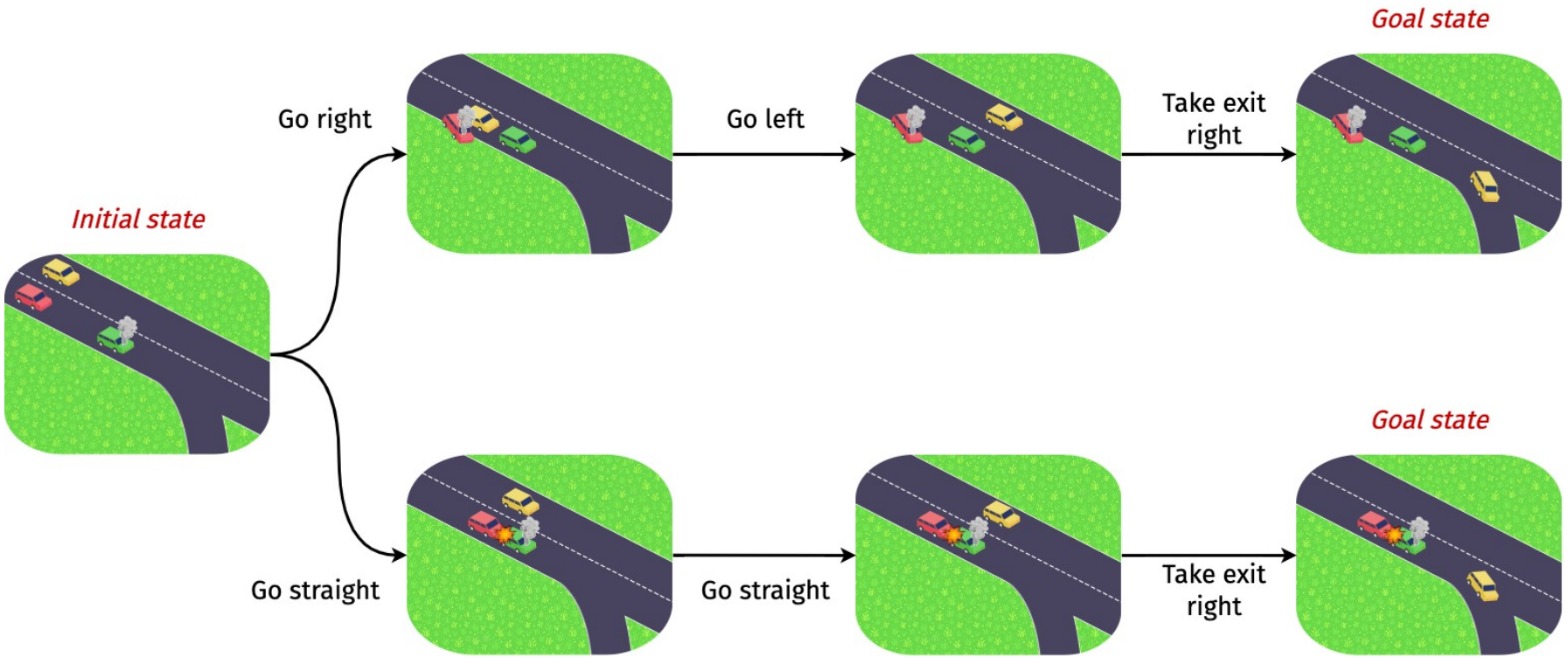
   ⇒ **Learning preferences**.

Outline

Background notions: classical planning

Background notions: classical planning

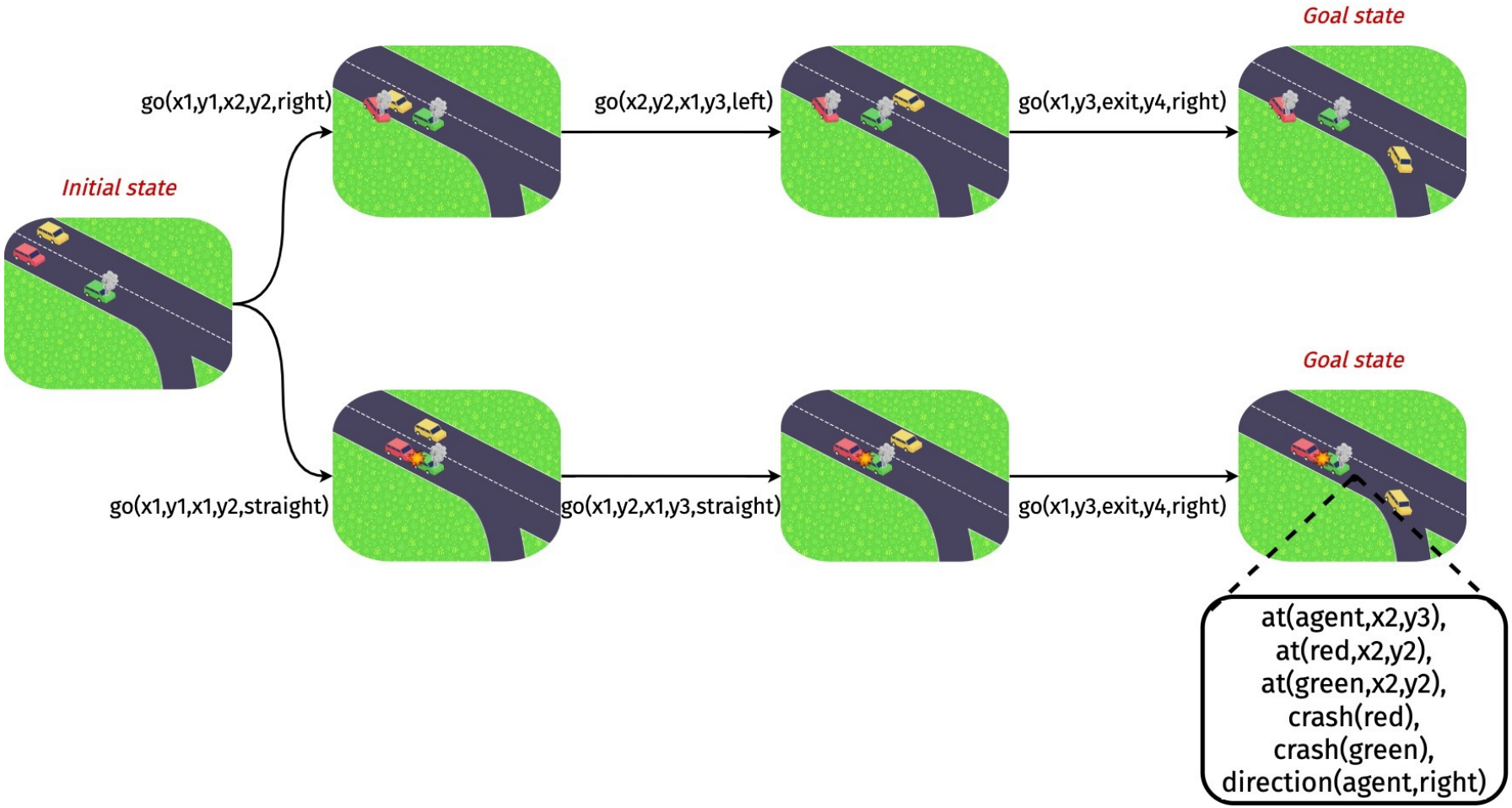
Classical planning, at a glance:



Background notions: classical planning

A **classical planning problem** is a tuple $T = \langle F, O, s_0, g \rangle$, where:

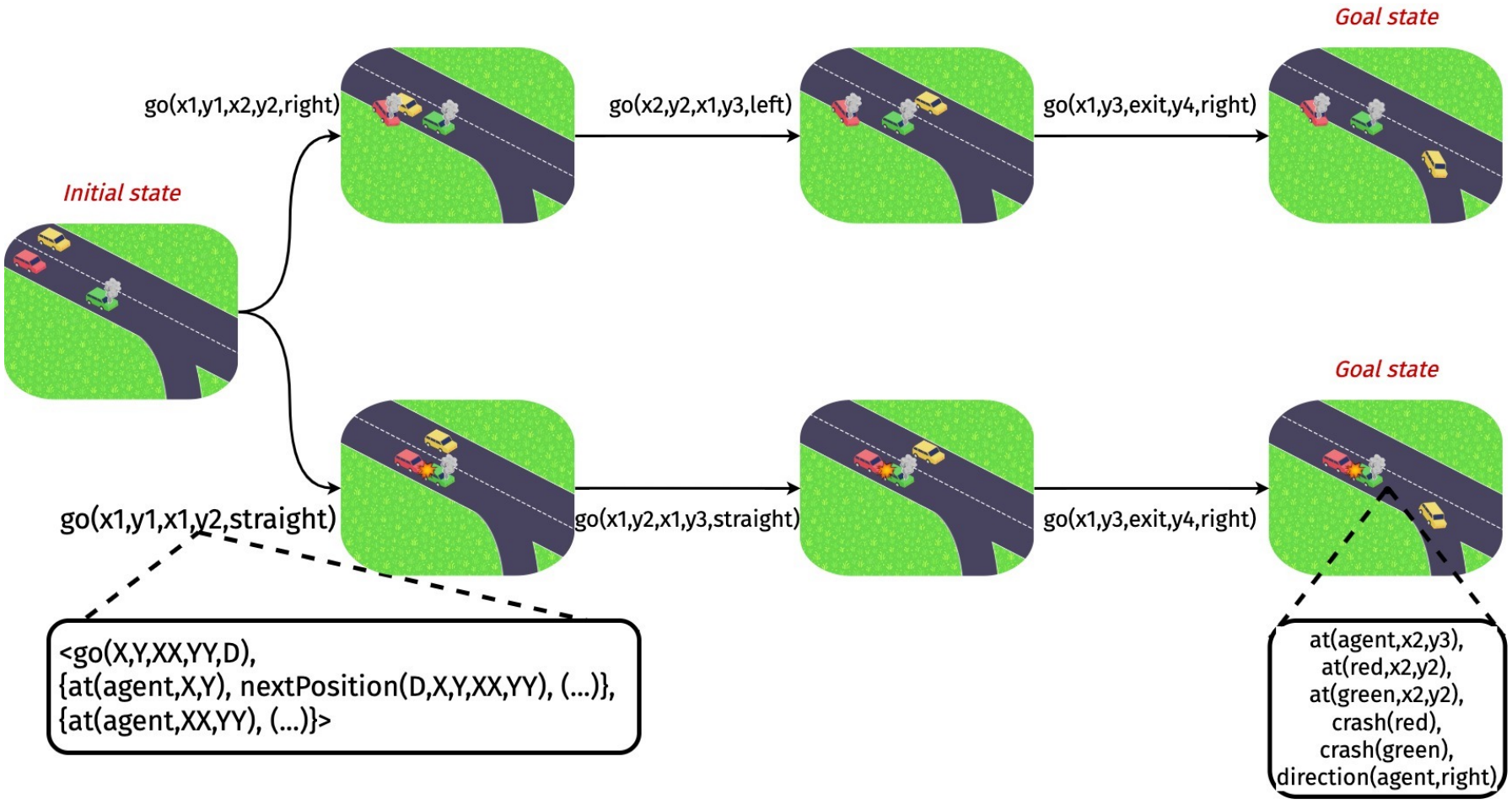
- F is the set of all state properties (atoms over $\mathcal{L}$), called **fluents**, e.g: $at(agent, x_1, y_1), direction(agent, left)$, etc.



