# Adversarial Inverse Reinforcement Learning for Mean Field Games

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## ABSTRACT

Goal-based agents respond to environments and adjust behaviour accordingly to reach objectives. Understanding incentives of interacting agents from observed behaviour is a core problem in multi-agent systems. Inverse reinforcement learning (IRL) solves this problem, which infers underlying reward functions by observing the behaviour of rational agents. Despite IRL being principled, it becomes intractable when the number of agents grows because of the curse of dimensionality and the explosion of agent interactions. The formalism of Mean field games (MFGs) has gained momentum as a mathematically tractable paradigm for studying large-scale multi-agent systems. By grounding IRL in MFGs, recent research attempts to push the limits of the agent number in IRL. However, the study of IRL for MFGs is far from being mature as existing methods assume strong rationality, while real-world agents often exhibit bounded rationality due to the limited cognitive or computational capacity. Towards a more general and practical IRL framework for MFGs, this paper proposes Mean-Field Adversarial IRL, a novel framework capable of tolerating bounded rationality. We build it upon the maximum entropy principle, adversarial learning, and a new equilibrium concept for MFGs. We evaluate our machinery on simulated tasks with imperfect demonstrations resulting from bounded rationality. Experimental results demonstrate the superiority of MF-AIRL over existing methods in reward recovery.

## KEYWORDS

Inverse Reinforcement Learning; Mean Field Games; Maximum Entropy Principle; Adversarial Learning

## 1 INTRODUCTION

Game theory provides a general framework for predicting the strategic behaviours of interacting agents [11]. It concerns itself with a

set of reward (or utility) functions and understands the behaviours of rational agents, i.e., the equilibrium, to be the outcome of utility-maximising strategies. An inverse problem naturally arises from this setting: how to infer the reward functions from observed behaviours? This problem is known as *multi-agent inverse reinforcement learning* (MAIRL) [36]. More precisely, it seeks to find domain parameters for reward functions that induce observed behaviours of rational decision-makers.

The recent surge in the scale of real-world multi-agent systems (MAS) [13, 27, 45] has raised the need for solving MAIRL in the presence of a large number of agents. In fact, we can identify at least two motivations for MAIRL in large-scale MAS. A straightforward one is as its name implies – we wish to detect and understand the behaviour of a population of agents by modelling them using reward functions. Examples include modelling infection spread [24], discovering pricing strategies in large-scale markets [37] and understanding the mechanism of social-norm emergence in a large population [26]. A second motivation is for the sake of designing environments for large-scale MAS so that the expected behaviour emerges if agents are rational. The behaviour of a MAS is uncertain, and unexpected behaviour is likely to arise; the growing size of the system will further exacerbate this. If one is able to pinpoint the causal relations between rewards and rational behaviours, he can manipulate the system's behaviour by tuning the reward functions. Contrary to the examples above, applications here can be controlling and restraining infection spread, making pricing strategies in large-scale markets, and even guiding and shaping the emergence of social norms in communities, all in a data-driven manner.

However, MAIRL is notoriously intractable in the face of a large number of agents. This is because MAIRL typically takes *stochastic games* [25] as the mathematical model, where a (Nash) equilibrium is computationally intractable when the number of agents scales to tens or hundreds [6]. To accommodate the need for MAIRL in large-scale MAS, we thus ask for a mathematically tractable substitute model. The recent paradigm of *mean field games* (MFGs) [22, 23] achieves tractability by borrowing the idea of mean field approximation from statistical physics to simplify agent interactions. It takes the limit as the number of agents approaches infinity and reduces the whole-system interactions to those between a single individual agent and the *mean field*, a virtual agent that represents aggregated behaviour of the population at large. This dual-view interplay gives rise to *mean field Nash equilibrium* (MFNE), which

stipulates bidirectional constraints between the two sides: every agent's policy maximises its rewards given the mean field and, in turn, the mean field is uniquely resulted by all agents' policies. Importantly, MFNE is shown to be an approximate Nash equilibrium in the corresponding finite-agent stochastic games [34]. To break through the limitation of agent number in MAIRL, it is thereby promising to transfer the concept of IRL to MFGs.

Unfortunately, IRL remains largely unexplored in MFGs, albeit there are two recent attempts. Yang et al. [41] first proposed a *centralised* IRL method for MFGs by showing that an MFG can be reduced to a *Markov decision process* (MDP) that describes the population's collective behaviour and average rewards; they thus applied single-agent IRL methods on top of this MDP. Subsequently, Chen et al. [4] revealed that this reduction holds only if the MFNE is *socially optimal*, i.e., it maximises the population's average rewards; they thus framed the problem at the *decentralised* setting, i.e., inferring the reward function for an individual agent from the observed individual behaviour rather than the population behaviour. They put forward *Mean Field IRL* (MFIRL), a more general approach effective for both socially optimal and ordinary MFNE.

However, both methods above are still limited in terms of practical use. First, due to limited cognitive or computational capability, an agent often has *bounded rationality* in real life, i.e., choosing satisfactory rather than optimal actions [19]. Consequently, the resulting behaviour possesses uncertainties in general. For example, a customer in a restaurant orders an acceptable dish which is not necessarily his favourite as he is rush in time. These two methods cannot reason about such uncertainties as agents in MFNE are assumed never to take suboptimal behaviour. This makes both methods unsuitable for situations where the agents are bounded rational. Then, since an MFNE is not unique in general [5], the observed behaviour may be insufficient for us to learn a reward function that determines a unique policy. In this sense, from an application standpoint, the existing methods are also not useful for environment design for large-scale MAS.

Towards a more general and practical IRL method for MFGs, we invoke the idea of Maximum Entropy IRL (MaxEnt IRL) [46, 47], which provides a general probabilistic framework to tackle bounded-rational behaviour. It is state-action trajectory-centric and assumes the observed trajectories follow a distribution (in terms of rewards) with the maximum entropy. It thus allows us to find a reward function that rationalises observed behaviour with the *least commitment*. Moreover, since a policy leading to the maximum entropy trajectory distribution is unique given a reward function, MaxEnt IRL is more useful for environment design. However, extending MaxEnt IRL to MFGs is challenging. First, since MFNE assumes agents never take suboptimal behaviour, it is incompatible with MaxEnt IRL in the sense that it cannot provide a trajectory distribution that can be used for the probabilistic reward inference. Second, since in MFGs, the individual and population dynamics are intertwined (the policy and mean field are interdependent), the trajectory distribution is intractable to express in terms of rewards, which would prevent us from performing probabilistic inference for reward functions.

The primary contribution of this paper lies in the proposal of a new probabilistic IRL framework, *Mean-Field Adversarial IRL* (MF-AIRL), for MFGs. MF-AIRL integrates ideas from decentralised IRL for MFGs, MaxEnt IRL, and adversarial learning [15] into a unified

probabilistic model for reward inferences in large-scale MAS. We summarise specific contributions as follows: **(1)** We build MF-AIRL upon a new equilibrium concept termed *entropy-regularised MFNE* (ERMFNE) (see Sec. 3). We show that ERMFNE can characterise an individual's trajectory distribution induced by a reward function in a principled way (see Theorem 1). **(2)** Taking ERMFNE as the solution concept, we extend MaxEnt IRL to MFGs (see Sec. 4). We decouple individual and population dynamics by deriving the empirical value of the mean field from the observed behaviour (see Theorem 2). **(3)** By using adversarial learning to solve MaxEnt IRL in MFGs efficiently, we develop the practical MF-AIRL framework (see Sec. 5). **(4)** We evaluate MF-AIRL on tasks that simulate scenarios of marketing strategy making, virus propagation modelling and social norm emergence, all on a large scale (see Sec. 7). Results demonstrate the outperformance of MF-AIRL over existing methods in reward recovery.

