Beyond Rewards: a Hierarchical Perspective on Offline Multiagent Behavioral Analysis

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Abstract

Each year, expert-level performance is attained in increasingly-complex multiagent domains, notable examples including Go, Poker, and StarCraft II. This rapid progression is accompanied by a commensurate need to better understand how such agents attain this performance, to enable their safe deployment, identify limitations, and reveal potential means of improving them. In this paper we take a step back from performance-focused multiagent learning, and instead turn our attention towards agent behavior analysis. We introduce a model-agnostic method for discovery of behavior clusters in multiagent domains, using variational inference to learn a hierarchy of behaviors at the joint and local agent levels. Our framework makes no assumption about agents' underlying learning algorithms, does not require access to their latent states or models, and can be trained using entirely offline observational data. We illustrate the effectiveness of our method for enabling the coupled understanding of behaviors at the joint and local agent level, detection of behavior changepoints throughout training, discovery of core behavioral concepts (e.g., those that facilitate higher returns), and demonstrate the approach's scalability to a high-dimensional multiagent MuJoCo control domain.

1 Introduction

Multiagent approaches have driven numerous advances in artificial intelligence research, with seminal examples including TD-gammon [1], DeepBlue [2], AlphaGo [3], AlphaZero [4], Libratus [5], AlphaStar [6], OpenAI Five [7], and Pluribus [8]. During training, many of these approaches seek to push the performance of agents as measured by a reward signal, or derivatives thereof.

Despite this, post-hoc methods that seek to *understand* agent interactions often use less reward-centric techniques. Instead, insights are drawn from behavioral analysis to identify unique or interesting agent strategies. Examples include clustering-based analysis of neuron activations and trajectories in capture-the-flag [9], inspection of trajectories in a hide-and-seek domain to detect interesting behaviors such as agents that learn to exploit the underlying physics engine [10], monitoring of statistics such as pass ranges and frequencies in humanoid football [11], and analysis of AlphaZero's acquisition of chess knowledge [12]. Crucially, such insights are often drawn via manual analysis and detection of behavioral clusters, or use of statistics associated with certain behaviors as defined by humans experts (e.g., various skills and relevant metrics in humanoid football).

As evident above, understanding emergent multiagent behaviors is enriched by techniques beyond pure reward-based analysis, as behavioral signifiers are not always discernible via rewards. Figure 1a provides intuition on this notion, illustrating returns (sum of rewards) throughout training for a multiagent hill-climbing domain (later described in detail). We highlight two independent training trials (A and B) with similar final returns. Despite this, comparing the trajectories generated via the agents' deterministic policies at the end of each trial's training (Fig. 1b) reveals entirely different

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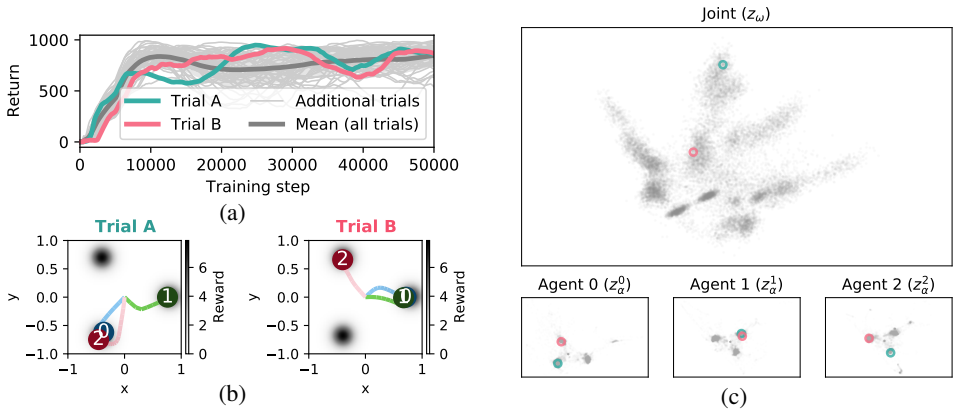


Figure 1: Reward alone is not enough to understand underlying behaviors in a 3-agent hill-climbing domain. Agents here start at the origin, each receiving rewards by navigating to any of 3 equidistant hills. (a) visualizes the total returns of agents throughout training, over 50 independent trials. Two trials (A and B) with similar final returns are highlighted. (b) visualizes the actual converged behaviors of the agents at the end of Trials A and B, which are distinct despite their similar returns. Visualizing these same trajectories in the behavior space learned by our approach immediately reveals differences in the joint behavior of agents in the top panel of (c), where the two color markers correspond to the trajectories from each trial. Simultaneously analyzing the agent-wise latent spaces in the bottom 3 panels of (c) highlight that agent 1 behaves the same way in both trials, in contrast to agents 0 and 2.