Background notions: classical planning

A **classical planning problem** is a tuple $T = \langle F, O, s_0, g \rangle$, where:

- O are the **operators** (over F), and an **action** is a grounded operator.

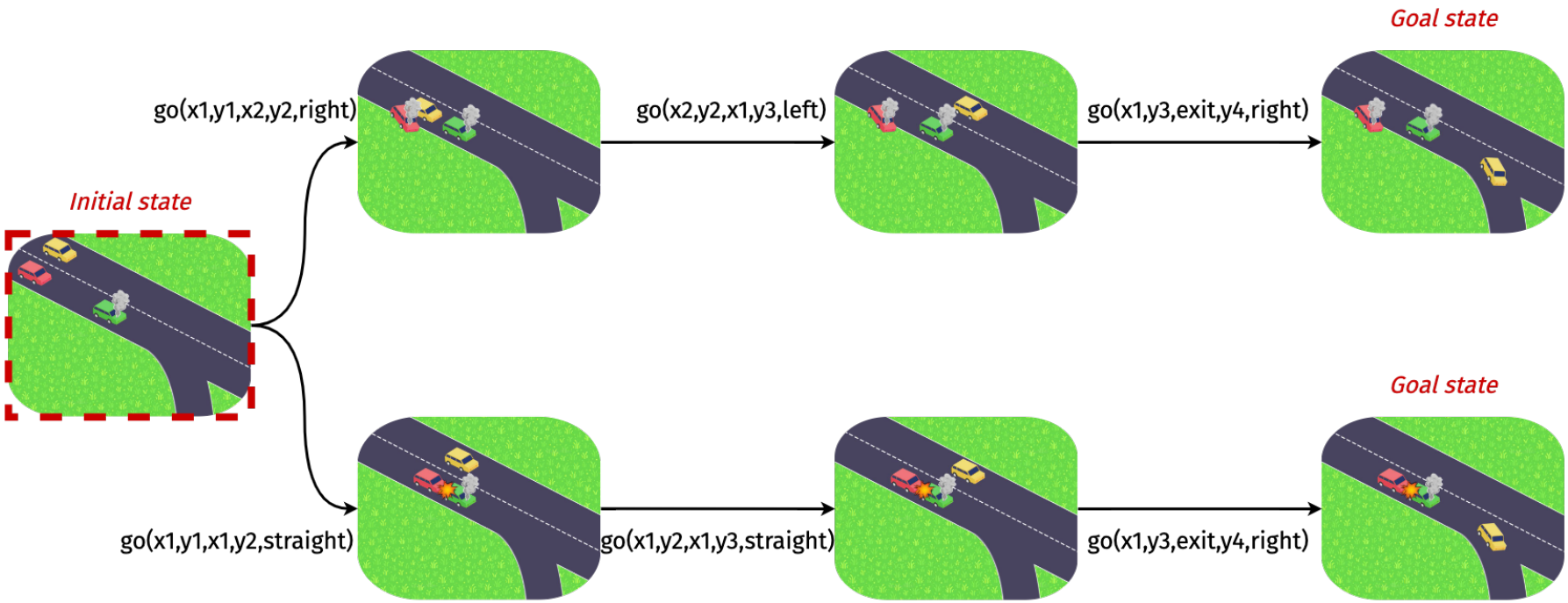


Background notions: classical planning

A **classical planning problem** is a tuple $T = \langle F, O, s_0, g \rangle$, where:

- $s_0 \subseteq F$ is the **initial state**, e.g:

$$s_0 = \{at(agent, x_1, y_1), direction(agent, straight),$$
$$at(red, x_2, y_1), at(green, x_2, y_3), \ldots\}$$

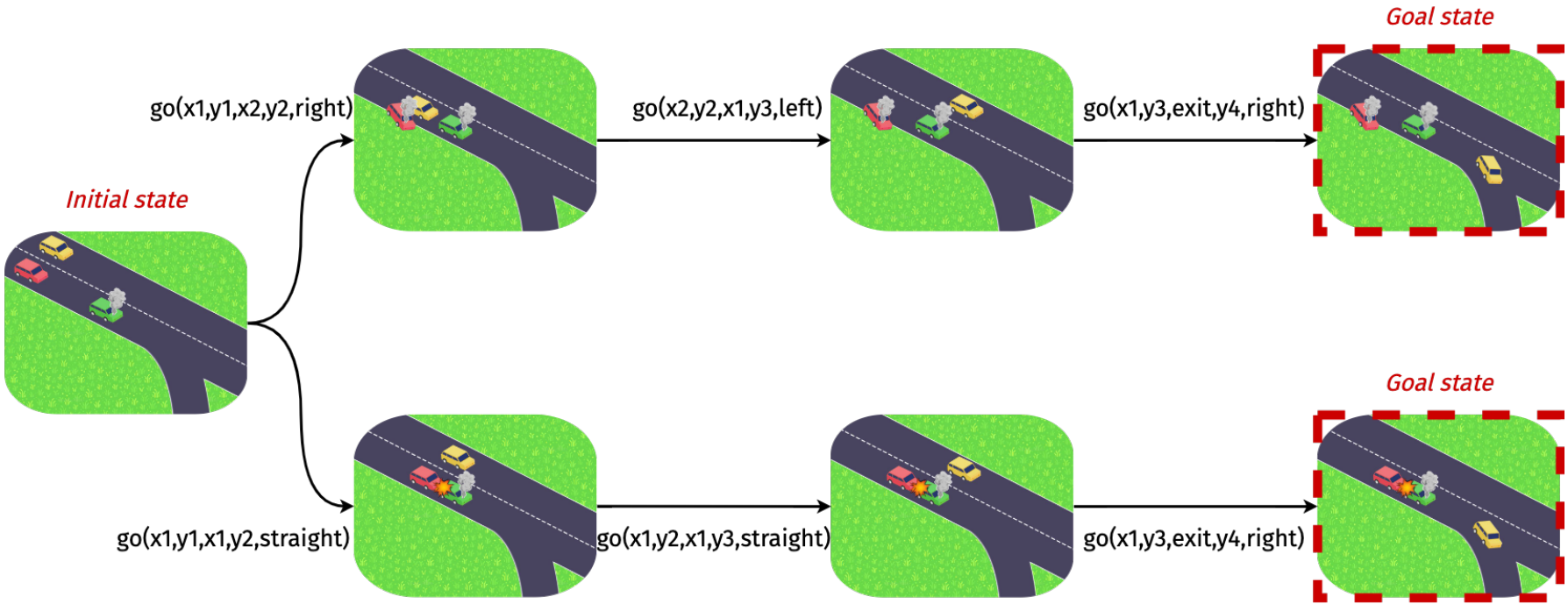


Background notions: classical planning

A **classical planning problem** is a tuple $T = \langle F, O, s_0, g \rangle$, where:

- g is the **goal** (a logic formula over F), denoting success, e.g:

$$g = at(agent, exit, y_4) \wedge direction(agent, right)$$

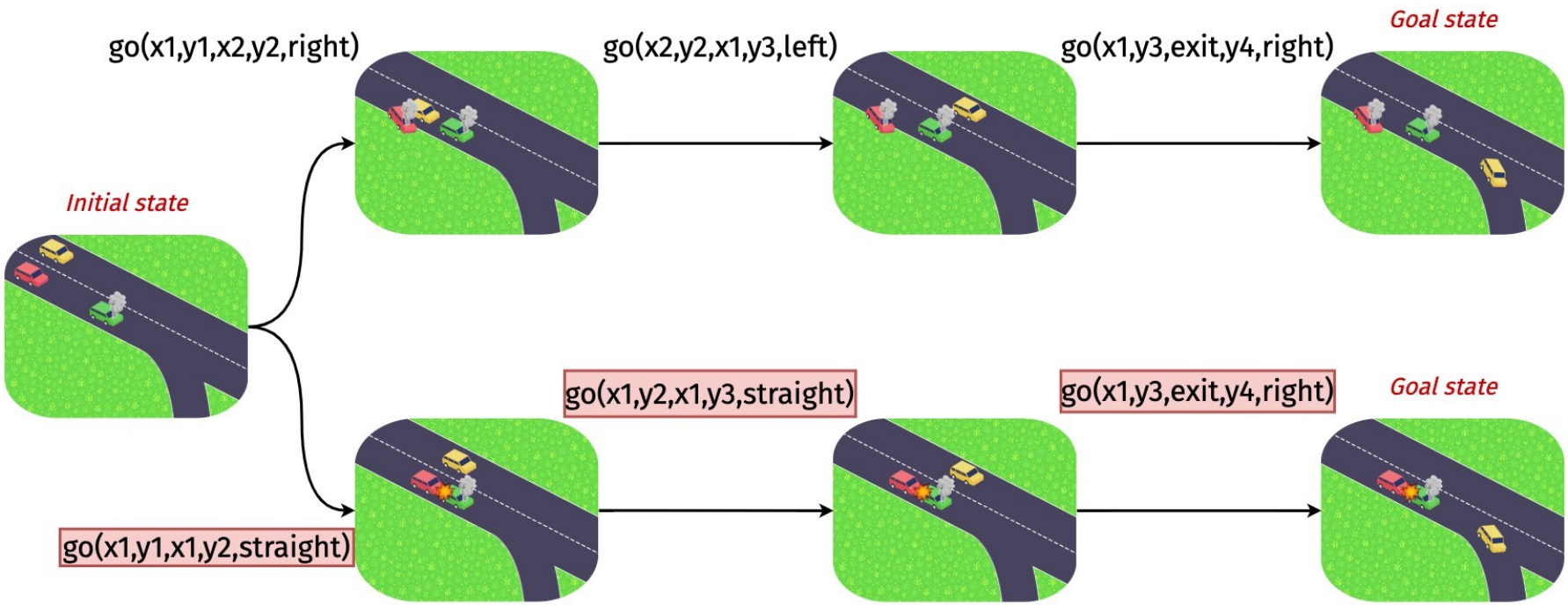


Background notions: classical planning

A **classical planning problem** is a tuple $T = \langle F, O, s_0, g \rangle$, where:

- A **plan** is a sequence of actions $\pi = [a_0, a_1, \ldots, a_n]$ such that: $Succ(a_n, \ldots, Succ(a_1, Succ(a_0, s_0))) \models g$

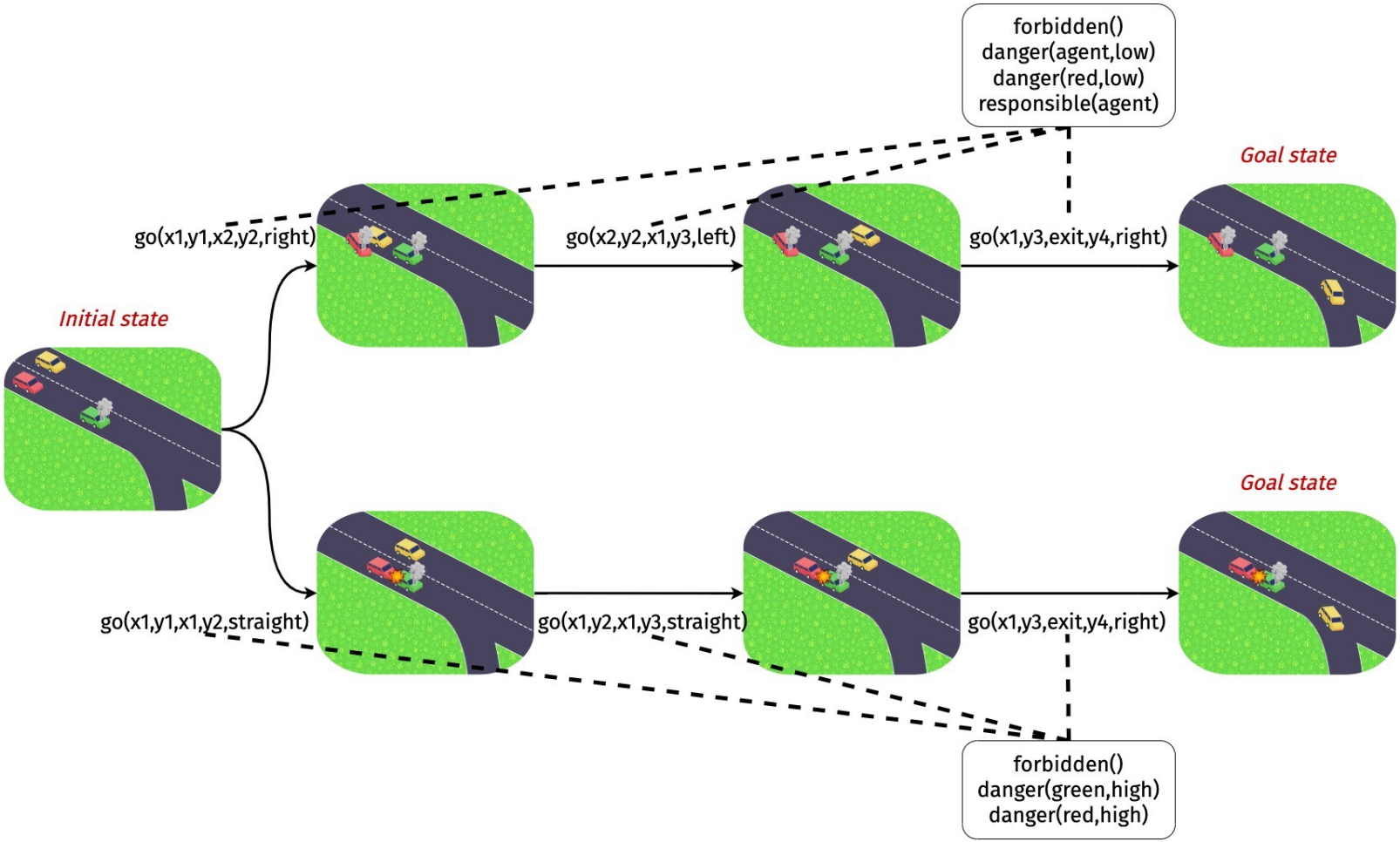
  E.g: $\pi = [go(x_1, y_1, x_1, straight), go(x_1, y_2, x_1, y_3, straight),$
  $go(x_1, y_3, exit, y_4, right)]$



Representing ethics in classical planning

Representing ethics in classical planning

Previous research [Ganascia, 2007, Tolmeijer et al., 2020] has shown how to represent certain ethical theories for decision-making and planning problems.



Question: how can we compare plans ethically?

Representing ethics in classical planning: ethical features

★ **Contribution 1**: an extension [Jedwabny et al., 2021] of classical planning for ethical representation and alignment, we called **ethical planning problem**:

$$T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$$

- E is the set of **ethical features**,

  E.g: $\mathit{forbidden}()$, $\mathit{responsible}(\mathit{agent})$, $\mathit{danger}(\mathit{agent}, \mathit{low})$, $\mathit{danger}(\mathit{agent}, \mathit{high})$, $\mathit{danger}(\mathit{red}, \mathit{low}), \ldots$

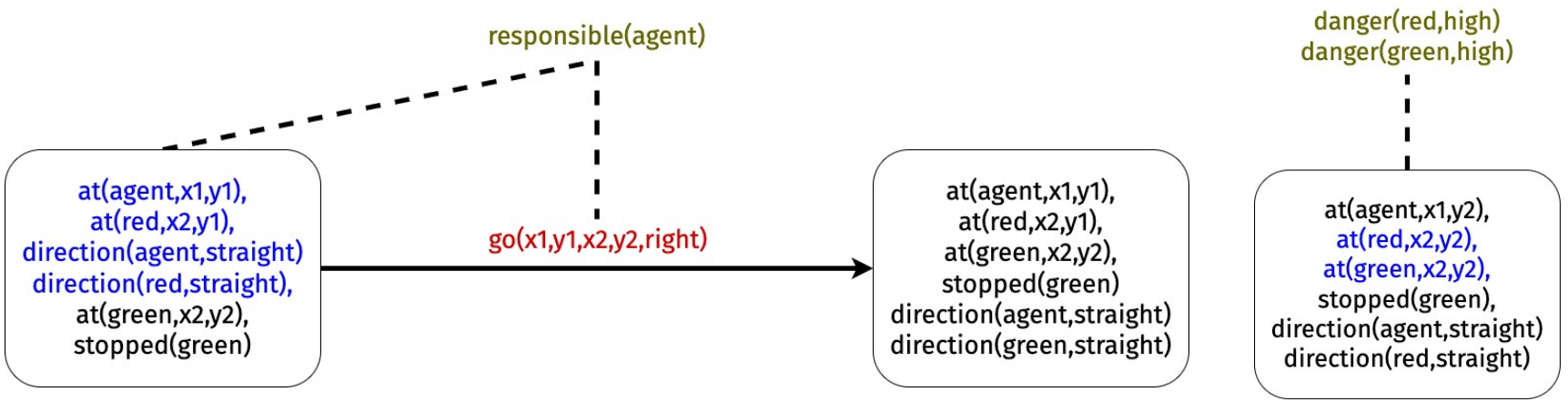
Representing ethics in classical planning: ethical rules