## 2 PRELIMINARIES

This section introduces *mean field games* (MFGs) and the *maximum entropy inverse reinforcement learning* (MaxEnt IRL) framework. The marriage of the two gives rise to our proposed multi-agent IRL approach dedicated to large-scale multi-agent systems.

### 2.1 Mean Field Games

Following the conventional MFG model in the learning setting, we focus on MFGs with finite state and action spaces and, more generally, a finite time horizon [8]. Consider an $N$-player symmetric game, i.e., all agents share the same *local state* space $\mathcal{S}$, *action* space $\mathcal{A}$, and a reward function that is invariant under the permutation of identities of agents without changing their states and actions. Let $(s^1, \ldots, s^N) \in \mathcal{S}^N$ denote a *joint state*, where $s^i \in \mathcal{S}$ is the state of the $i$th agent. As $N$ grows large, the game becomes intractable to analyse due to the curse of dimensionality. MFGs achieve tractability by considering the asymptotic limit when $N$ approaches infinity. Formally, take the limit as $N \to \infty$. Due to the homogeneity of agents, MFGs use an empirical distribution $\mu \in \mathcal{P}(\mathcal{S})$, called a *mean field*, to represent the statistical information of the joint state:

$$\mu(s) \triangleq \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} \mathbb{1}_{\{s^i = s\}}.$$

Here, $\mathcal{P}(\mathcal{S})$ represents the set all probability measures over $\mathcal{S}$ and $\mathbb{1}$ denotes the indicator function, i.e., $\mathbb{1}_x = 1$ if $x$ is true and 0 otherwise. The *transition function* $P \colon \mathcal{S} \times \mathcal{A} \times \mathcal{P}(\mathcal{S}) \times \mathcal{P}(\mathcal{S}) \to [0, 1]$ specifies how states evolve, i.e., an agent transits to the next state $s_{t+1}$ with the probability $P(s_{t+1}|s_t, a_t, \mu_t)$. Let $T \in \mathbb{N}^+$ denote a finite time horizon. A *mean field flow* (MF flow for short) thus consists of a sequence of $T + 1$ mean fields $\boldsymbol{\mu} \triangleq \{\mu_t\}_{t=0}^{T}$. The initial mean field $\mu_0$ is given. The *running reward* at each step is determined by a bounded *reward function* $r \colon \mathcal{S} \times \mathcal{A} \times \mathcal{P}(\mathcal{S}) \to \mathbb{R}$. Let $\tau \triangleq \{(s_t, a_t)\}_{t=0}^{T}$ denote a state-action *trajectory* of an agent. We write an agent's long-term reward under a given MF flow $\boldsymbol{\mu}$ as $\mathcal{R}(\tau) \triangleq \sum_{t=0}^{T-1} r(s_t, a_t, \mu_t)$.[1] In summary, an MFG is defined as a tuple $(\mathcal{S}, \mathcal{A}, P, \mu_0, r)$.

A time-varying stochastic *policy* $\boldsymbol{\pi} \triangleq \{\pi_t\}_{t=0}^{T}$ is adopted to characterise a strategic agent, where each $\pi_t \colon \mathcal{S} \to \mathcal{P}(\mathcal{A})$ is the

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[1] Following the convention [4, 8, 41], we set the reward at the last step ($t = T$) as 0.

*per-step policy*, i.e., an agent chooses actions following $a_t \sim \pi_t(\cdot|s)$. Given an MF flow $\mu$ and a policy $\pi$, an agent's *expected return* (cumulative rewards) is written as

$$J(\mu, \pi) \triangleq \mathbb{E}_{\tau \sim (\mu, \pi)}[\mathcal{R}(\tau)], \tag{1}$$

where $s_0 \sim \mu_0, a_t \sim \pi_t(\cdot|s_t), s_{t+1} \sim P(\cdot|s_t, a_t, \mu_t)$.

## 2.2 Mean Field Nash Equilibrium

Fixing an MF flow $\mu$, a policy $\pi$ is called a *best response* to $\mu$ if it maximises $J(\mu, \pi)$. We denote the set of all best-response policies to $\mu$ by $\Psi(\mu) \triangleq \arg\max_{\pi} J(\mu, \pi)$. However, since all agents optimise their policies simultaneously, the MF flow would shift. Thus, the solution must consider how a policy at the individual level affects the MF flow at the population level. Due to the homogeneity of agents, everyone would follow the same policy at optimality. The dynamics of the MF flow can thus be governed by the (discrete-time) *McKean-Vlasov* (MKV) equation [3]:

$$\mu_{t+1}(s') = \sum_{s \in \mathcal{S}} \mu_t(s) \sum_{a \in \mathcal{A}} \pi_t(a|s) \, P(s'|s, a, \mu_t). \tag{2}$$

Given a policy $\pi$, denote $\mu = \Phi(\pi)$ as the MF flow that fulfils MKV equation. We say $\mu$ is *consistent* with $\pi$ if $\mu = \Phi(\pi)$. This consistency guarantees that a single agent's state marginal distribution flow matches the MF flow at the population level. The conventional solution concept for MFGs is the *mean field Nash equilibrium*.

DEFINITION 1. *A pair* $(\mu^{\star}, \pi^{\star})$ *is called a* mean field Nash equilibrium *(MFNE) if it satisfies:*

(1) ***Agent rationality:*** $\pi^{\star} \in \Psi(\mu^{\star})$;
(2) ***Population consistency:*** $\mu^{\star} = \Phi(\pi^{\star})$.

Computing an MFNE typically requires a fixed-point iteration procedure for the MF flow [16]. Formally, through defining any mapping $\hat{\Psi} : \mu \mapsto \pi$ that identifies a best response in $\Psi(\mu)$, we obtain a fixed point iteration for $\mu$ by alternating between $\pi = \hat{\Psi}(\mu)$ and $\mu = \Phi(\pi)$. The assumption for the uniqueness of MFNE is that the fixed-point iteration will converge to a unique $\mu$ [16]. However, the fixed-point iteration is not guaranteed to converge to a unique $\mu$, and multiple MFNE can coexist [5].

## 2.3 Maximum Entropy IRL

We next give an overview of MaxEnt IRL [46, 47] in the context of a Markov decision process (MDP) defined by a tuple $(\mathcal{S}, \mathcal{A}, P, \rho, r)$, where $r(s, a)$ is the reward function, and the environment dynamics is determined by the transition function $P(s'|s, a)$ and initial state distribution $\rho(s)$. In (forward) reinforcement learning (RL), an optimal policy may not exist uniquely. MaxEnt RL solves this ambiguity by augmenting the expected return with a *causal entropy*[2] [46] regularisation term $\mathcal{H}(\pi) \triangleq \mathbb{E}_{\pi}[-\log \pi(a|s)]$, i.e., the objective is to find a (stationary) policy $\pi^{\star}$ such that

$$\pi^{\star} = \arg\max_{\pi} \mathbb{E}_{\tau \sim \pi}\left[\sum_{t=0}^{T-1} r(s_t, a_t) + \beta\mathcal{H}(\pi(\cdot|s_t))\right],$$

where $\tau$ is a state-action trajectory sampled via $s_0 \sim \rho_0, a_t \sim \pi(\cdot|s_t)$, $s_{t+1} \sim P(\cdot|s_t, a_t)$ and $\beta > 0$ controls the relative importance of reward and entropy.