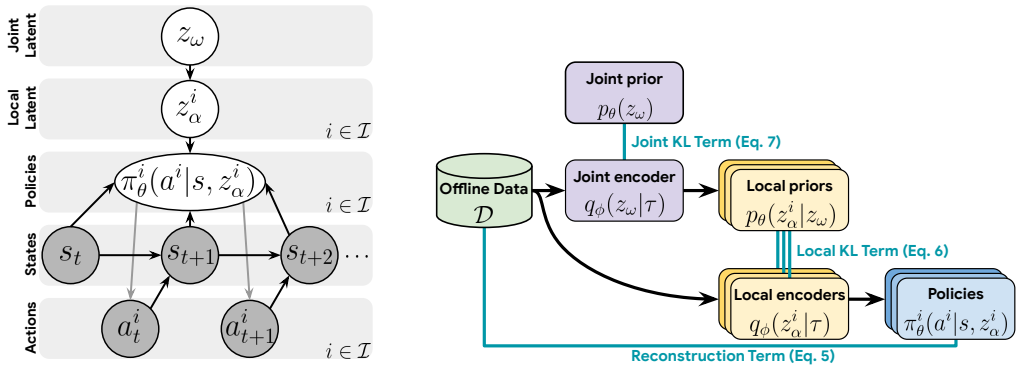
behaviors. Analogous examples are evident in the above works (e.g., Fig. 1 of Baker et al. [10], where substantial behavior changes occur in multiagent hide-and-seek despite a smooth reward curve).

This paper formalizes the problem of offline multiagent behavior analysis. Our proposed algorithm, Multiagent Offline Hierarchical Behavior Analyzer (MOHBA), learns a hierarchical latent space that simultaneously reveals behavior clusters at the joint level (i.e., interactions *between* agents) and local level (i.e., behaviors of *individual* agents). Our method is agnostic of the underlying algorithm used to generate agents' behaviors, does not assume availability of a reward signal, and does not require access to agents' models or internal states. We conduct experiments that investigate the structure of the learned behavior space, which goes beyond prior works on latent-clustering by identifying relationships between individual agent and joint behaviors. We illustrate that clusters identified by MOHBA are meaningful and useful for highlighting similarities and differences in behaviors throughout training. We also quantitatively analyze the completeness of discovered behavior clusters by adopting a modified version of the concept-discovery framework of Yeh et al. [13] to identify interesting behavior concepts in our multiagent setting. Finally, we test the scalability of our approach by using it for behavioral analysis of a high-dimensional multiagent MuJoCo environment [14].

2 Related Work

Significant research has been conducted in single-agent skill discovery, which seeks to learn reusable policies useful for downstream tasks [15–28]. Related approaches seek to discover motor primitives to express longer-horizon policies [29], including use of offline reinforcement learning (RL) for learning useful behaviors [30]. Option discovery methods focus on learning temporally-abstracted actions (i.e., options [31]), chained together to form cohesive skills [32–37]. In contrast to our work, these approaches focus on maximizing performance in single-agent settings. Recent works have also focused on hierarchical skill learning in multiagent reinforcement learning (MARL). Lee et al. [38] use the mutual information maximization objective introduced in Eysenbach et al. [16] to learn multiagent policies. Yang et al. [39] use a bi-level policy to learn agent skills: a high-level policy first generates latent vectors for each agent, and a low-level policy conditions behaviors on said vector to perform the task. In Wang et al. [40], distinct 'roles' are learned for agents to enable decomposition of tasks. Many MARL approaches have noted the emergence of interesting behaviors in multiagent systems in specific domains of interest [41–45]. In contrast to our focus, these approaches use RL to maximize agent performance, rather than understand arbitrary behaviors via offline analysis.

RL interpretability methods primarily focus on single-agent settings and either modify the RL algorithm itself to increase transparency, or conduct post-hoc explainability [46]. These approaches



(a) (b)

Figure 2: Approach overview. (a) Graphical model of the latent-conditioned trajectory generation process that MOHBA uses to learn multiagent behavior clusters. The joint behavior latent parameter z_ω informs local (agent-wise) behavior parameters z^i_α, which affects their behavioral policies. Our approach learns these joint and local behavior spaces given a state-action trajectory dataset. (b) Architecture overview of the MOHBA model with variational lower bound terms (5) to (7) indicated.

represent agent policies as programming languages [47], extract visual summaries of behaviors using 'interestingness' statistics such as uncertainty in selected actions or the value of state-transitions [48], or combine agent neuron activations with gradient information to construct behavioral embeddings [49]. Behavioral clusters in our work share similarities with concept-based explanation approaches in non-RL domains. Detecting 'concepts' in pre-trained models has been explored in vision [50–52], discrete games [12], and language [53, 54]. In vision, clustering-based approaches describe discovered concepts using examples [50] or use generative modeling to create new data to describe concepts [52]. Ghorbani et al. [50] uses a vision-specific method (i.e., superpixels) to sub-divide input before conducing clustering; while sub-division is less natural in RL, our LSTM and VAE baselines serve as an RL-adopted counterpart of such works.

Works using latent-clustering and analysis are also related to ours. These include approaches using multi-level variational autoencoders [55–58] to learn compositional latent spaces, although not in decision-making domains such as ours. Hierarchical latent approaches have been used in single-agent RL [59, 60]. Behavior analysis has also been conducted by embedding agent neuron activations into a low-dimensional space, using a (non-hierarchical) variational approach [9]. The representation power of agents' internal states has also been gauged by predicting future events [11]. Overall, the key difference between the above works and ours is that our method combined hierarchical learning with behavior analysis and applies it to the multiagent setting.

3 Offline Analysis of Multiagent Behaviors

This section introduces the offline multiagent behavioral analysis problem and our proposed algorithm.