An extension of classical planning for ethical representation and alignment, we called **ethical planning problem**:

$$T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$$

- R is the set of **ethical rules**, which *assign* ethical features to plans:

$$r = \langle ruleName(X, Y, \ldots), Pre(r), Act(r), E(r) \rangle$$



(a) $Act(r) = go$

(b) $Act(r) = null$

Representing ethics in classical planning: preferences

An extension of classical planning for ethical representation and alignment, we called **ethical planning problem**:

$$T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$$

- b is the **ethical ranked base**, which compares plans π and π' on ethical terms:

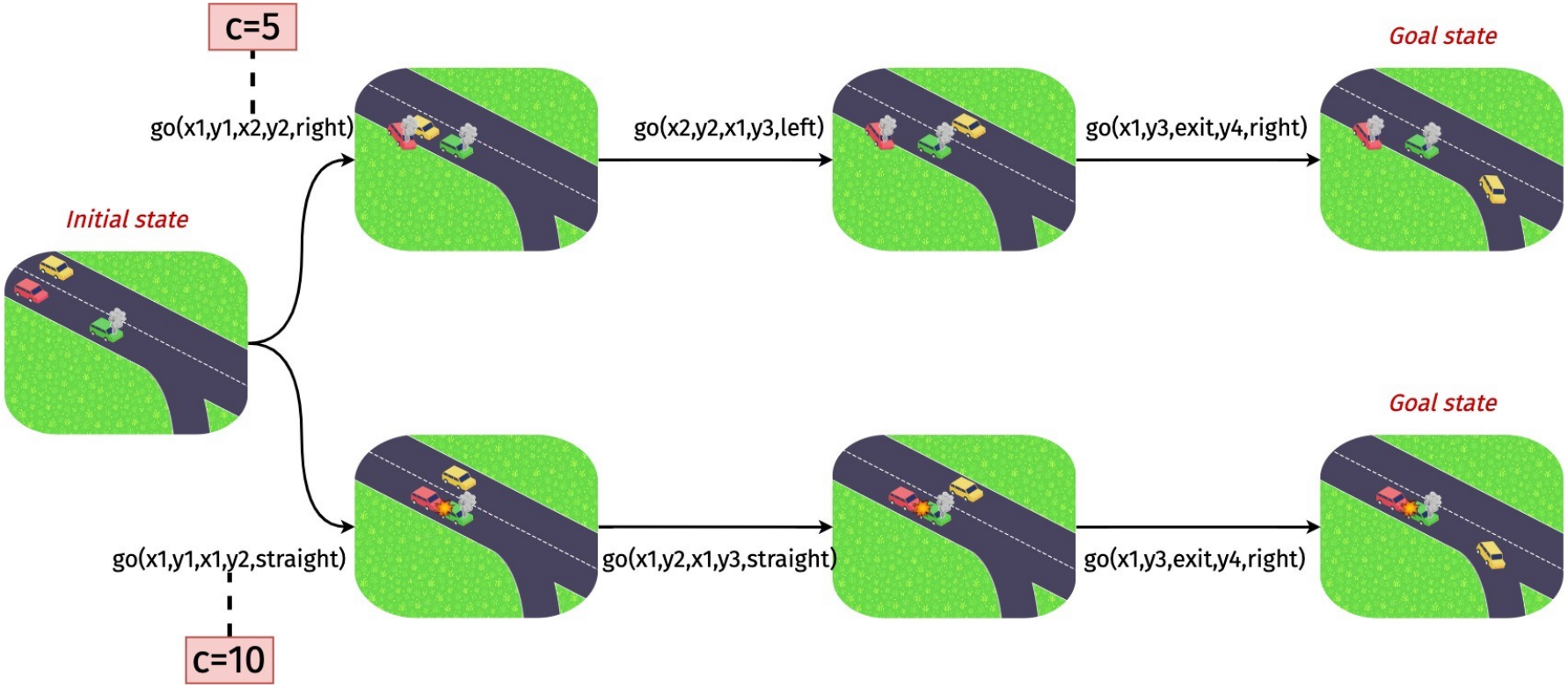
$$\pi \succeq_b \pi' \iff E(\pi) \succeq_b E(\pi')$$

Question: how to compare sets of ethical features?

Representing ethics in classical planning: utilities

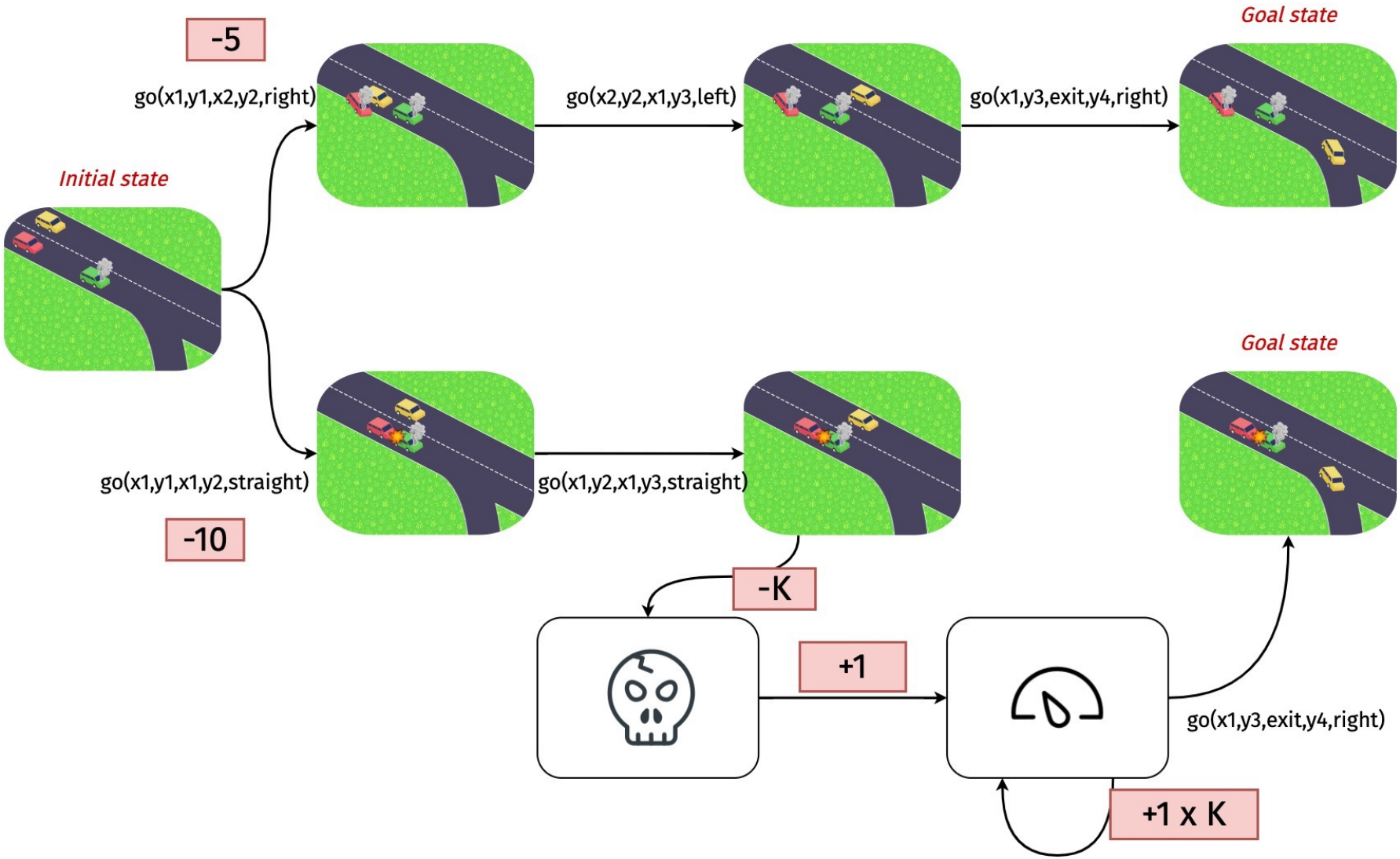
Planning problems can be extended with **action costs** and **utilities** (soft goals) [Gerevini and Long, 2005] as $T = \langle F, O, s_0, g, c, u \rangle$, where:

- $c : A \mapsto \mathbb{R}_{\geq 0}$ is the action cost function,
- $u : S \mapsto \mathbb{R}_{\geq 0}$ is the utility/soft goal function,
- A plan π is **optimal** if $u(\pi) \geq u(\pi')$ for every other plan π'



Representing ethics in classical planning: utilities

Problem: cannot prevent this unless with a **qualitative model**.