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[2]Throughout the rest of the paper, we refer to the term entropy as the causal entropy.

Suppose we have no access to the reward function but have a set of observed trajectories sampled from an *unknown* expert policy $\pi^E$ obtained by the above MaxEnt RL procedure. MaxEnt IRL aims to infer a reward function that rationalises the observed behaviour, which reduces to the following maximum likelihood estimation (MLE) problem (assume $\beta = 1$ [44]):

$$p_{\omega}(\tau) \propto \rho(s_0) \cdot \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t) \cdot e^{R_{\omega}(\tau)}, \tag{3}$$

$$\max_{\omega} \mathbb{E}_{\tau \sim \pi^E}[\log p_{\omega}(\tau)] = \mathbb{E}_{\tau \sim \pi^E}[R(\tau)] - \log Z_{\omega}. \tag{4}$$

Here, $R_{\omega}(\tau) \triangleq \sum_{t=0}^{T-1} r_{\omega}(s_t, a_t)$ where $r_{\omega}$ is an $\omega$-parameterised reward function, and $Z_{\omega} \triangleq \sum_{\tau \sim \pi^E} e^{R_{\omega}(\tau)}$ is the *partition function* of the distribution defined in Eq. (3), i.e., a summation over all feasible trajectories. Exactly computing $Z_{\omega}$ is intractable if the state-action space is large.

*Adversarial IRL* (AIRL) was proposed by [9] as an efficient sampling-based approximation to MaxEnt IRL, which reframes Eq. (4) as optimising a *generative adversarial network* [15]. It uses a discriminator $D_{\omega}$ (a binary classifier) and a *adaptive sampler* $\pi_{\theta}$ (a policy). Particularly, the discriminator takes the following form:

$$D_{\omega}(s, a) = \frac{e^{f_{\omega}(s,a)}}{e^{f_{\omega}(s,a)} + \pi_{\theta}(a|s)},$$

where $f_{\omega}$ serves as the parameterised reward function. The update of $D_{\omega}$ is interleaved with the update of $\pi_{\theta}$: $D_{\omega}$ is trained to update the reward function by distinguishing between the trajectories sampled from the expert and the adaptive sampler; while $\pi_{\theta}$ is trained to maximise

$$\mathbb{E}_{\tau \sim \pi_{\theta}}\left[\sum_{t=0}^{T-1} \log D_{\omega}(s_t, a_t) - \log(1 - D_{\omega}(s_t, a_t))\right].$$

IRL faces the ambiguity of *reward shaping* [29], i.e., multiple reward functions can induce the same optimal policy. To mitigate this ambiguity, Fu et al. [9] further restrict the parameterised reward in $D_{\omega}$ to a specific structure by supplying a state-only *potential-based reward shaping* function $h_{\phi} : \mathcal{S} \to \mathbb{R}$:

$$f_{\omega,\phi}(s_t, a_t, s_{t+1}) = r_{\omega}(s_t, a_t) + h_{\phi}(s_{t+1}) - h_{\phi}(s_t).$$

Shown in [9], under certain conditions, $r_{\omega}(s, a) + h_{\phi}(s)$ will recover the ground-truth reward function up to a constant.

## 2.4 IRL for MFGs

We adopt the general decentralised IRL setting for MFGs as in [4], which aims to infer the individual reward function from observed individual behaviour. More formally, let $(\mathcal{S}, \mathcal{A}, P, \mu_0, r)$ be an MFG. Suppose we do not know $r(s, a, \mu)$ but have a set of $M$ observed expert behaviour $\mathcal{D}_E = \{\tau_j\}_{j=1}^M$ sampled from an *unknown* equilibrium $(\mu^E, \pi^E)$, where each $\tau = \{(s_t, a_t)\}_{t=0}^T$ is an individual agent's state-action trajectory sampled via $s_0 \sim \mu_0$, $a_t \sim \pi_t(\cdot|s_t)$, $s_{t+1} \sim P(\cdot|s_t, a_t, \mu_t)$. IRL for MFG asks for a reward function $r(s, a, \mu)$ under which $(\mu^E, \pi^E)$ constitutes an equilibrium.

## 3 ENTROPY-REGULARISED MFNE

This section introduces and justifies a new solution concept for MFGs, which allows us to characterise the bounded rationality of agents and thereby extend MaxEnt IRL to MFGs.

## 3.1 A New Equilibrium Concept for MFGs

To extend MaxEnt IRL to MFGs, we need to characterise the trajectory induced by a reward function with a particular distribution as analogous to Eq. (3). However, MFNE cannot *explicitly* define a tractable trajectory distribution as it requires agents never to take suboptimal actions, whereas, in MaxEnt IRL, an agent can take sub-optimal actions with certain low probabilities. To bridge the gap between MFGs and MaxEnt IRL, we need a "soft" equilibrium concept that can characterise uncertainties in observed behaviour as against MFNE being a "hard" equilibrium. To this end, a natural way in game theory is to incorporate policy entropy into rewards [12, 31], which enables *bounded rationality*, i.e., agents can take satisfactory rather than optimal actions. This inspires a new solution concept – *entropy-regularised MFNE* (ERMFNE) – where an agent aims to maximise the entropy-regularised rewards:

$$\tilde{J}(\boldsymbol{\mu}, \boldsymbol{\pi}) \triangleq \mathbb{E}_{\tau \sim (\boldsymbol{\mu}, \boldsymbol{\pi})} \left[ \sum_{t=0}^{T-1} r(s_t, a_t, \mu_t) + \beta \mathcal{H}(\pi_t(\cdot|s_t)) \right].$$

Definition 2. *A pair of MF flow and policy $(\tilde{\boldsymbol{\mu}}^\star, \tilde{\boldsymbol{\pi}}^\star)$ is called an* entropy-regularised MFNE (ERMFNE) *if it satisfies:*

(1) **Agent bounded rationality:** $\tilde{J}(\tilde{\boldsymbol{\mu}}^\star, \tilde{\boldsymbol{\pi}}^\star) = \max_{\boldsymbol{\pi}} \tilde{J}(\tilde{\boldsymbol{\mu}}^\star, \boldsymbol{\pi})$;
(2) **Population consistency:** $\tilde{\boldsymbol{\mu}}^\star = \Phi(\tilde{\boldsymbol{\pi}}^\star)$.