Preliminaries. We first formalize the problem of offline multiagent behavioral analysis. Consider a rewardless multiagent Markov Decision Process (MA-MDP), defined by tuple $(\mathcal{I}, \mathcal{S}, \mathcal{A}, \mathcal{T})$, where $\mathcal{I} = \{1, ..., N\}$ is the set of N agents, $\mathcal{S}$ is the state space, $\mathcal{A}$ is the action space, and $\mathcal{T}$ denotes the state transition probability function. By not relying on the presence of rewards, behaviors generated even without reliance on a reward function (e.g., human interactions, or agents using curiosity-based exploration) can be considered. We use the term 'local' for elements associated with individual agents, and 'joint' for those associated with the entire system. At each timestep $t \in \{0, \ldots, T-1\}$, the agents execute joint action $a_t \in \mathcal{A}$ in state s_t using joint policy $\pi(a_t|s_t)$, causing the state to transition to s_{t+1} with probability $p(s_{t+1}|s_t, a_t) = \mathcal{T}(s_{t+1}, a_t, s_t)$. As standard in multiagent frameworks [61], we assume the joint action space factorizes as $\mathcal{A} = \times_i \mathcal{A}^i$, such that $a_t = (a^1_t, \ldots, a^N_t)$, where $i \in \mathcal{I}$ and $a^i_t \in \mathcal{A}^i$. Similarly, $\pi^i(a^i_t|s_t)$ is the local policy for agent i, and $\pi = \prod_i \pi^i$ is the joint policy.

Let $\tau = \big(s_0, (a^i_0)_{i\in\mathcal{I}}, \ldots, (a^i_{T-1})_{i\in\mathcal{I}}, s_T\big)$ denote a trajectory induced by this process, and $\mathcal{D} = \{\tau_1, \ldots, \tau_K\}$ denote a dataset of K such trajectories. This dataset may consist of trajectories from

multiple training runs, including variations over agent algorithms, hyperparameters, random seeds, or other factors influencing emergent behaviors. Given dataset $\mathcal{D}$, the offline multiagent analysis problem seeks to uncover potential clusters of agent behaviors.

Approach. Our approach, called the Multiagent Offline Hierarchical Behavior Analyzer (MOHBA), uses offline trajectory data to discover behaviors exhibited by agents at the local and joint level.

We first use Fig. 2a to build intuition before discussing technical details. Let the agent interactions exhibited in a trajectory τ be encoded by a latent variable, $z_\omega \in \mathbb{R}^{D_\omega}$, capturing their joint behavior. For example, z_ω may encode (at a high level) whether agents were cooperating or competing in a given trajectory; conditioned on joint signal z_ω, each agent then exhibits its own local behavior. Let local latent vectors $z_\alpha = (z_\alpha^1, \ldots, z_\alpha^N)$ encode individual agent behaviors, where $z_\alpha^i \in \mathbb{R}^{D_\alpha^i}$. Conditioned on the local behavior vector z_α^i, each agent then executes actions using a behavior-conditioned policy $\pi^i(a^i|s, z_\alpha^i)$. Given trajectory dataset $\mathcal{D}$, we seek to learn the latent-conditioned policies and distributions over latent vectors, such that we can reconstruct *any* behaviors exhibited by the agents in $\mathcal{D}$. Thus, latent vectors z_ω and z_α will encode the agents' behavioral spaces and, ideally, identify behavioral clusters in the dataset. Given this framework, the joint policy is decomposed,

$$\pi(a_t|s_t) = \int_{z_\alpha, z_\omega} \pi(a_t|s_t, z_\alpha) p(z_\alpha|z_\omega) p(z_\omega) d_{z_\alpha} d_{z_\omega} \tag{1}$$

$$= \int_{z_\alpha, z_\omega} \prod_{i=1}^{N} \pi^i(a_t^i|s_t, z_\alpha^i) p(z_\alpha^i|z_\omega) p(z_\omega) d_{z_\alpha} d_{z_\omega} \,, \tag{2}$$

where in (1) we have assumed that each agent's latent-conditioned policy is conditionally-independent of the high-level latent behavior z_ω given its low-level latent z_α^i. Next, given initial state distribution $p(s_0)$ and latent behavior spaces, the probability of a trajectory τ under joint policy $\pi(\cdot)$ is as follows:

$$p^\pi(\tau) = p(s_0) \prod_{t=0}^{T-1} p(s_{t+1}|s_t, a_t) \pi(a_t|s_t) \tag{3}$$

$$= \int_{z_\alpha, z_\omega} p(s_0) \prod_{t=0}^{T-1} p(s_{t+1}|s_t, a_t) \prod_{i=1}^{N} \pi^i(a_t^i|s_t, z_\alpha^i) p(z_\alpha^i|z_\omega) p(z_\omega) d_{z_\alpha} d_{z_\omega} \,. \tag{4}$$

We seek to learn the distributions over variables z_α and z_ω, alongside the latent-conditioned policies $\pi^i(a^i|s_t, z_\alpha^i)$, which maximize trajectory probabilities (4). In Appendix A.1, we derive the following variational lower bound, enabling approximation of these components using parametric models:

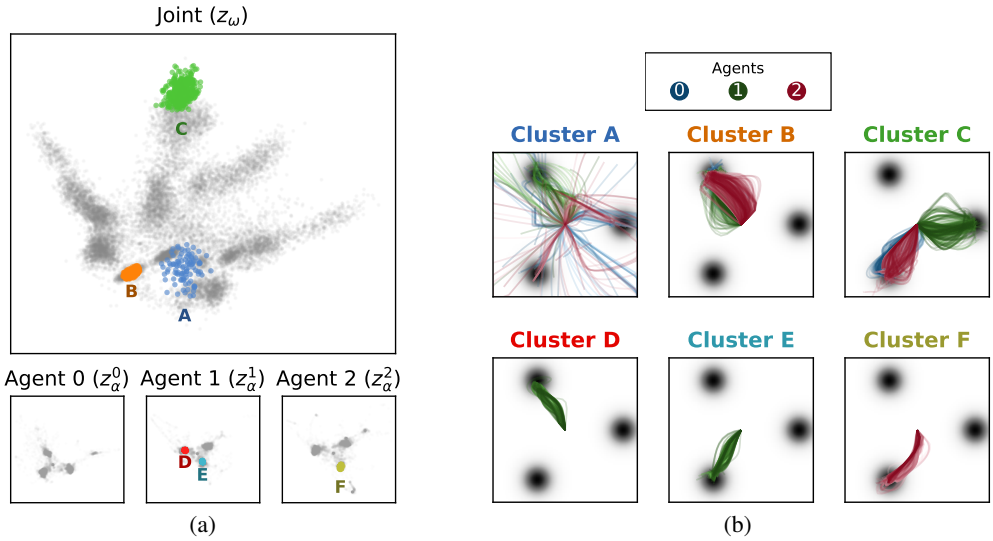
$$J_{lb} = \mathbb{E}_{\tau\sim\mathcal{D}, z_\alpha \sim q_\phi(z_\alpha|\tau)} \Big[\sum_{t,i} \log \pi_\theta^i(a_t^i|s_t, z_\alpha^i) \Big] \tag{5}$$

$$-\beta \Bigg[\mathbb{E}_{\tau\sim\mathcal{D}, z_\omega \sim q_\phi(z_\omega|\tau)} \Big[\sum_{i} D_{\mathrm{KL}}(q_\phi(z_\alpha^i|\tau) || p_\theta(z_\alpha^i|z_\omega)) \Big] \tag{6}$$

$$+\mathbb{E}_{\tau\sim\mathcal{D}} \left[D_{\mathrm{KL}}(q_\phi(z_\omega|\tau) || p_\theta(z_\omega)) \right] \Bigg] \,, \tag{7}$$

where $q_\phi(z_\alpha^i|\tau)$ and $p_\theta(z_\alpha^i|z_\omega)$ are, respectively, learned encoder (posterior) and prior distributions over the local behavior latents z_α^i; likewise, $q_\phi(z_\omega|\tau)$ and $p_\theta(z_\omega)$ are, respectively, learned encoder and prior distributions over the joint behavior latent z_ω; β is a KL-weighting term as in β-VAEs [62].

Figure 2b illustrates MOHBA's model architecture, which is informed by the three bound components (5) to (7). During training, each trajectory $\tau \sim \mathcal{D}$ is simultaneously passed through the joint and local encoders, which respectively produce parameters for distributions over z_ω and z_α (e.g., parameters of Gaussian distributions). Samples of low-level latent vectors z_α are passed to the reconstructed agent policies $\pi_\theta^i(a_t^i|s_t, z_\alpha^i)$, which are trained via the reconstruction component (5). The local KL-divergence component (6) induces the local encoder distribution (which is conditioned directly on τ) to be similar to the local prior distribution (which is conditioned only on samples z_ω), thus enabling meaningful correlations between the encoded local and joint latent space, as later shown. Finally, the joint KL-divergence component (7) is akin to that in a standard variational autoencoder [63, 64]. Overall, MOHBA enables learning of a hierarchical behavioral space (at the joint and local agent levels, z_ω and z_α, respectively) that exposes interesting behavioral clusters.



(a) (b)

Figure 3: Results for 3-agent hill climbing domain (see interactive version here). (a) Example behavioral clusters discovered by MOHBA. (b) Trajectories corresponding to each cluster. Clusters A to C highlight joint agent behaviors, whereas D to F separately highlight those of individual agents (with other agents faded out in the latter clusters' trajectory plots for readability).

4 Experiments

Our experiments showcase a variety of use-cases for MOHBA, which enrich the typical reward-centric performance monitoring used during training. Data generation, training, networks, computation resources, and hyperparameter details are provided in Appendix A.2 of the supplementary materials.

MARL data generation. Multiagent trajectory data is generated for each considered domain via the Acme RL library [65], using the TD3 algorithm [66] in a decentralized fashion, with dataset management handled using RLDS [67]. Trajectories are collected at constant intervals throughout training, which also enables analysis of behavioral emergence. We conduct a wide sweep over random seeds for data generation, yielding a diverse set of trajectories to analyze using MOHBA.