Representing ethics in classical planning: ethical ranked bases

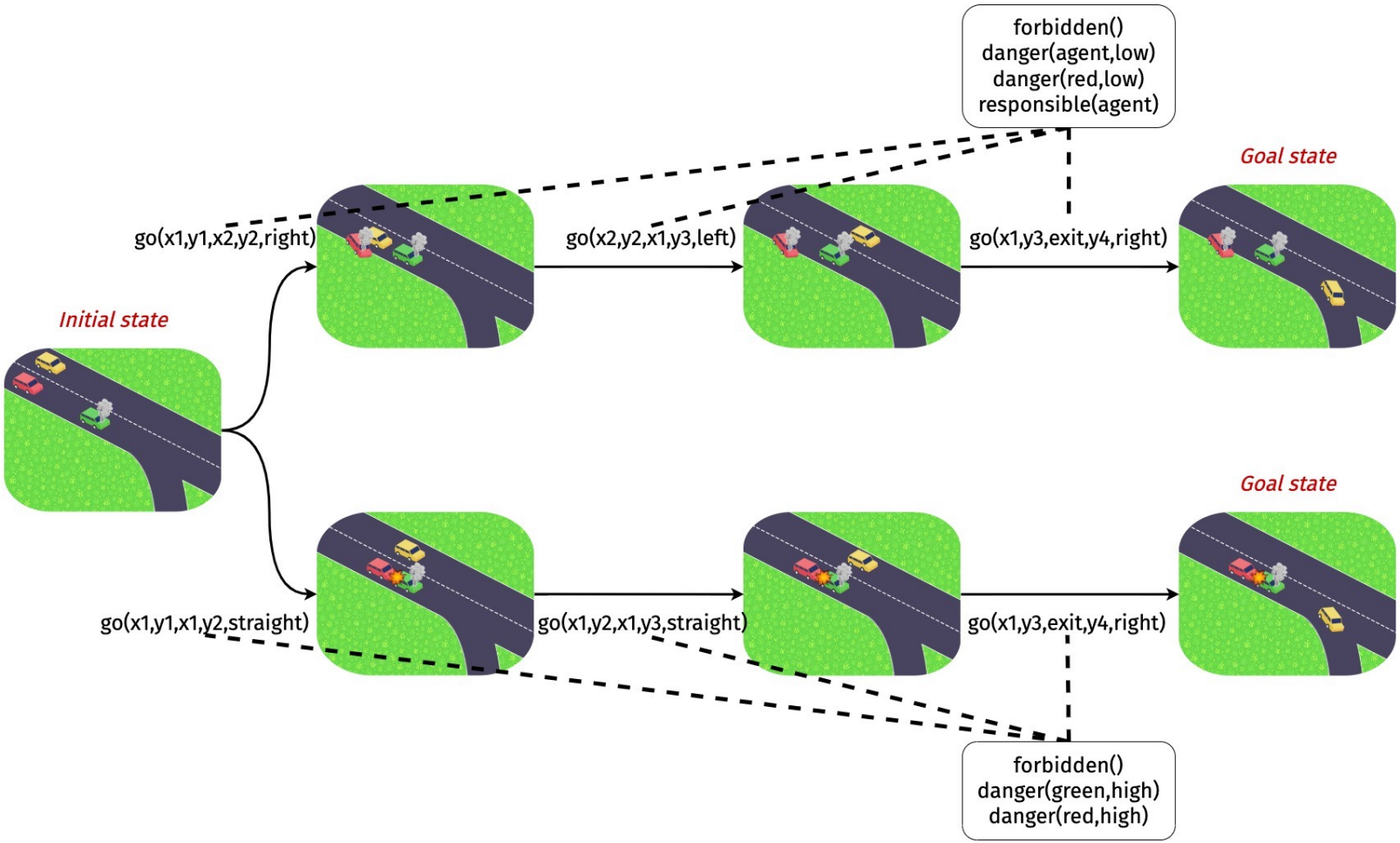
Given an ethical planning problem $T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$ and $e \in E$:

- $b(e) = \langle Type(e), Rank(e) \rangle$ where:
  - $Type(e) \in \{+, -\}$, and
  - $Rank(e) \in \mathbb{N}_0$.
- For example:
  $b(forbidden()) = \langle -, 4 \rangle$,
  $b(danger(X, high)) = \langle -, 3 \rangle$
  $b(danger(X, low)) = \langle -, 2 \rangle$
  $b(responsible(agent)) = \langle -, 1 \rangle$.

Representing ethics in classical planning: ethical ranked bases

Given an ethical planning problem $T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$ and $e \in E$:

- b compares plans π and π' on ethical terms: $\pi \succeq_b \pi' \iff E(\pi) \succeq_b E(\pi')$



Representing ethics in classical planning: ethical ranked bases

Given an ethical planning problem $T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$:

- For example:

$$\pi \succeq_b \pi' \iff$$

$$E(\pi) \succeq_b E(\pi') \iff$$

$$\{forbidden(),danger(agent,low),(...)\} \succeq_b \{forbidden(),danger(green,high),(...)\}$$

Rank 4: $forbidden() \in E(\pi)$ and $forbidden() \in E(\pi')$
$\Rightarrow E(\pi) \succeq_b^4 E(\pi')$

Rank 3: $danger(green, high) \notin E(\pi)$ and $danger(green, high) \in E(\pi')$
$\Rightarrow E(\pi) \succ_b^3 E(\pi')$

Therefore, $E(\pi) \succ_b E(\pi')$

Representing ethics in classical planning: ethical ranked bases

Given an ethical planning problem $T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$:

- b compares plans π and π' on ethical terms:

$$\pi \succeq_b \pi' \iff \boldsymbol{E(\pi) \succeq_b E(\pi')}$$

- Let $A, B \subseteq E$, then $\boldsymbol{A \succeq_b B}$ if and only if:

$\forall i \in \mathbb{N}$, it holds that $b_i^+(A) = b_i^+(B)$ and $b_i^-(A) = b_i^-(B)$, or

$\exists i \in \mathbb{N}$, such that $\big(b_i^+(B) \subset b_i^+(A) \wedge b_i^-(A) \subseteq b_i^-(B)$, or

$b_i^+(B) \subseteq b_i^+(A) \wedge b_i^-(A) \subset b_i^-(B)\big)$, and

$\forall j > i : b_j^+(A) = b_j^+(B)$ and $b_j^-(A) = b_j^-(B)$.

Where given $i \in \mathbb{N}$ and a set of ethical features $C \subseteq E$:

$$b_i^+(C) = \{e \in C : \ Type(e) = +, \ Rank(e) = i\}$$
$$b_i^-(C) = \{e \in C : \ Type(e) = -, \ Rank(e) = i\}$$

Modeling ethical theories

Additionally, in the thesis:

★ **Contribution 2**: we show how to model adaptations of:

- Consequentialism,
- Deontological permissibility,
- Virtue ethics,
- Prima facie duties,
- Doctrine of double effect, and
- Do-no-harm principle.

Modeling ethical theories: example

Representing ethical theories, example:

Consequentialist ethics:

$$
\begin{aligned}
e_1 &= danger(agent, high) \\
r_1 &= \langle ruleConq_1(), \\
&\quad \{hasCrashed(agent)\}, \\
&\quad null, \\
&\quad \{danger(agent, high)\}\rangle \\
b(e_1) &= \langle -, 3\rangle
\end{aligned}
$$

$$
\begin{aligned}
e_2 &= danger(red, high) \\
r_2 &= \langle ruleConq_2(), \\
&\quad \{hasCrashed(red)\}, \\
&\quad null, \\
&\quad \{danger(red, high)\}\rangle \\
b(e_2) &= \langle -, 3\rangle
\end{aligned}
$$

Deontological ethics:

$$
\begin{aligned}
e_3 &= forbidden() \\
r_3 &= \langle ruleDento(C1, X1, X2, X3, \\
&\quad Y1, D1, D2), \\
&\quad \{at(agent, X1, Y1), \\
&\quad at(C1, X2, Y1), \\
&\quad direction(agent, D1), \\
&\quad direction(C1, D2), \\
&\quad nextX(D1, X1, X3), \\
&\quad nextX(D2, X2, X3), \\
&\quad \neg equal(C1, agent)\}, \\
&\quad go(), \\
&\quad \{forbidden()\}\rangle \\
b(e_3) &= \langle -, 4\rangle
\end{aligned}
$$

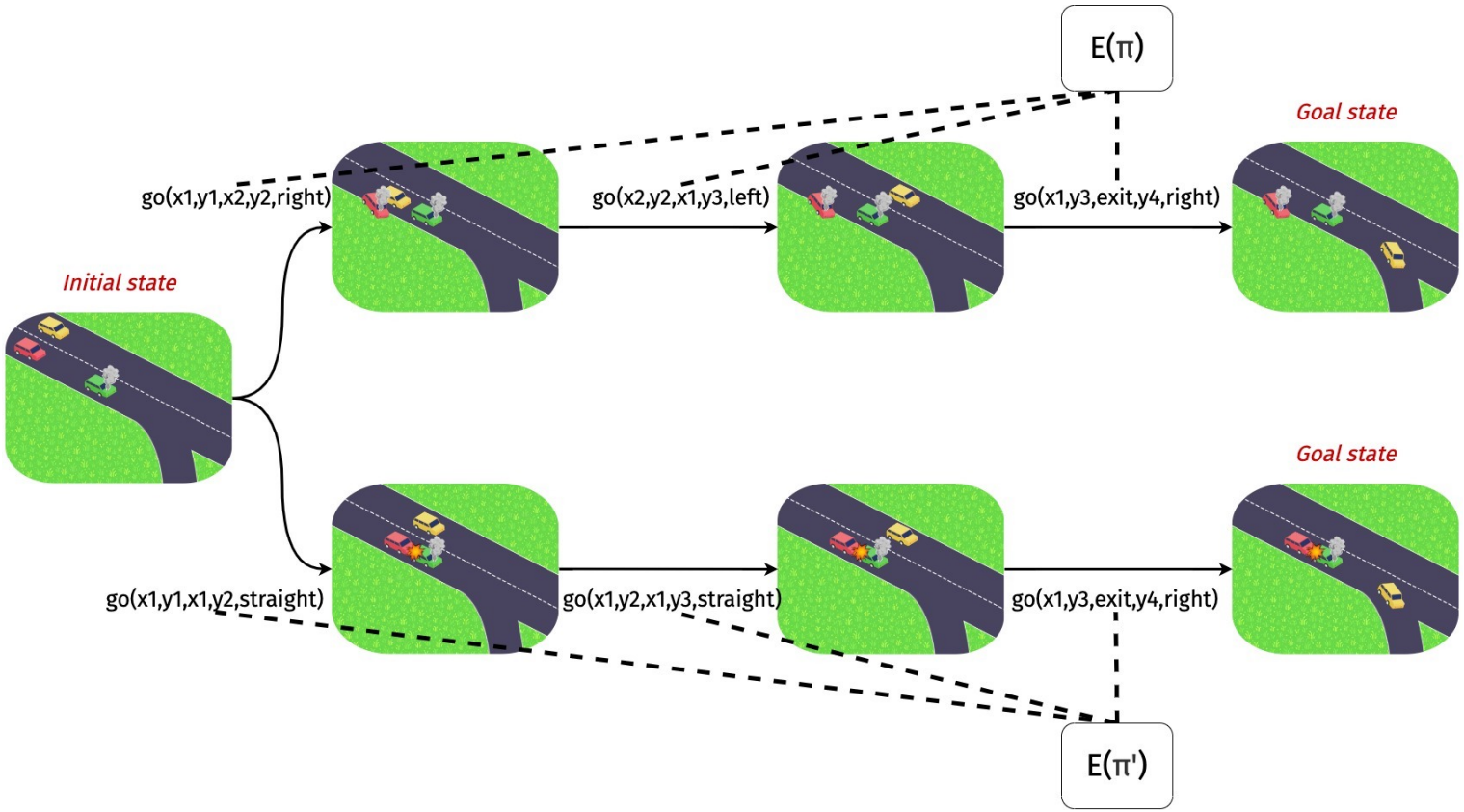
Planning with ethical preferences

Planning with ethical preferences

- We can use ethical features and ranks to align an agent's behavior:

$$T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$$

- π **optimal** iff $\forall \pi'$ plan, $E(\pi) \succeq_b E(\pi')$



- **Question**: how can we find ethically optimal plans?

Planning complexity and heuristics

Finding plans is highly difficult:

- Determining if a plan exists is PSPACE-complete
  [Bäckström and Nebel, 1995] for propositional classical planning,
- Finding an optimal plan is **very hard in practice** and requires heuristics.
- International Planning Competitions (IPCs):
  - Planning Domain Definition Language (PDDL) [Ghallab et al., 1998].
  - PDDL planners:
    - IPC5 [Gerevini et al., 2009]: **utilities** (soft goals) + **action costs**.
    - More recent IPCs [Torralba and Pommerening, 2018]: only **action costs**.

Planning with preferences: research results

Research results:

PDDL + rank-based preferences

$\Downarrow$ [Feldmann et al., 2006]

PDDL + utilities (soft goals)

$\Downarrow$ [Keyder and Geffner, 2009]

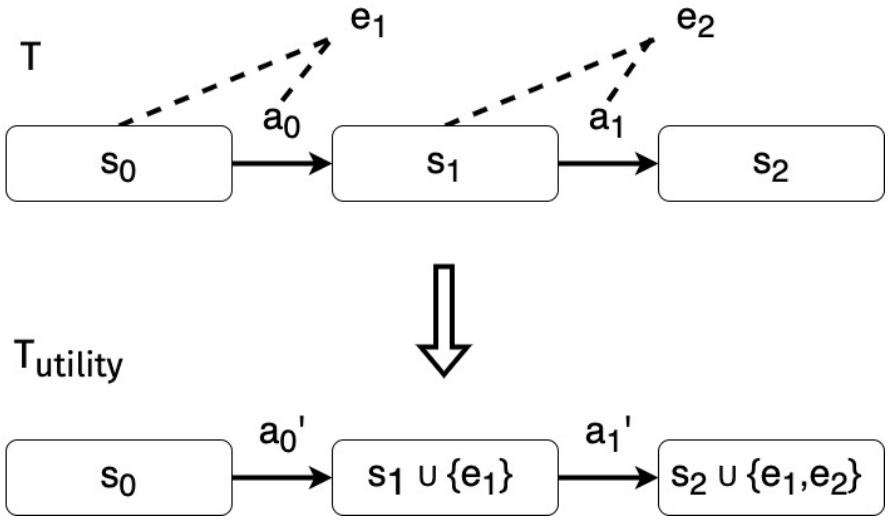
PDDL + action costs

Translation into utilities and action costs

★ **Contribution 3**: demonstrated that ethical planning problems can be translated into utility planning [Jedwabny et al., 2021]:

$$T = \langle F, O, s_0, g, E, R, b \rangle \Rightarrow T_{utility} = \langle F', O', s_0, g', \varnothing, u \rangle$$

Proof intuition: plan **validity** and **optimality**:



- $u(s) = \sum_{i \in \mathbb{N}} |b_i^+(E \cap s) \cup (b_i^-(E) - b_i^-(E \cap s))| \times val_i$
- $u(\pi_1) \geq u(\pi_2) \Rightarrow E(\pi_1) \succeq_b E(\pi_2)$

Implementation of ethical planning problems

★ **Contribution 4**: we implement our model as an extension [Jedwabny et al., 2021] of PDDL, that encodes $T = \langle F, O, s_0, g, E, R, b \rangle$ as:

Math:

$e_1 = danger(agent, high)$

$e_2 = danger(red, high)$

$e_3 = danger(green, high)$

$r_1 = \langle ruleConq(C),$
$\{hasCrashed(C)\},$
$null,$
$\{danger(C, high)\}\rangle$

$b(e_1) = \langle -, 3\rangle$

$b(e_2) = \langle -, 3\rangle$

$b(e_3) = \langle -, 3\rangle$

Code:

```
(:ethical-features
    (danger ?C ?G))
```

```
(:ethical-rule ruleConseq1
    :parameters (?C)
    :precondition (hasCrashed ?C)
    :activation null
    :features (danger ?C high))
```

```
(:ethical-rank
    :feature (danger ?C high)
    :type -
    :rank 3)
```

Translation into utilities and action costs

★ **Contribution 5**: implementation of translation routines:

- Routine 1:

$$\text{PDDL} + \text{ethical}$$

$$\Downarrow \text{(parsing} + \text{translation)}$$

$$\text{PDDL} + \text{utilities (soft goals)}$$

- Routine 2:

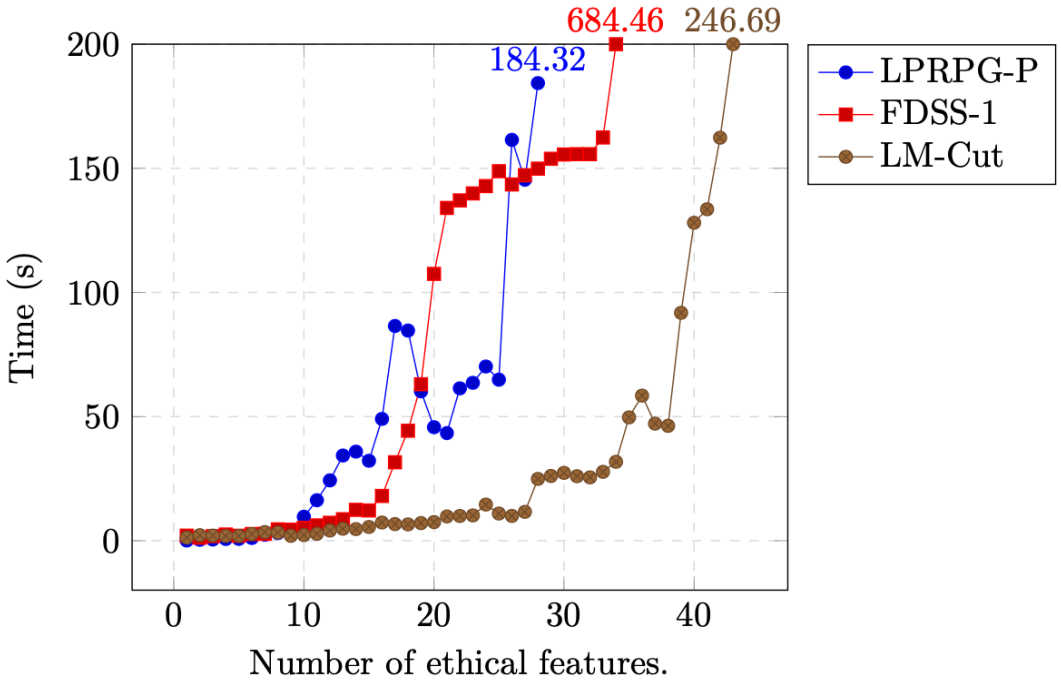
$$\text{PDDL} + \text{ethical}$$

$$\Downarrow \text{(parsing} + \text{translation)}$$

$$\text{PDDL} + \text{action costs}$$

Experimentation: ethical features

Experimentation results (planning time vs. ethical features):

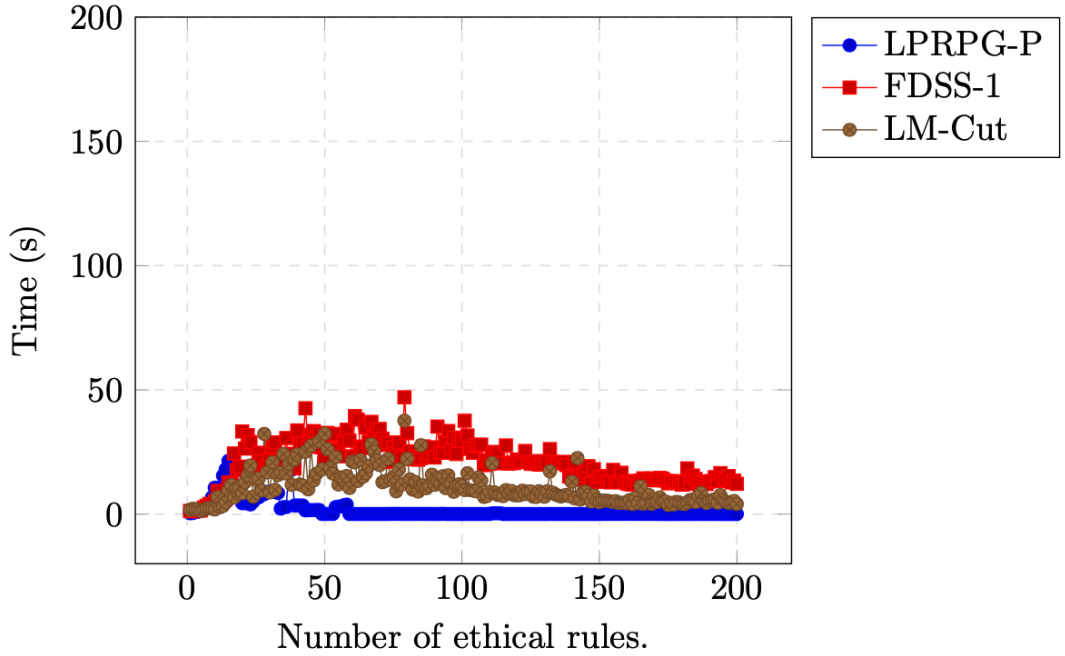


Openstacks planning runtime by ethical features.