Despite the entropy-regularised MFGs have been studied in the literature [1, 5, 17], existing work is motivated from a computational perspective, that is, entropy regularisation can improve the stability and the convergence of algorithms for computing an equilibrium. Particularly, Cui and Koeppl [5] independently proposed a similar solution concept and showed that entropy regularisation relaxes the condition for uniqueness as opposed to the unregularised case: **(1)** With entropy regularisation, the best-response policy $\tilde{\boldsymbol{\pi}}$ to an MF flow $\boldsymbol{\mu}$ exists *uniquely*; [3] **(2)** ERMFNE exists for any $\beta > 0$ if $r(s, a, \mu)$ and $P(s'|s, a, \mu)$ are continuous. Using $\tilde{\boldsymbol{\pi}} = \tilde{\Psi}(\boldsymbol{\mu})$ to denote the unique best-response policy to $\boldsymbol{\mu}$, we obtain the the fixed point iteration for ERMFNE by alternating between $\boldsymbol{\pi} = \tilde{\Psi}(\boldsymbol{\mu})$ and $\boldsymbol{\mu} = \Phi(\boldsymbol{\pi})$. The fixed point iteration converges to a unique MF flow if $\beta$ is large (according to the reward function scale), thereby implying a *unique* ERMFNE.

Note that in ERMFNE, we recover optimality (MFNE) if $\beta = 0$. Although the optimality and uniqueness are approached respectively at two extremes of $\beta$, in this paper, we prioritise the property of uniqueness to ensure the well-definedness of IRL for MFGs, i.e., we assume trajectories are observed from a unique ERMFNE (with a suitable $\beta$) so that the observed behaviour can be interpreted with a unique equilibrium. Since we can adjust the relative importance between rewards and entropy by scaling reward functions, following the convention in MaxEnt IRL [9, 43, 44] and without loss of generality, we assume $\beta = 1$ in the remainder of the analysis.

## 3.2 Trajectory Distributions under ERMFNE

Besides uniqueness, in this paper, we take a step further to show that the entropy regularisation endows ERMFNE with the capability of reasoning about uncertainties in observed behaviour in a principled way. Specifically, we show that trajectory distributions induced

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[3]Hereafter, we will slightly abuse the term "best response" to denote the policy that maximises the entropy-regularised rewards.
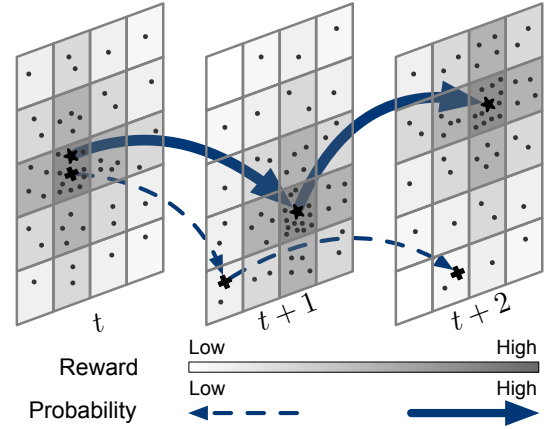


**Figure 1: Illustration for the trajectory distribution induced by ERMFNE. A group of agents (dots) drift in a grid world over three time steps. Each grid represents a specific state. The distribution of agents represents the mean field. A darker grey background denotes a higher reward associated with a state. Two individual agents marked with "★" and "+" start at the same state. The solid arrows denote the trajectory of ★, which can be observed with an exponentially higher probability than the trajectory of + depicted using dashed arrows. Note that the rewards of states change over time because of the evolution of mean fields.**

by ERMFNE can be characterised by an *energy-based model*, i.e., trajectories with high expected cumulative rewards are generated with exponentially high probabilities, as is illustrated in Fig. 1. It can thus be used for the probabilistic reward inference.

THEOREM 1. *Let $(\tilde{\boldsymbol{\mu}}^\star, \tilde{\boldsymbol{\pi}}^\star)$ be the ERMFNE for an MFG $(\mathcal{S}, \mathcal{A}, P, \mu_0, r)$, and $D_{\mathrm{KL}}$ denote the Kullback-Leibler (KL) divergence. Then, $(\tilde{\boldsymbol{\mu}}^\star, \tilde{\boldsymbol{\pi}}^\star)$ is the optimal solution to the following constrained optimisation problem:*

$$\min_{\boldsymbol{\mu}, \boldsymbol{\pi}} D_{\mathrm{KL}} \left( p_1(\tau) \parallel p_2(\tau) \right) \ s.t. \ \boldsymbol{\mu} = \Phi(\boldsymbol{\pi})$$

$$p_1(\tau) = \mu_0(s_0) \cdot \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t, \mu_t) \cdot \prod_{t=0}^{T} \pi_t(a_t|s_t)$$

$$p_2(\tau) \propto \mu_0(s_0) \cdot \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t, \mu_t) \cdot e^{\mathcal{R}(\tau)} \quad (5)$$

PROOF. See Appendix A. □

## 4 EXTENDING MAXENT IRL TO MFGS

From now on, we assume that observed trajectories are sampled from a unique ERMFNE $(\boldsymbol{\mu}^E, \boldsymbol{\pi}^E)$. Let $r_\omega(s, a, \mu)$ be an $\omega$- parameterised reward function and $(\boldsymbol{\mu}^\omega, \boldsymbol{\pi}^\omega)$ denote the ERMFNE induced by $\omega$. Then, recovering the underlying reward function reduces to tuning $\omega$. The probability of a trajectory $\tau = \{(s_t, a_t)\}_{t=1}^{T}$ induced by ERMFNE with $r_\omega$ is defined by the following generative process:

$$p_\omega(\tau) = \mu_0(s_0) \cdot P(s_{t+1}|s_t, a_t, \mu_t^\omega) \cdot \prod_{t=0}^{T} \pi_t^\omega(a_t|s_t). \quad (6)$$

In the spirit of MaxEnt IRL, we should tune $\omega$ by maximising the likelihood of the observed trajectories concerning the distribution defined in Eq. (6). By Theorem 1, we can instead optimise the likelihood with respect to the distribution defined in Eq. (5) as a variational approximation:

$$\max_\omega \mathcal{L}(\omega) \triangleq \mathbb{E}_{\tau \sim (\mu^E, \pi^E)} \left[ \mathcal{R}_\omega(\tau) + \sum_{t=0}^{T-1} \log P(s_{t+1} | s_t, a_t, \mu_t^\omega) \right] - \log \mathcal{Z}_\omega,$$
(7)

where $\mathcal{Z}_\omega$ is the partition function of the distribution defined in Eq. (5), i.e., a summation over all feasible trajectories:

$$\mathcal{Z}_\omega \triangleq \sum_\tau e^{R_\omega(\tau)} \prod_{t=0}^{T-1} \log P(s_{t+1} | s_t, a_t, \mu_t^\omega). \tag{8}$$

However, directly optimising the likelihood objective in Eq. (7) is intractable because we cannot analytically derive the MF flow $\mu^\omega$. This problem arises from the nature of MFGs that the policy and MF flow in ERMFNE are interdependent because $\tilde{\pi}^\star = \Psi(\tilde{\mu}^\star)$ and in turn $\tilde{\mu}^\star = \Phi(\tilde{\pi}^\star)$. This issue poses the main challenge for extending MaxEnt IRL to MFGs. Worse yet, the transition function $P$ also depends on $\mu^\omega$, posing an extra layer of complexity as the environment dynamics is generally unknown in practice.