MOHBA setup. To analyze the above data using MOHBA, we use a GMM (Gaussian Mixture Model) for the joint prior, a bidirectional LSTM (long short-term memory network) with GMM head for the joint encoder, an MLP (multi-layer perceptron) with Gaussian head for the local priors, a bidirectional LSTM with Gaussian head for the local encoder, and an MLP for reconstructed policies. GMMs are used for the joint prior and encoder as they produce discernible joint behavior clusters [68], whereas the conditioning of the local prior on z_ω yields such clusters at the local level with a standard Gaussian head. We use parameter-sharing across local priors, local encoders, and reconstructed policies, as common in multiagent setups [69], with a unique one-hot vector identifier appended to agent-specific network inputs to enable heterogeneity in model outputs. We conduct a wide sweep of MOHBA hypereparameters, including the latent space dimensionality (4 and 8-dimensional), MLP hidden sizes (64 and 128 units), LSTM hidden sizes (64 and 128 units), Adam optimizer [70] learning rates (0.001 and 0.0001), with 3 seeds per parameter set (see appendix for full details).

Independent analysis of joint (z_ω) and local (z_α) behavioral clusters. We here analyze the hierarchical latent structure learned by MOHBA. Specifically, we highlight differences in agent behaviors as identified at the joint and local levels, respectively, by z_ω and z_α. We first consider trajectories generated in a 3-agent hill-climbing domain (our earlier example in Fig. 1b). States and actions correspond, respectively, to 2D positions (x, y) and forces $(\Delta x, \Delta y)$ imparted by each agent for movement. Agents spawn at the origin and are each rewarded for climbing any of three hills within the domain in episodes of 50 timesteps (with rewards at each position indicated in Fig. 1b). We generate a dataset using 50 independent MARL training trials, each conducted for $1e5$ environment steps; trajectories are saved every 200 steps, yielding $1.25e6$ frames of data (25000 trajectories).

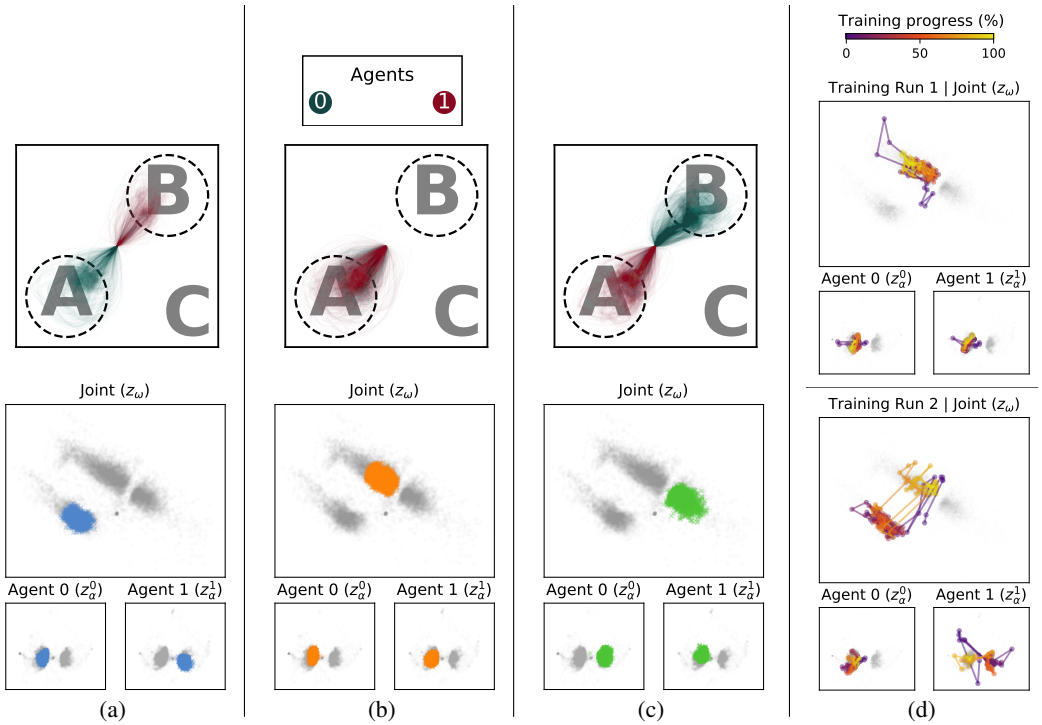


Figure 4: Results for two-agent coordination game (see interactive version here). (a) to (c) visualize key joint clusters, their corresponding local clusters for each agent, and the associated trajectories in the actual domain. (d) visualizes the progression of agent behaviors throughout the original MARL training phase, for two example training runs (top and bottom panels).

Figure 3a highlights several example clusters of joint and local behaviors identified by MOHBA, using samples of z_ω and z_α from the joint and local encoders. We use Euclidean distances in the original latent spaces to identify nearby vectors, then visualize their 2D projection using principal component analysis. For each cluster, we visualize all associated trajectories in Fig. 3b, thus enabling analysis of behaviors captured in latent space. Clusters A, B, and C correspond to examples of joint behaviors (z_ω). Cluster A contains trajectories early in training, where agents behave nearly randomly and have not learned to converge to a particular rewarding hill in the domain. In Cluster B, all three agents have learned to navigate towards the top-left hill. In Cluster C, agents 0 and 2 show preference for the bottom-left hill, whereas agent 1 prefers the right hill. Overall, the behavioral clusters at the joint level capture the collective behaviors of agents in a meaningful manner.

Next, we analyze individual agent clusters. Note that for all agents, three prominent clusters are apparent in their respective z_α spaces, as each training trial in the data generation process can lead to various agent-wise hill preferences. We compare two such clusters, D and E, for agent 1, observing in the trajectory plots that these corresponds to this agent preferring the top-left and bottom-left hills, respectively. Similarly, Cluster F corresponds to trajectories where agent 2 prefers the bottom-left hill. These results illustrate that the local latents reasonably disentangle each agent's observed behaviors.

