Combining Normative Ethics Principles to Learn Prosocial Behaviour

Extended Abstract

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ABSTRACT

Principles from normative ethics—*the philosophical study of morality*—can be operationalised in the decision-making capacities of agents to discern ethically acceptable actions and promote prosocial behaviour, defined as behaviours that support the well-being of others. Challenges exist in operationalising principles: (1) individual principles may be unintuitive; (2) while incorporating multiple principles mitigates issues with individual principles, conflicts may arise between them. We present PriENE, a method for combining multiple principles to encourage agents to learn prosocial behaviour.

CCS CONCEPTS

• **Computing methodologies → Multi-agent systems**; *Cooperation and coordination.*

KEYWORDS

ethical decision-making; cooperation; fairness; prosociality

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1 INTRODUCTION

Principles from normative ethics, the rational and systematic study of right and wrong, provide frameworks for guiding moral judgements [14, 23]. Operationalising principles in decision-making enables agents to consider the well-being of others and discern ethically acceptable actions [26]. Where prosociality refers to acting in ways intended to benefit others [16, 20], implementing principles in decision-making capacities supports agents considering others and learning behaviours that are prosocial insofar as they support the well-being of others as well as the agent's own needs [1, 10].

Previous works cultivate cooperation and prosociality by appeal to existing behaviours [2, 5, 9, 18, 22]. However, learning from others without evaluating behaviour to identify better options risks perpetuating existing injustices. Implementing normative ethics mitigates difficulties, as principles are prescriptive, denoting *what ought to happen*, rather than descriptive, denoting *what is happening* [7]. However, challenges arise with operationalising principles.

(1) Individual principles may be unintuitive. Ethics can be defined in various ways, each with strengths and weaknesses [24]. Applying specific principles in certain situations may yield unintuitive outcomes; for instance, utilitarianism, which aims to maximise total utility [11], can lead to unfair treatment of minorities. Using multiple principles in decision-making allows for diverse perspectives and helps mitigate issues with individual principles.

(2) Principles may conflict. Considering multiple principles broadens ethical reasoning; however, these principles may conflict. For instance, maximin prioritises improving the minimum experience in society [17], while egoism seeks the best outcome for oneself [19]. Aggregating various principles can help resolve conflicts and balance their recommendations.

Contribution. We present PriENE, a method to operationalise and combine normative ethics principles egoism, utilitarianism, maximin, and egalitarianism in the decision-making of individual agents to learn prosocial behaviours.

Novelty. PriENE advances prior work by (1) implementing a variety of principles in learning mechanisms; (2) aggregating multiple principles to mitigate weaknesses with individual principles.

We empirically evaluate PriENE in a simulated berry harvesting scenario to examine the effects of decision-making in a society with unequal resource distribution. We compare PriENE societies with societies of agents implementing individual principles. Interestingly, we find that PriENE societies do better where one might expect individual principles to have an advantage: PriENE minimises inequality more than egalitarianism; raises minimum experience above maximin; improves total social welfare above utilitarianism.

2 PRIENE

We now present the PriENE method. We model PriENE agents using reinforcement learning (RL), in which an agent optimises long-term return by repeatedly interacting with its environment [21]. A PriENE agent operationalises egoism, which promotes achieving the greatest outcome possible for oneself [19], through basic Q-learning with DQN. DQN is an RL algorithm that uses a neural network to parametrise an approximate Q-function [12].

To consider well-being of others and learn prosocial behaviour, a PriENE agent operationalises normative ethics. We adapt the utility function proposed by Leben [8] to model a distribution of resources d and well-being of each member of society. From Leben [8], $u_i(d) \rightarrow (v_i)$ models a distribution of resources d for an agent i; n is the number of living agents; (v_i) is a measurement of well-being for each agent $ag_1, \dots, ag_n$; $u_t(d, v_i)$ is utility for agent i

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given its resources d at time t; $U_t = \{u_t(d, v_1), \ldots, u_t(d, v_n)\}$ is the set of utilities for all agents in a society at t. To operationalise each principle, compare U_t, before acting and U_{t+1}, after acting. A sanction is a reaction to approved or disapproved behaviour [15]. PriENE agent perceives a self-directed sanction f (directed towards and affecting only its sender [15]) from each principle $p_1, \ldots, p_m$ indicating whether utility improved, worsened, or did not change.
Utilitarianism. Maximise total net utility [11]. Compute utility distributions by summing aggregate utilities, thus $UT = \sum_{i=1}^{n} u(d, v_i)$.
Maximin. Prioritise well-being of the worst-off [17]. Compute minimum experience–lowest utility of an agent, $MA = min_i u(d, v_i)$.
Egalitarianism. Confer equal shares to each individual [3]. Compute accumulated difference of each agent's utility to an ideal where all agents are perfectly equal. Thus, $EG = \sum_{i=1}^{n} |u(d, v_i) - \mu(U)|$ where $\mu(U) = \frac{\sum_{i=1}^{n} u(d,v_i)}{n}$ denotes average utility of the society.