While, notice that if we have access to an "oracle" (known a priori) MF flow that determines the shape of the observed MF flow $\mu^E$, an individual would be decoupled from the population. Inspired by this fact, we sidestep this problem by substituting $\mu^\omega$ with the empirical value of $\mu^E$, denoted by $\hat{\mu}^E \triangleq \{\mu_t^E\}_{t=0}^T$, estimated from observations $\mathcal{D}_E = \{\tau_j\}_{j=1}^M$ by calculating the occurrence frequencies of states:

$$\hat{\mu}_t^E(s) \triangleq \frac{1}{M} \sum_{j=1}^M \mathbb{1}_{\{s_{j,t}^i = s\}}.$$

Since the population consistency condition in ERMFNE guarantees that the state marginal distribution of a single agent matches the mean field at each time step, $\hat{\mu}^E$ achieves an unbiased estimator of $\mu^E$. Meanwhile, by substituting $\hat{\mu}^E$ for $\mu^\omega$, the transition function $P(s_t, a_t, \hat{\mu}_t^E)$ is decoupled the from the reward parameter $\omega$ as $\hat{\mu}^E$ does not depend on $\omega$, and henceforth being omitted in the likelihood function. Finally, with this substitution, we obtain a tractable version of the original MLE objective in Eq. (7):

$$\max_\omega \hat{\mathcal{L}}\left(\omega; \hat{\mu}^E\right) \triangleq \mathbb{E}_{\tau \sim \mathcal{D}_E} \left[\hat{\mathcal{R}}_\omega(\tau)\right] - \log \hat{\mathcal{Z}}_\omega, \tag{9}$$

which resembles the formulation of the MLE objective of MaxEnt IRL as given in Eq. (4). Here, $\hat{\mathcal{R}}_\omega(\tau) \triangleq \sum_{t=0}^{T-1} r_\omega(s_t, a_t, \hat{\mu}_t^E)$ and $\hat{\mathcal{Z}}_\omega \triangleq \sum_{\tau \in \mathcal{D}_E} e^{\hat{\mathcal{R}}_\omega(\tau)}$ denotes the simplified partition function in Eq. (8).

Statistically, Eq. (9) can be interpreted as that we use a likelihood function of a "mis-specified" model that treats the policy and MF flow as being independent and replaces the MF flow with its empirical value. In this manner, we estimate the optimal solution to the original MLE problem by maximising a simplified form of the actual likelihood function defined in Eq. (7). Although we sacrifice the accuracy for achieving tractability due to the estimation error of $\hat{\mu}^E$, we show that Eq. (9) preserves the property of the asymptotic consistency, as $\hat{\mu}^E$ converges almost surely to $\mu^E$ as the number of samples tends to infinity due to the law of large numbers.

THEOREM 2. *Let the observed trajectories in $\mathcal{D}_E = \{\tau_j\}_{j=1}^M$ be independent and identically distributed and sampled from a unique ERMFNE induced by an unknown parameterised reward function. Suppose for all $s \in \mathcal{S}$, $a \in \mathcal{A}$ and $\mu \in \mathcal{P}(\mathcal{S})$, $r_\omega(s, a, \mu)$ is differentiable w.r.t. $\omega$. Then, with probability $1$ as the number of samples $M \to \infty$, the equation $\nabla_\omega \hat{\mathcal{L}}\left(\omega; \hat{\mu}^E\right) = 0$ has a root $\hat{\omega}$ such that $\hat{\omega}$ is a maximiser of the likelihood objective $\mathcal{L}(\omega)$ in Eq. (7).*

PROOF. The gradient of $\hat{\mathcal{L}}$ concerning $\omega$ is given by:

$$\begin{aligned}
\nabla_\omega \hat{\mathcal{L}}\left(\omega; \hat{\mu}^E\right) &= \frac{1}{M} \sum_{j=1}^M \nabla_\omega \hat{\mathcal{R}}_\omega(\tau_j) - \nabla_\omega \log \hat{\mathcal{Z}}_\omega \\
&= \frac{1}{M} \sum_{j=1}^M \nabla_\omega \hat{\mathcal{R}}_\omega(\tau_j) - \frac{1}{\hat{\mathcal{Z}}_\omega} \nabla_\omega \hat{\mathcal{Z}}_\omega \\
&= \frac{1}{M} \sum_{j=1}^M \nabla_\omega \hat{\mathcal{R}}_\omega(\tau_j) - \sum_{j=1}^M \frac{e^{\hat{\mathcal{R}}_\omega(\tau_j)}}{\hat{\mathcal{Z}}_\omega} \nabla_\omega \hat{\mathcal{R}}_\omega(\tau_j).
\end{aligned} \tag{10}$$

Let $\mathrm{Pr}_{\mathcal{D}_E}(\tau) \triangleq \frac{1}{M} \sum_{j=1}^M \mathbb{1}_{\{\tau_j = \tau\}}$ denote the empirical trajectory distribution, then Eq. (10) is equivalent to

$$\begin{aligned}
\nabla_\omega \hat{\mathcal{L}}\left(\omega; \hat{\mu}^E\right) &= \sum_{j=1}^M \mathrm{Pr}_{\mathcal{D}_E}(\tau_j) \nabla_\omega \hat{\mathcal{R}}_\omega(\tau_j) - \sum_{j=1}^M \frac{e^{\hat{\mathcal{R}}_\omega(\tau_j)}}{\hat{\mathcal{Z}}_\omega} \nabla_\omega \hat{\mathcal{R}}_\omega(\tau_j) \\
&= \sum_{j=1}^M \left( \mathrm{Pr}_{\mathcal{D}_E}(\tau_j) - \frac{e^{\hat{\mathcal{R}}_\omega(\tau_j)}}{\hat{\mathcal{Z}}_\omega} \right) \nabla_\omega \hat{\mathcal{R}}_\omega(\tau_j).
\end{aligned} \tag{11}$$

When the number of samples $M \to \infty$, $\mathrm{Pr}_{\mathcal{D}_E}(\tau)$ tends to the true trajectory distribution $p(\tau)$ (see Eq. (5)) induced by ERMFNE. Meanwhile, according to the law of large numbers, $\hat{\mu} \to \mu^E$ with probability one as the number of samples $M \to \infty$. Let $\omega^\star$ be a maximiser of the likelihood objective in Eq. (7). Taking the limit as $M \to \infty$ and the optimality $\omega = \omega^\star$, we have:

$$\frac{e^{\mathcal{R}_{\omega^\star}(\tau_j)}}{\hat{\mathcal{Z}}_{\omega^\star}} = \frac{e^{\mathcal{R}_{\omega^\star}(\tau_j)}}{\sum_{j=1}^M e^{\mathcal{R}_{\omega^\star}(\tau_j)}} = \mathrm{Pr}(\tau_j) = \mathrm{Pr}_{\mathcal{D}_E}(\tau_j).$$

Therefore, the gradient in Eq. (11) will be zero. □

## 5 MEAN FIELD ADVERSARIAL IRL

Theorem 2 bridges the gap between optimising the original intractable MLE objective in Eq. (7) and the tractable empirical MLE objective in Eq. (9). However, as mentioned in Sec. 2.3, exactly computing the partition function $\hat{Z}_\omega$ is generally difficult. Similar to AIRL [9], we adopt *importance sampling* to estimate $\hat{Z}_\omega$ with *adaptive samplers*. Since policies are time-varying in MFGs, we use a set of $T$ adaptive samplers $\pi^\theta \triangleq (\pi^{\theta_0}, \pi^{\theta_1}, \ldots, \pi^{\theta_{T-1}})$, where each $\pi^{\theta_t}$ serves as the parameterised per-step policy.