Coupled analysis of joint (z_ω) and local (z_α) behavioral clusters. The above experiments independently analyzed the joint and local latent spaces. We can also concurrently analyze them to better understand local agent contributions to joint behaviors. Consider a two-agent domain with close inter-agent coordination (visualized in the top of Fig. 4a), with state and actions-spaces similar to the hill domain and episodes consisting of 50 timesteps. Three regions are defined in this domain: A and B (circular regions), and C (region exterior to the circles). When an agent enters a given region, it 'activates' the corresponding strategy in Table 1, with agents receiving rewards at each timestep according to the joint strategy they have activated. For example, if both agents enter region A, they each receive a reward of 1, whereas

Table 1: Coordination rewards.

		Agent 1		
		A	B	C
Agent 0	A	$(1,1)$	$(1,1)$	$(0,0)$
	B	$(1,1)$	$(0,0)$	$(0,0)$
	C	$(0,0)$	$(0,0)$	$(0,0)$

if one agent enters A while the other is in exterior region C, neither receives a reward. This domain involves a significant degree of coordination as agents must discover the rewarding regions, while receiving a sparse reward signal until a valid combination of strategies is discovered. There is also potential for miscoordination: navigating to region B is rewarding assuming the other agent navigates to A, but yields 0 reward if the other agent instead navigates to B (potentially destabilizing training). We run 50 independent MARL sweeps in this domain, yielding $1e6$ data frames (20000 trajectories).

As shown in Fig. 4, MOHBA discovers three dominant joint behavior clusters z_ω here. In each of Figs. 4a to 4c, we highlight one of these clusters and its corresponding local behavior latents z_α for each agent. MOHBA reveals that across the dataset, the agents have learned to cover all 3 optimal joint behaviors in Table 1: (A, A), (A, B), and (B, A). Moreover, despite each agent discovering two local behaviors (A and B), z_ω highlights only the 3 observed joint behaviors (i.e., does not simply highlight 4 clusters consisting of the Cartesian product of individual agents' behavior spaces).

Behavior emergence throughout MARL training. We next use MOHBA's latent space to inspect behavior emergence *during* MARL training. Figure 4d visualizes the training progression of two MARL runs used for data generation, tracking behavior changes throughout. In Training Run 1 (top panel of Fig. 4d), the agents converge to and maintain a fixed joint behavior throughout training. By contrast, Training Run 2 (bottom panel) has numerous behavior changepoints, where agents flip back and forth between preferring one of two clusters in z_ω. Concurrently inspecting the z_α space for Training Run 2, we observe that agent 0 converges to and maintains a consistent behavior, whereas agent 1 changes its preference sporadically, also explaining the detected changes in joint behaviors.

Baseline comparisons. We next compare against baselines previously used for multiagent behavioral analysis in the literature [9, 11]. An LSTM baseline conducts next-action prediction at each step in a trajectory τ, using an action-prediction loss (APL), defined as the $\mathcal{L}_2$ loss over predicted vs. ground truth actions. A flat-VAE baseline provides a non-hierarchical ablation of MOHBA that simply feeds the joint latent z_ω (rather than z^i_α) to reconstructed agent policies (i.e., $\pi^i_\theta(a^i|s, z_\omega)$); we use our usual loss (with the local KL term (6) removed) to train this VAE. We conduct a hyperparameter sweep for the baselines (see Appendix A.2), reporting the best results averaged over 3 random seeds.

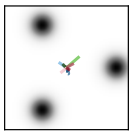
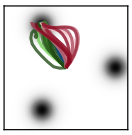
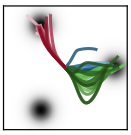
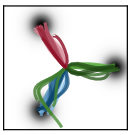
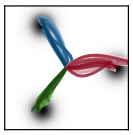
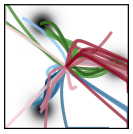
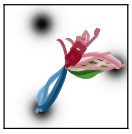
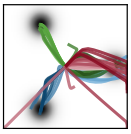
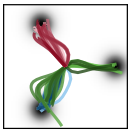
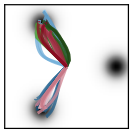
Table 2: Baseline comparisons. Action-prediction loss (APL) and intra-cluster trajectory distance (ICTD); lower is better for both.

	Hill-climbing domain		Coordination game	
	APL	ICTD	APL	ICTD
LSTM	4.8 ± 0.1	0.47 ± 0.19	2.9 ± 0.1	0.34 ± 0.15
VAE	6.9 ± 0.4	$\mathbf{0.18 \pm 0.13}$	5.0 ± 0.3	$\mathbf{0.16 \pm 0.10}$
MOHBA	$\mathbf{1.3 \pm 0.1}$	$\mathbf{0.17 \pm 0.13}$	$\mathbf{2.4 \pm 0.3}$	$\mathbf{0.16 \pm 0.10}$

Comparisons are conducted at the joint behavior level: for the LSTM, we use the final hidden state as an encoding of each trajectory; for our method and the VAE, we use z_ω directly. Table 2 compares the methods in the hill-climbing and coordination game domains. Here we note the APL, which measures how well each method reconstructs ground truth policies. Additionally, we use K-means (sweeping over the # of clusters) to identify behavior clusters for each method, then report the intra-cluster trajectory distance (ICTD), defined as the average distance of all trajectories in a cluster from the mean trajectory in said cluster (akin to intra-cluster point scatter, a common cluster analysis statistic [71]) . Combined, these measures provide a proxy for evaluating the latent representations in terms of enabling accurate reconstructions (APL) while clustering similar trajectories together (ICTD). MOHBA significantly outperforms the LSTM and VAE baselines in terms of APL, while also clustering similar trajectories at the z_ω level in terms of ICTD. We provide additional results including APL throughout training, full ICTD sweeps, and visualizations of the latent spaces for the baselines in Appendix A.3.