Aggregating principles mitigates difficulties with individual principles. A PriENE agent computes aggregated sanction F from mean of all sanctions $f_{p_1}, \ldots, f_{p_m}$ so that $F(f_{p_1}, \ldots, f_{p_m}) = \frac{1}{m} \sum_{i=1}^{m} f_{p_i}$. Various ways of combining principles may be appropriate for distinct scenarios, e.g., aggregating to a negative sanction if any principle is negative, or aggregating to the most common sanction.

To make decisions, at each time step t, PriENE agent observes state s_t and selects action a with predicted max Q-value from DQN. After acting, agent perceives reward r from the environment. For each principle, agent calculates self-directed sanction $f_{p_1}, \ldots, f_{p_m}$, and aggregates them to obtain sanction F. The agent combines F with the environment reward r through reward shaping, which provides immediate feedback based on heuristics [27], resulting in $r' = r + F$. Finally, the agent passes r' to DQN for learning.

3 EXPERIMENTAL SETUP

We create a harvest environment, illustrated in Figure 1, in which an agent can move, forage for berries, eat berries, throw berries to other agents [25]. To examine the effects of various principles, we train five agent types: egoistic, egalitarian, maximin, utilitarian, and PriENE. We run $e = 1000$ episodes. Each episode runs until all agents have died or $t_{\max} = 200$ steps.

Reproducibility. Our simulation codebase, including complete simulation parameters, is publicly available [25].

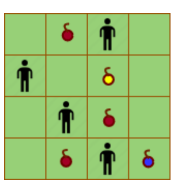

Figure 1: Colours harvest. Each agent moves freely but only collects berries of a specific colour. Some colours are more plentiful, giving those agents access to more resources. Agents can throw berries to each other across the grid.

Metrics. We examine the quality of individual agents' experience, measured by ag_{berries}. To evaluate fairness, we compute:
M_1 (inequality). Gini index (distance to perfect equality [6]) of accumulated ag_{berries} across the society. Lower is better.
M_2 (minimum experience). Minimum individual accumulated ag_{berries} at the end of each episode. Higher is better.

To evaluate sustainability, we assess the following metrics:
M_3 (maximum experience). Maximum individual accumulated ag_{berries} at the end of each episode. Higher is better.
M_4 (social welfare). Total ag_{berries} accumulated at the end of each episode. Higher is better.
M_5 (robustness). Length of each episode. Higher is better.

4 RESULTS

Table 1 displays preliminary results of ag_{berries} mean for PriENE societies and societies implementing individual principles.

Table 1: Comparing PriENE with individual principles mean for each metric. Grey highlight indicates best results.

Society	M_1	M_2	M_3	M_4	M_5
Egoism	0.43	2.06	35.48	69.12	95.08
Utilitarian	0.48	1.96	42.9	77.14	100.55
Maximin	0.42	2.09	37.95	79.51	106.2
Egalitarian	0.38	3.23	29.28	65.82	94.83
PriENE	0.37	2.81	35.0	78.64	106.85

M_1 (inequality) is lowest in PriENE societies and highest in utilitarian societies. M_2 (minimum experience) is highest egalitarian followed by PriENE. M_3 (maximum experience) is highest in utilitarian societies, followed by maximin, egoistic, PriENE, then egalitarian. M_4 (social welfare) is highest in maximin societies followed by PriENE. M_5 (robustness) is highest in PriENE societies.

5 CONCLUSIONS AND DIRECTIONS

PriENE is a method for operationalising multiple normative ethics principles in agents' individual decision-making capacities. Overall, results show that PriENE societies lead to lowest inequality, second highest minimum experience and social welfare, and highest robustness. Interesting highlights include: one might expect egalitarianism to minimise inequality but PriENE minimises inequality further than egalitarian; one might expect maximin to have highest minimum experience but PriENE improves minimum more than maximin; one might expect utilitarianism to have highest social welfare but PriENE is higher than utilitarianism. These results suggest that PriENE encourages agents to learn prosocial behaviours.

To expand analysis to more complex settings, future directions involve evaluating heterogeneous societies where agents operationalise different principles to one another; implementing scenarios closer to the real world; increasing the agent population; inferring well-being of others utilising solely local information; exploring the influence of context on ethical decision-making including social norms, which are standards of expected behaviour [4, 13]; implementing additional principles [24].

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