Now, we are ready to present to our *Mean-Field Adversarial IRL* (MF-AIRL) framework, which trains a discriminator

$$\hat{D}_\omega(s_t, a_t) \triangleq \frac{e^{f_\omega(s_t, a_t, \hat{\mu}_t^E)}}{e^{f_\omega(s_t, a_t, \hat{\mu}_t^E)} + \pi^{\theta_t}(a_t | s_t)}$$

as

$$\max_{\omega} \mathbb{E}_{\tau \sim \mathcal{D}_E}\left[\sum_{t=0}^{T-1} \log \hat{D}_\omega(s_t, a_t)\right] + \mathbb{E}_{\tau \sim \boldsymbol{\pi}^\theta}\left[\sum_{t=0}^{T-1} \log(1 - \hat{D}_\omega(s_t, a_t))\right],$$

(12)

and trains adaptive importance samplers $\boldsymbol{\pi}^\theta$ as

$$\max_{\boldsymbol{\theta}} \mathbb{E}_{\tau \sim \boldsymbol{\pi}^\theta}\left[\sum_{t=0}^{T-1} \log \hat{D}_\omega(s_t, a_t) - \log(1 - \hat{D}_\omega(s_t, a_t))\right]$$

$$= \mathbb{E}_{\tau \sim \boldsymbol{\pi}^\theta}\left[\sum_{t=0}^{T-1} f_\omega(s_t, a_t, \hat{\mu}_t^E) - \log \pi^{\theta_t}(a_t|s_t)\right].$$

(13)

The update of policy parameters $\boldsymbol{\theta}$ is interleaved with the update of the reward parameter $\omega$. Intuitively, tuning $\boldsymbol{\pi}^\theta$ can be viewed as a *policy optimisation* procedure, which is to find the ERMFNE policy induced by the current reward parameter in order to minimise the variance of importance sampling; $f_\omega$ is trained to estimate the reward function by distinguishing between the observed trajectories and those generated by the current adaptive samplers $\boldsymbol{\pi}^\theta$. We can use *backward induction* to train $\boldsymbol{\pi}^\theta$, i.e., tuning $\pi^{\theta_t}$ based on $\pi^{\theta_{t+1}}, \ldots, \pi^{\theta_{T-1}}$ that are already tuned. [4] At optimality, $f_\omega$ will approximate the underlying reward function for the observed ERMFNE and $\boldsymbol{\pi}^\theta$ will approximate the observed policy.

## 5.1 Reward Shaping in MFGs

As mentioned in Sec. 2.3, IRL faces reward ambiguity. This issue is called the effect of *reward shaping* [29], i.e., there is a class of reward transformations that induce the same set of optimal policies, where IRL cannot identify the ground-truth one without prior knowledge of environments. It is shown that for any state-only *potential function $h : \mathcal{S} \to \mathbb{R}$*, the reward transformation

$$r'(s_t, a_t, s_{t+1}) = r(s_t, a_t) + h(s_{t+1}) - h(s_t)$$

is the sufficient and necessary condition to ensure policy invariance for both MDPs and stochastic games [7]. We show that a similar idea can be extended to MFGs: for any potential function $g : \mathcal{S} \times \mathcal{P}(\mathcal{S}) \to \mathbb{R}$, the potential-based reward shaping can ensure the invariance of both ERMFNE and MFNE. The detailed justification and proofs are deferred until Appendix B.

To mitigate the effect of reward shaping, similar to AIRL [9], we assume that the parameterised reward function $f_\omega$ is in the following structure:

$$f_{\omega,\phi}(s_t, a_t, \mu_t, s_{t+1}, \mu_{t+1}) = r_\omega(s_t, a_t, \mu_t) +$$
$$g_\phi(s_{t+1}, \mu_{t+1}) - g_\phi(s_t, \mu_t).$$

Here, $g_\phi$ is the $\phi$-parameterised potential function for MFGs. To summarise, we present the pseudocode in Alg. 1.

## 6 RELATED WORK

We continue from the introduction to relate our work to the existing literature. MFGs were pioneered by [22, 23] in the continuous setting of stochastic differential games. The discrete MFG model was then proposed in [14], which was adopted in the learning setting. Recently, learning MFG has attracted significant attention [2], and

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[4]Since the reward at $t = T$ is 0, $\pi_T$ always selects actions with ties broken arbitrarily to maximise the policy entropy.

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**Algorithm 1** Mean-Field Adversarial IRL

1: **Input:** MFG with parameters $(\mathcal{S}, \mathcal{A}, P, \mu_0)$ and observed trajectories $\mathcal{D}_E = \{\tau_j\}_{j=1}^M$.
2: **Initialisation:** reward parameter $\omega$, adaptive samplers $\boldsymbol{\theta}$ and potential function parameter $\phi$.
3: Estimate the empirical expert MF flow $\hat{\boldsymbol{\mu}}^E$ from $\mathcal{D}_E$.
4: **for** each iteration **do**
5:   Sample a set of trajectories $\mathcal{D}_{\boldsymbol{\pi}} = \{\tau_j\}$ from $\boldsymbol{\pi}^\theta$ via $s_0 \sim \mu_0$, $a_t \sim \pi^{\theta_t}(\cdot|s_t)$, $s_{t+1} \sim P(\cdot|s_t, a_t, \mu_t)$.
6:   Sample subsets $\mathcal{X}_E, \mathcal{X}_{\boldsymbol{\pi}}$ from $\mathcal{D}_E, \mathcal{D}_{\boldsymbol{\pi}}$.
7:   Update $\omega, \phi$ using $\mathcal{X}_E, \mathcal{X}_{\boldsymbol{\pi}}$ according to Eq. (12).
8:   **for** $t = T - 1, \ldots, 0$ **do**
9:     Update $\theta_t$ with respect to the reward estimate $r_\omega(s, a, \mu) + g_\phi(s, \mu)$ according to Eq. (13).
10:   **end for**
11: **end for**
12: **Output:** Learned reward function $r_\omega$.

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most methods are based on reinforcement learning [5, 16, 37, 42], *fictitious play* [2, 8, 40], or a combination of the two [32]. While these methods require a well-designed reward function that is challenging to hand-tune in practice. In contrast, our method recovers a reward function from the observed behaviour.

IRL was introduced by [30] in the single-agent setting. Early IRL methods were based on *margin optimisation* [33], which makes IRL ill-defined. *Maximum entropy* (MaxEnt) *IRL* [46, 47] addresses this issue by providing a probabilistic approach to find a most noncommittal reward function whose induced state-action trajectory distribution has the MaxEnt among those matching the reward expectation of the observed behaviour. However, it is only suitable for small and discrete problems since MaxEnt IRL requires iteratively solving an RL problem while tuning a reward function. *Adversarial IRL* (AIRL) [9] was later proposed, which scales MaxEnt IRL to high-dimensional or continuous domains. It implements a sampling-based approximation to MaxEnt IRL by drawing an analogy between *generative adversarial networks* [15] and MaxEnt IRL, thereby being able to partially solve each RL problem associated with reward tuning.