Discovering behavioral concepts for user-desired characteristics. Next, consider a scenario where a user wishes to identify behavioral concepts associated with multiagent characteristics of interest (e.g., concepts that yield high agent returns). We adopt the completeness-aware concept-based explanations framework of Yeh et al. [13], with slight changes to make it amenable to this setting (see Appendix A.2.5 for details). At a high-level, given a set of inputs, a set of concept vectors C in the same space as inputs, and prediction targets (e.g., characteristics of interest, such as agent returns in our domain), Yeh et al. [13] define a framework to compute class-conditioned Shapley values, called ConceptSHAP. To do so, every input is projected onto each of the concept vectors, yielding a vector of 'concept scores', which is then passed to a simple prediction head g (e.g., small MLP or linear model) to predict the targets and compute the ConceptSHAP. ConceptSHAP provides numerical

Table 3: Discovered concepts using z_ω in hill-climbing domain. For each user-desired concept (agent dispersion and return), 5 classes are constructed using the ground truth information in trajectories τ. The concept explanation framework of Yeh et al. [13] is then used to first predict the correct classes (using only z_ω, rather than the trajectory τ, as input), then identify core concepts related to each class.

Concept	Top discovered concept using z_ω (per class, with average concept measure beneath)				
	Class 0	Class 1	Class 2	Class 3	Class 4
Agent Dispersion (Classification accuracy: 54.27%)	 0.05 ± 0.13	 0.15 ± 0.06	 1.79 ± 0.10	 2.18 ± 0.19	 2.36 ± 0.10
Total Return (Classification accuracy: 60.98%)	 361.0 ± 256.0	 671.4 ± 115.1	 611.1 ± 244.2	 764.9 ± 72.4	 820.4 ± 155.0

scores interpreted as the importance of each concept in C for predicting a given target class, which is useful for identifying key concepts (and nearby inputs) associated with certain domain characteristics.

In Table 3, we use this technique to identify behavioral concepts in z_ω space associated with several characteristics of interest in the hill-climbing domain. The set of concepts C we consider are generated using K-means in the z_ω space (see Appendix A.2.5 for details), and a simple 2-layer MLP with 8-hidden units for prediction head g. The first row of Table 3 shows classes corresponding to increasing levels of agent dispersion in the domain (with dispersion defined as the sum of $\mathcal{L}_2$-distances of agents from their centroid at the final timestep of the episode). For each trajectory τ, we compute the associated dispersion, creating 5 classes of equal-sized bins (with labels 0 through 4 mapping to bins of increasing dispersion). We create a train-validation split of 80-20, then train the MLP g via a softmax-cross entropy loss to predict the correct classes using only z_ω as input (rather than the actual trajectory τ). We attain a validation set accuracy of 54.27%, signifying the predictive capabilities of z_ω. Next, we compute the class-conditioned ConceptSHAP, thus identifying the top-scoring concept vector for each class. In Table 3, we visualize the 20 trajectories with the closest z_ω to the top-scoring concept for each class (with the mean agent dispersion across these trajectories listed under each image). Intuitively, the identified concepts involve agents becoming increasingly dispersed, with agents first nearly stationary at the center (class 0), then all converging to the same hill (class 1), spreading across two hills (class 2), and finally covering all hills (classes 3 and 4).

The second row of Table 3 repeats the same experiment, now using classes associated with the sum of returns of agents. We attain a validation set accuracy of 60.98%, and similarly observe behavioral trajectories associated with generally increasing reward by identifying top clusters for each class (with some overlaps, e.g., classes 1 and 2 with high standard deviation in returns). Overall, this line of experiments provides both a means of quantifying the representational capacity of z_ω, and also of identifying clusters of behavioral concepts that summarize key user-defined characteristics.

Scalability to high-dimensional domains. We next test MOHBA's scalability to high-dimensional domains using the 2-Agent HalfCheetah multiagent MuJoCo domain [14], where agents 0 and 1, respectively, control the back and front limbs of a cheetah to coordinate movement. Each agent's state consists of a 6D vector summarizing velocity and position information for the 3 joints it controls, with its 3D action space corresponding to motor torques applied to said joints. The agents coordinate to maximize the forward-speed of the cheetah over episodes of 200 timesteps each. We generate data using 30 independent trials of MARL training, collecting $1e5$ total trajectories to train MOHBA.