- Planning time degradation is above linear w.r.t. ethical features.

Experimentation: ethical rules

Experimentation results (planning time vs. ethical rules):



Openstacks planning runtime parametrized by rules.

- Fixed amount of ethical features ⇒ more ethical rules do not necessarily make planning harder.

Learning ethical preferences

Learning ethical preferences

We have so far shown:

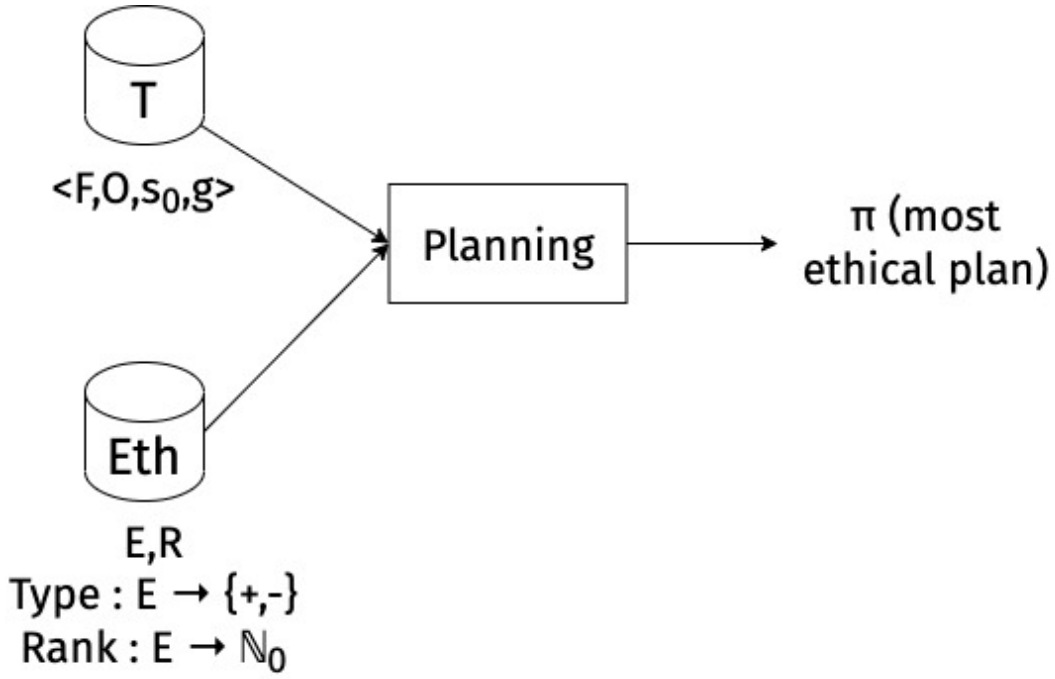
- How to represent ethical features and compare plans on ethical terms to align an agent.
- How to obtain an optimal plan via a translation routine and state-of-the-art planners.

However: how do we align the preferences to societal values?

Learning ethical preferences

So far:

- An ethical planning problem is $T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$.

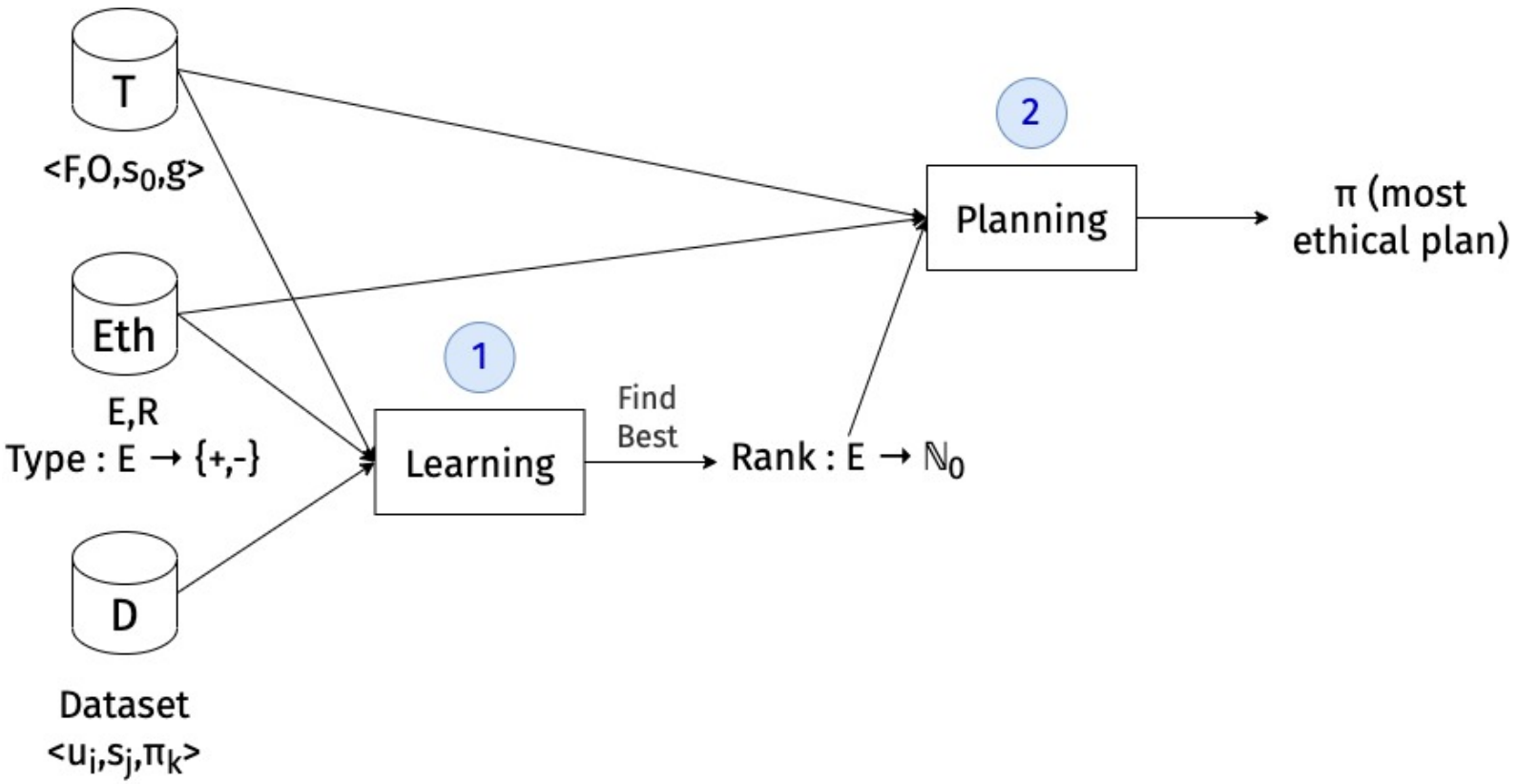


- How do we align the preferences to societal values?
  $\Rightarrow$ **Rank learning**.