Another line of work extends ILR to the multi-agent setting, where the problem is cast to finding individual reward functions of stochastic games. They typically take a specific equilibrium concept, such as the conventional Nash equilibrium [10], logistic stochastic best response equilibrium [43] and equilibrium for the cooperative setting [28], and assume the equilibrium exists uniquely in order to guarantee the well-definedness (as we assumed in this paper). However, these methods scale poorly to large-scale scenarios due to the exponential growth of state-action spaces and agent interactions. By extending MaxEnt IRL to MFGs, our method realises an effective IRL framework for large-scale scenarios.

## 7 EXPERIMENTS

We seek to answer the following fundamental question via experiments: *Can MF-AIRL effectively and efficiently recover a suitable reward function of an MFG by observing bounded rational behaviour?*
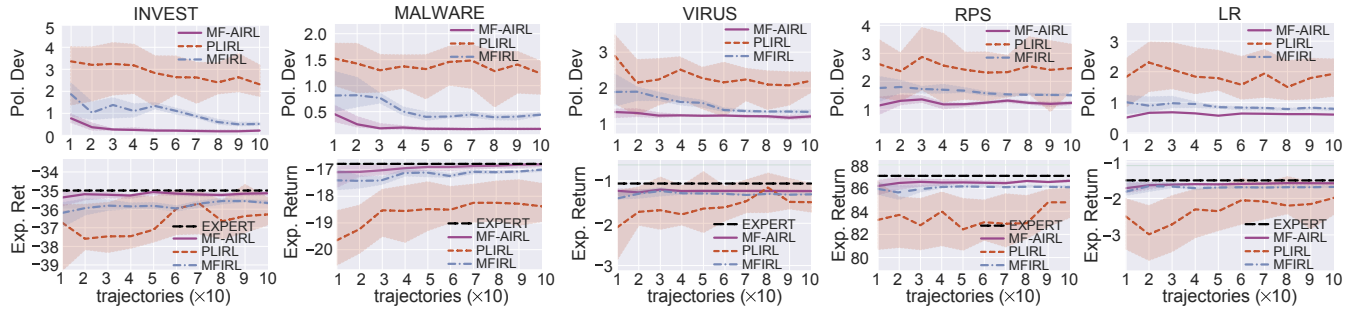
**Figure 2: Results for numerical tasks. The line and shade are the median and variance over 10 independent runs.**

To that end, we evaluate MF-AIRL on a series of simulated tasks motivated by real-world applications, where the observed behaviour is sampled from an ERMFNE.

### 7.1 Experimental Setup

*7.1.1 Tasks.* We adopt five MFG tasks: *investment in product quality* (INVEST for short), *malware spread* (MALWARE), *virus infection* (VIRUS), *Rock-Paper-Scissors* (RPS) and *Left-Right* (LR), which simulate a series of large-scale multi-agent scenarios in the contexts of marketing, virus propagation modelling and norm emergence. These tasks were originally studied in [5, 20, 21, 37, 39] and adapted by [4]. Detailed descriptions and settings are in Appendix C.

*7.1.2 Baselines.* We compare MF-AIRL against the two IRL methods above for MFGs: **(1)** The centralised method [41] relies on the reduction from MFG to MDP. Since it aims to recover the population's average rewards, we call it *population-level IRL* (**PLIRL**). Shown by [4], PLIRL is only compatible with socially optimal equilibria that maximise the population's average rewards; otherwise, it can result in biased reward inference. **(2)** The decentralised method, *Mean Field IRL* (**MFIRL**) [4], is based on margin optimisation, i.e., finding a reward function by minimising the margin (in terms of expected return) between the observed equilibrium and every other equilibrium; it is able to recover the ground-truth reward function with no bias, regardless of whether the observed equilibrium is socially optimal or not.

*7.1.3 Performance Metrics.* The quality of a learned reward function $r_\omega$ can be evaluated by the difference between its induced best-response policy to $\mu^E$, denoted by $\pi^\omega$, and $\pi^E$, because a best-response policy is unique under the entropy regularisation. We adopt the following two metrics that measure the difference between $\pi^\omega$ and $\pi^E$ reflected in the statistical distance and the expected return, respectively:

(1) *Policy Deviation* (Pol. Dev). We use the cumulative KL- divergence,

$$\sum_{t=0}^{T-1} \sum_{s \in \mathcal{S}} D_{\mathrm{KL}}\big(\pi_t^E(\cdot|s) \parallel \pi_t^\omega(\cdot|s)\big),$$

to measure the statistical distance between two policies.
(2) *Expected return* (Exp. Ret). The difference between two expected returns $J(\mu^E, \pi^\omega)$ and $J(\mu^E, \pi^E)$ under the ground-truth reward function.

**Table 1: Results for new environment dynamics. Mean and variance are taken across 10 independent runs.**

| Task | Metric | Algorithm | | |
| --- | --- | --- | --- | --- |
| | | MF-AIRL | PLIRL | MFIRL |
| INVEST | Pol. Dev | **0.24** (0.02) | 1.06 (0.21) | 0.78 (0.18) |
| | Exp. Ret | **-35.19** (0.51) | -37.73 (2.76) | -35.92 (0.98) |
| MALWARE | Pol. Dev | **0.52** (0.01) | 1.54 (1.20) | 0.73 (0.14) |
| | Exp. Ret | **-18.49** (0.14) | -19.59 (0.29) | -18.82 (0.05) |
| VIRUS | Pol. Dev | **1.48** (0.01) | 1.76 (0.18) | 1.55 (0.03) |
| | Exp. Ret | **-1.71** (0.02) | -2.66 (0.14) | -2.16 (0.06) |
| RPS | Pol. Dev | **6.11** (0.46) | 6.47 (0.98) | 6.56 (0.82) |
| | Exp. Ret | **93.36** (2.51) | 91.99 (0.44) | 91.28 (2.15) |
| LR | Pol. Dev | **0.57** (0.04) | 0.62 (0.22) | 0.71 (0.07) |
| | Exp. Ret | **-1.70** (0.01) | -2.67 (1.01) | -1.93 (0.06) |

*Note:* The Exp. Ret of the observed behaviour for five tasks are -35.87, -18.90, -1.24, 93.16 and -0.64, respectively.

*7.1.4 Training Procedures.* In all tasks, we have access to the ground-truth reward functions and environment dynamics, which allows us to numerically compute an ERMFNE through the fixed point iteration as introduced in Sec. 3. Unless specified otherwise, we set the entropy regularisation coefficient $\beta = 1$. After obtaining the ERMFNE, we sample trajectories from them, each with a length of 50 time steps, the same as the number used in [4, 36, 43]. We use one-hot encoding to represent states and actions. All three algorithms share the same neural network architecture as the reward model: two hidden layers of 64 leaky rectified linear units each. Implementation details are given in Appendix D.