Figure 5a visualizes the behavior space learned by MOHBA, wherein we observe several clusters. We highlight three example trajectories stemming from distinct clusters in the joint behavior space z_ω, showing the corresponding HalfCheetah behaviors in Fig. 5b. The left panel of each example provides a view of the cheetah's overall movement, where we observe key behavior differences: in

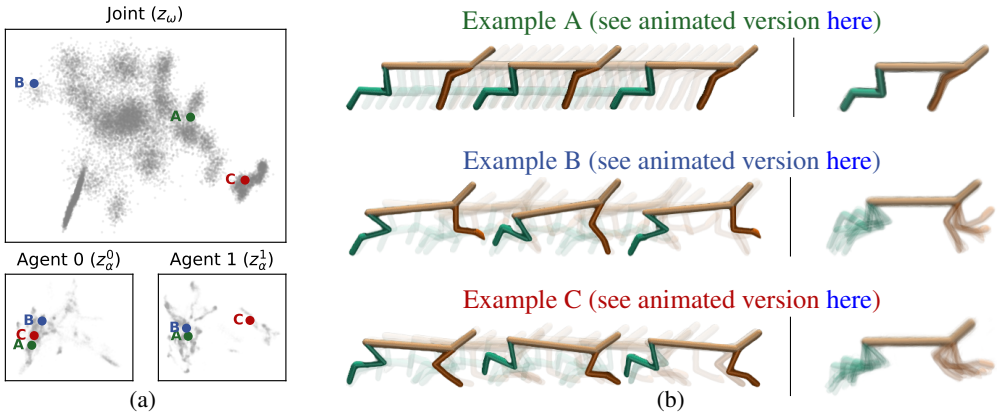


Figure 5: Multiagent MuJoCo HalfCheetah behavioral space (see interactive version here). Agent 0 and 1, respectively, control the back and front limbs, coordinating to move the cheetah. (a) Detected behavioral space, with three example trajectories indicated. (b) HalfCheetah behavior corresponding to the same three examples (left panels showing trajectory frames, and right panels showing the same frames with the cheetah torso aligned to disambiguate the back and front leg agent behaviors).

Example A, the cheetah runs forward using subtle vibration of its limbs; in Example B, it bounces forward with its torso arched up due to its front limb (agent 1) being more extended than its back limb (agent 0); in Example C, it moves closer to the ground with its torso arched down. In the latent space (Fig. 5a), we observe that for Examples B and C, the z_α^0 (back limb) latents are close to one another, while the z_α^1 (front limb) latents are far apart. To investigate these local agent behavioral differences, the right panel of Fig. 5b provides an overlaid view of the same frames, with the torso now aligned (making it easier to discern the behaviors of agent 0 vs. agent 1). Here we observe that the back limb (agent 0) behaves similarly across both examples, while the front limb (agent 1) stays much closer to the head for Example C, in contrast to Example B, which coincides with the findings in the z_α space.

5 Discussion

Our proposed method, MOHBA, leverages multiagent trajectory data to better understand agent behaviors, both during and after training. MOHBA assumes no knowledge of the agents' underlying training algorithms, does not require access to their hidden states or internal models, and applies even to reward-free settings. Our experiments showcased a variety of applications of MOHBA, including the analysis of joint and local agent behaviors, monitoring of behavior emergence throughout training, and discovery of behavioral concepts associated with certain user-specified criteria.

While we believe our approach is an important step in terms of increasing the understanding of multiagent systems, there are several limitations and potential societal impacts of note. A key limitation of our approach is related to the collection of a dataset of agent behaviors. By collecting this dataset throughout agent training, we ensure that the most prominent behaviors that can occur in a given environment can be identified using our method. However, this requires both storage of larger datasets than usual agent training requires, and also the use of a large enough sweep of agent training to sufficiently capture key behaviors. It may be interesting to consider follow-ups to our model that learn behavioral clusters in a streaming fashion, thus building knowledge of behaviors over time and permitting older data to be discarded throughout agent training.

Moreover, the study of behavioral interactions in multiagent systems can potentially be used for both positive and negative societal applications. For example, such an approach could be used to prevent certain undesirable behaviors by agents that interact with humans (e.g, self-driving cars), but potentially also used by adversaries to predict and exploit other behaviors (e.g., exploiting certain human preferences for harm), or even inadvertently cause harm due to misinterpretation of certain behavioral modes. As such, further research and evaluation will be required prior to deployment of this and related behavioral analysis approaches to human-facing domains. Nonetheless, as agent capabilities continue to grow, our view is that behavioral analysis of multiagent systems will become increasingly important and should complement traditional reward-based performance monitoring.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] We include these in the Discussions section.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] We include these in the discussions section.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes] These are provided in the main paper and the proofs included in the appendix.
   (b) Did you include complete proofs of all theoretical results? [Yes] Proofs are provided in the appendix.
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] We provide details for experiment reproducibility in Appendix A.2. We intend to include code for the model upon paper acceptance.

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] We provide all training details in Appendix A.2.

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] We provide all computational details in Appendix A.2.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

(a) If your work uses existing assets, did you cite the creators? [N/A] Our work does not use existing assets.

(b) Did you mention the license of the assets? [N/A] Our work does not use existing assets.

(c) Did you include any new assets either in the supplemental material or as a URL? [No]

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A] Our work does not use existing assets.

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A] Our work does not use existing assets.

5. If you used crowdsourcing or conducted research with human subjects...

(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] Our work does not crowdsourced or human subject data.

(b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A] Our work does not crowdsourced or human subject data.

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A] Our work does not crowdsourced or human subject data.