Rank learning: overview

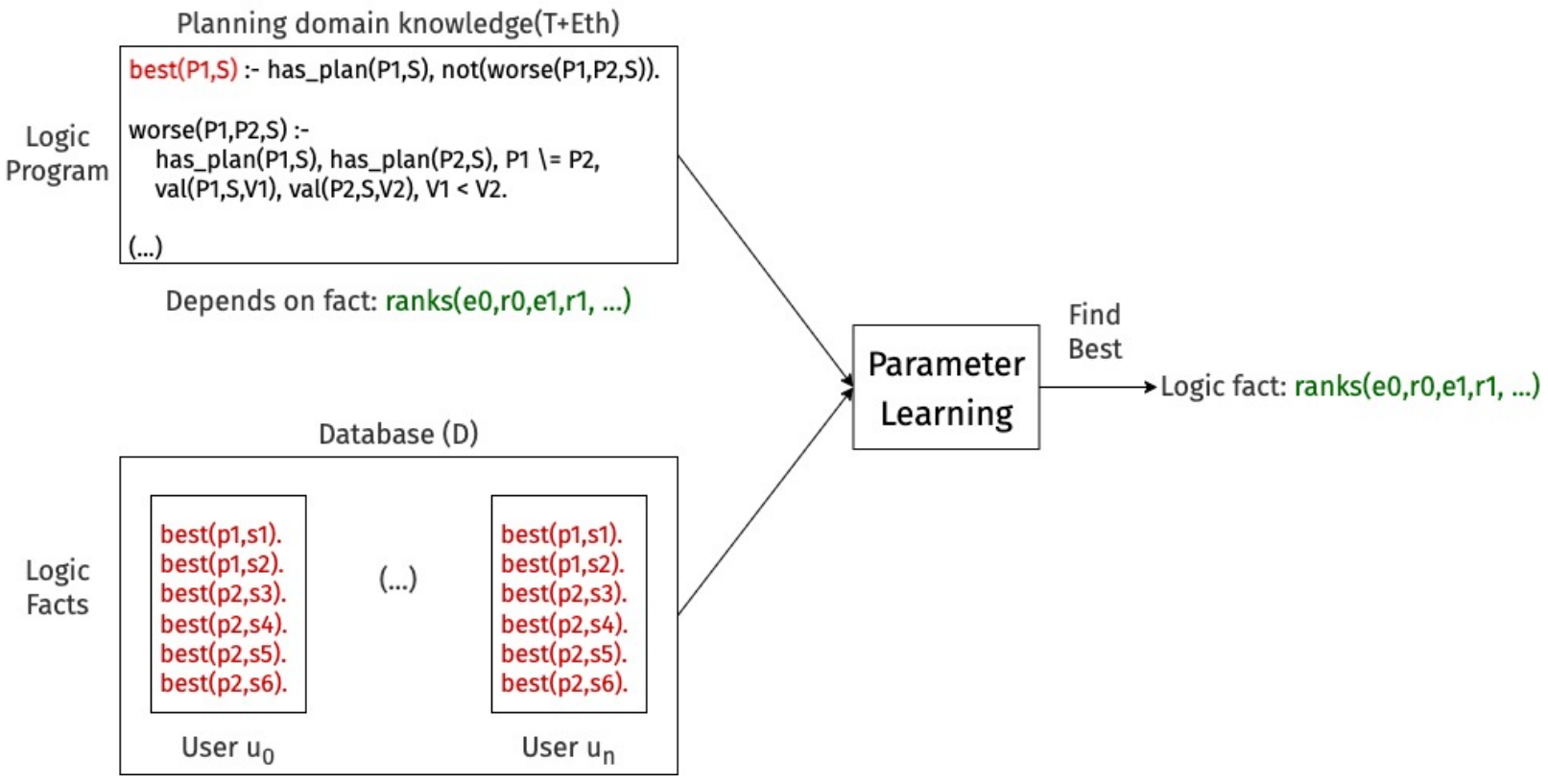
★ **Contribution 6**: an approach to learn ethical ranks from datasets.

- An ethical planning problem is $T = \langle \overbrace{F, O, s_0, g}^{\text{classical}}, \overbrace{E, R, b}^{\text{ethical}} \rangle$.
  Obs: $b(e) = \langle Type(e), Rank(e) \rangle$



Rank learning: implementation

Finding optimal ranks via **parameter learning** [Gutmann et al., 2011] and Problog [De Raedt et al., 2007] (probabilistic logic programming) :



Rank learning: example result

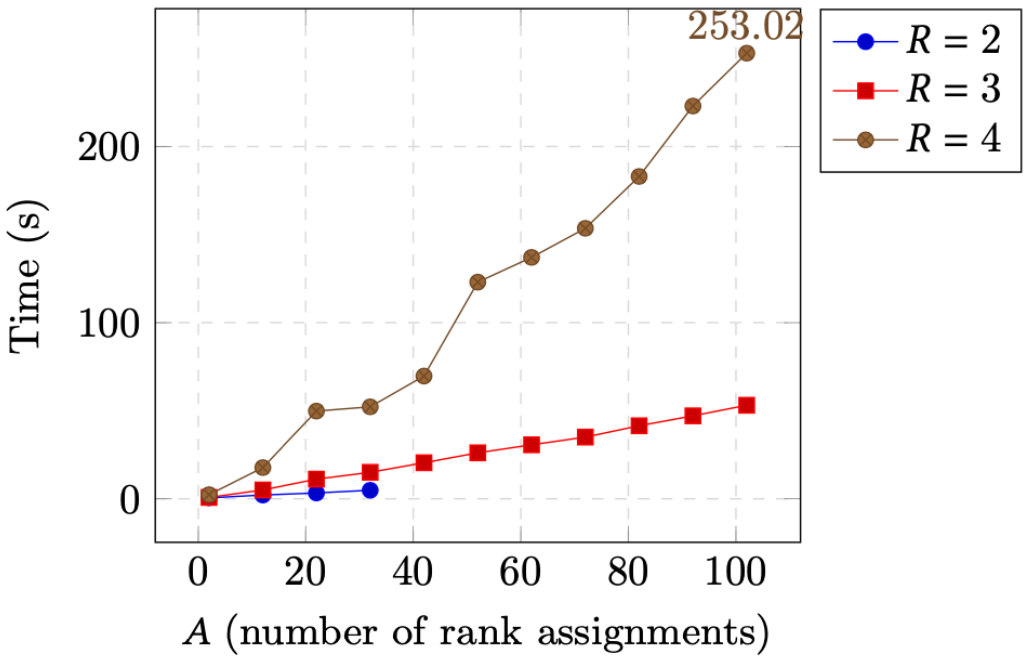
For example (result):

```
0.281427::ranks([danger(agent),1,
                 danger(c1),1,
                 danger(c2),1,
                 responsible(agent),1]).
 ⋮
0.323127::ranks([danger(agent),2,
                 danger(c1),1,
                 danger(c2),1,
                 responsible(agent),1]).
 ⋮
```

- **Observation**: we select the ranks with the maximal probabilistic annotation.

Experimentation: rank assignments

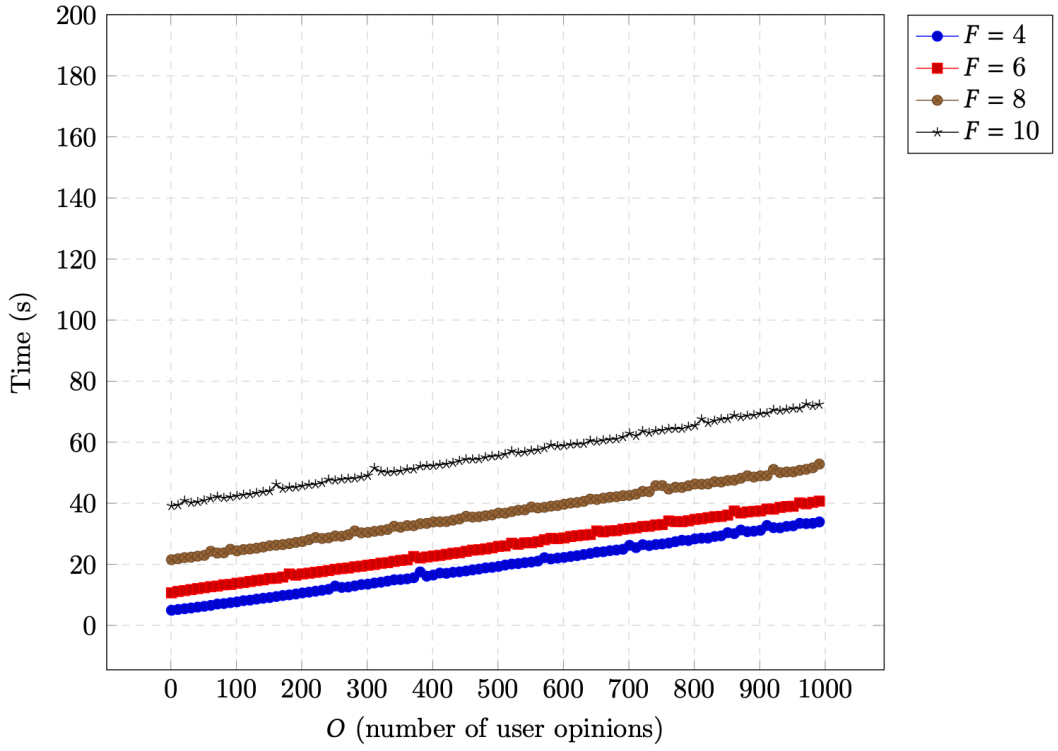
Experimental results (rank assignments):



- A = rank assignments = ethical feature × rank combinations.
- The number of rank assignments impacts the parameter learning time greatly.

Experimentation: dataset size

Experimental results (dataset):



- O = dataset size = number of user/expert opinions.
- The size of the dataset did not seem to affect the performance as much.

Conclusion

Conclusion

Summary:

- **Contribution 1**: we developed an extension of classical planning for ethical representation and alignment.
- **Contribution 2**: we show how to model adaptations of many well-known ethical theories with our framework.
- **Contribution 3**: we implement our model as an extension of PDDL.
- **Contribution 4**: we showed how to translate PDDL+ethical into PDDL with utilities or PDDL with action costs.
- **Contribution 5**: implementation of both translation routines.
- **Contribution 6**: we show how to learn preferences for PDDL+ethical with parameter learning.

Conclusion

List of publications:

- (2020) Explaining ethical planning using ASP - XLoKr (KR workshop).
- (2021) Generating preferred plans with ethical features - FLAIRS conference full paper.
- (2021) Probabilistic rule induction for transparent CBR under uncertainty - SGAI conference full paper.
- (2022) Scrutable Robot Actions Using a Hierarchical Ontological Model - ICCS conference full paper.

Conclusion

Future work:

- Real-life practical validation: test if people agree.
- Explainability testing: whether people can understand the reasoning process of the agent.
- Develop a planner specific to our model of ethics.
- Analyse the complexity of ethical planning.
- Generalize to other planning frameworks (e.g: non-deterministic, probabilistic).
- Improve implementations to handle planning and learning with more ethical features.

Thank you

Thank you for listening!

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