### 7.2 Reward Recovery with Fixed Dynamics

The first experiment tests the capability of reward recovery with fixed environment dynamics. Results are depicted in Fig. 2. On all tasks, MF-AIRL achieves the closest performance to the observed behaviour with the same number of trajectories and the fastest convergence with the number of trajectories increases, suggesting that among all three algorithms, MF-AIRL is the most effective and efficient for bounded-rational agents. MFIRL shows larger deviations even if the number of trajectories is large. This may be because MFIRL takes MFNE as the solution concept, thereby lacking the

**Table 2: Comparisons between MF-AIRL and MFIRL on varying entropy regularisation strength $\beta$.**

| Task | $\beta$ | Metric | Algorithm | | |
|------|---------|--------|-----------|---------|------|
| | | | OBSERVED | MF-AIRL | MFIRL |
| INVEST | 0 | Pol. Dev | – | 0.45 (0.03) | 0.44 (**0.02**) |
| | | Exp. Ret | -35.05 | -35.92 (**0.68**) | -35.54 (2.55) |
| | 0.1 | Pol. Dev | – | **0.31** (0.02) | 0.39 (0.04) |
| | | Exp. Ret | -36.37 | **-37.08** (0.71) | -37.40 (1.08) |
| MALWARE | 0 | Pol. Dev | – | 0.39 (0.07) | 0.38 (0.07) |
| | | Exp. Ret | -18.06 | -19.15 (**0.25**) | -18.52 (0.51) |
| | 0.1 | Pol. Dev | – | **0.41** (0.03) | 0.50 (0.10) |
| | | Exp. Ret | -19.36 | **-19.84** (0.22) | -20.39 (0.69) |
| VIRUS | 0 | Pol. Dev | – | 1.50 (**0.04**) | 1.34 (0.09) |
| | | Exp. Ret | -1.17 | -2.55 (**0.04**) | -1.61 (0.17) |
| | 0.1 | Pol. Dev | – | **1.54** (0.01) | 1.80 (0.07) |
| | | Exp. Ret | -2.15 | **-2.61** (0.06) | -2.98 (0.43) |
| RPS | 0 | Pol. Dev | – | 9.71 (**0.24**) | 9.36 (0.40) |
| | | Exp. Ret | 94.27 | 93.21 (**0.49**) | 93.58 (2.51) |
| | 0.1 | Pol. Dev | – | **7.09** (0.54) | 8.40 (0.40) |
| | | Exp. Ret | 91.43 | **90.43** (3.09) | 89.40 (0.96) |
| LR | 0 | Pol. Dev | – | 0.45 (**0.07**) | 0.37 (0.08) |
| | | Exp. Ret | -0.52 | -2.60 (**0.08**) | -1.70 (1.08) |
| | 0.1 | Pol. Dev | – | **0.68** (0.04) | 0.70 (0.04) |
| | | Exp. Ret | -0.64 | **-0.81** (0.04) | -0.96 (0.71) |

ability to tolerate suboptimal behaviours. PLIRL shows the largest deviation and variance. This is as expected because PLIRL is only suitable for socially optimal equilibria, while an ERMFNE is not socially optimal as it captures bounded rationality. Therefore, biased reward inferences occur when applying PLIRL to these tasks.

### 7.3 Policy Transfer across Varying Dynamics

The second experiment investigates the robustness against changing environment dynamics. We change the transition function (see Appendix C for details), recompute an ERMFNE ($\mu_{new}^E, \pi_{new}^E$) induced by the ground-truth reward function, compute the best-response policy $\pi_{new}^\omega$ to $\mu_{new}^E$ under the learned reward function (trained with 100 demonstrated trajectories), and calculate two metrics again. Results are summarised in Tab. 1. Consistently, MF-AIRL outperforms two baselines on all tasks. We attribute the high robustness of MF-AIRL to the following reasons: (1) MF-AIRL uses a potential function to mitigate the effect of reward shaping while two baselines do not; (2) The issue of biased inference in PLIRL can be exacerbated by the changing dynamics, as is argued in [4]. To summarise, MF-AIRL can recover ground-truth reward functions with high robustness to changing dynamics.

### 7.4 Weak Entropy Regularisation

Suppose the entropy regularisation in ERMFNE is too strong. In that case, it becomes easy and trivial to perform MaxEnt IRL as the policy tends to select actions uniformly due to the maximum entropy principle. Our third experiment thus investigates the performance

under weak entropy regularisation. Since PLIRL is known to lead to biased reward inference if the demonstrated equilibrium is not socially optimal, we eliminate it here and only compare two decentralised methods. To weaken the entropy regularisation, we set the coefficient $\beta$ in the observed ERMFNE to 0 and 0.1, respectively and sample 100 demonstrated trajectories from each. The environment dynamic is fixed. Results are summarised in Tab. 2. Note that an ERMFNE is recovered to an MFNE if $\beta = 0$; this complements the above two experiments where all trajectories are sampled from an ERMFNE with $\beta = 1$. It also enables a fair comparison between MF-AIRL and MFIRL as, technically, they are designed under two prescribed equilibrium concepts.

With trajectories sampled from an MFNE ($\beta = 0$), MF-AIRL shows a more significant deviation from the observed behaviour than MFIRL, but its variance is lower on average. This fact can be attributed to the reason that a best-response policy in MFNE does not exist uniquely, though MFIRL is unbiased under MFNE. In contrast, MF-AIRL can always recover a unique best-response policy from a learned reward function, though with bias under MFNE. This result again validates our argument that by taking MFNE as the solution concept, MFIRL fails to elicit a unique policy from the learned reward function. While, even with a positive yet small strength of entropy regularisation ($\beta = 0.1$), our MF-AIRL quickly outperforms MFIRL in terms of both accuracy and variance. This suggests that our MF-AIRL can handle imperfect behaviours resulting from bounded rationality, even with minor uncertainties.

## 8 CONCLUDING REMARKS

In this paper, we propose MF-AIRL, the first probabilistic IRL framework effective for MFGs with bounded-rational agents. We first extend MaxEnt IRL to MFGs based on the solution concept termed ERMFNE, which allows us to characterise uncertainties in observed behaviour using the maximum entropy principle. We then develop the practical MF-AIRL framework using an adversarial learning approach to solve MaxEnt IRL for MFGs efficiently. Experimental results on simulated tasks demonstrate the effectiveness and efficiency of MF-AIRL against existing IRL methods for MFGs.

We argue that MF-AIRL is worth following generalisations: **(1)** *Continuous states and actions.* The arguments in this paper still hold for continuous state-action spaces, except that some techniques (e.g., $\epsilon$-net [16]) are needed to discretise a mean field because it turns to a probability density function if states are continuous. **(2)** *Infinite time horizon.* When the time horizon tends to infinity, the mean field is shown to converge almost surely to a constant limit, resulting in the *stationary MFNE* [37]. MF-AIRL is compatible with infinite time horizons because non-stationary equilibria recover stationary ones as special cases. **(3)** *Generalised mean fields.* Some work [16] generalises the mean field $\mu \in \mathcal{P}(\mathcal{S})$ to $(\mu, \alpha) \in \mathcal{P}(\mathcal{S} \times \mathcal{A})$ by additionally considering population's average action $\alpha \in \mathcal{P}(\mathcal{A})$. MF-AIRL is adaptive to generalised mean fields by incorporating the marginal distribution $\alpha$ in all mean field arguments. **(4)** *Heterogeneous agents.* A large-scale heterogeneous multi-agent system can be converted to a homogeneous system by considering the type of the agent as a component of states [38]. Our MF-AIRL is, therefore, compatible with heterogeneous agents.

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