

# Novelty Assessment Report

**Paper:** When Is Diversity Rewarded in Cooperative Multi-Agent Learning?

**PDF URL:** <https://openreview.net/pdf?id=uJCGMBO6Qx>

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## Abstract

The success of teams in robotics, nature, and society often depends on the division of labor among diverse specialists; however, a principled explanation for when such diversity surpasses a homogeneous team is still missing. Focusing on multi-agent task allocation problems, we study this question from the perspective of reward design: what kinds of objectives are best suited for heterogeneous teams? We first consider an instantaneous, non-spatial setting where the global reward is built by two generalized aggregation operators: an inner operator that maps the  $N$  agents' effort allocations on individual tasks to a task score, and an outer operator that merges the  $M$  task scores into the global team reward. We prove that the curvature of these operators determines whether heterogeneity can increase reward, and that for broad reward families this collapses to a simple convexity test. Next, we ask what incentivizes heterogeneity to emerge when embodied, time-extended agents must learn an effort allocation policy. To study heterogeneity in such settings, we use multi-agent reinforcement learning (MARL) as our computational paradigm, and introduce Heterogeneity Gain Parameter Search (HetGPS), a gradient-based algorithm that optimizes the parameter space of underspecified MARL environments to find scenarios where heterogeneity is advantageous. Across different environments, we show that HetGPS rediscovers the reward regimes predicted by our theory to maximize the advantage of heterogeneity, both validating HetGPS and connecting our theoretical insights to reward design in MARL. Together, these results help us understand when behavioral diversity delivers a measurable benefit.

### Disclaimer

This report is **AI-GENERATED** using Large Language Models and WisPaper (a scholar search engine). It analyzes academic papers' tasks and contributions against retrieved prior work. While this system identifies **POTENTIAL** overlaps and novel directions, **ITS COVERAGE IS NOT EXHAUSTIVE AND JUDGMENTS ARE APPROXIMATE**. These results are intended to assist human reviewers and **SHOULD NOT** be relied upon as a definitive verdict on novelty.

Note that some papers exist in multiple, slightly different versions (e.g., with different titles or URLs). The system may retrieve several versions of the same underlying work. The current automated pipeline does not reliably align or distinguish these cases, so human reviewers will need to disambiguate them manually.

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## Core Task Landscape

This paper addresses: **Reward Design for Behavioral Diversity in Cooperative Multi-Agent Task Allocation**

A total of **12 papers** were analyzed and organized into a taxonomy with **13 categories**.

### Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Theoretical Foundations of Diversity and Reward Structure**
- **Intrinsic Reward and Incentive Mechanisms for Diversity**
- **Information-Theoretic and Representation-Based Diversity Promotion**
- **Population-Based and Multi-Policy Diversity Methods**
- **Distributed Task Allocation and Behavioral Heterogeneity**

### Complete Taxonomy Tree

- Reward Design for Behavioral Diversity in Cooperative Multi-Agent Task Allocation Survey Taxonomy
- Theoretical Foundations of Diversity and Reward Structure
  - Reward Curvature and Aggregation Operator Analysis ★ (1 papers)
  - [0] When Is Diversity Rewarded in Cooperative Multi-Agent Learning? (Anon et al., 2026) [View paper](#)
  - Economic Incentive Mechanisms for Cooperative Effort (1 papers)
  - [6] Incentives to help in multi-agent situations (Hideshi Itoh, 1991) [View paper](#)
- Intrinsic Reward and Incentive Mechanisms for Diversity
  - Peer-Based Social Incentive Rewards (1 papers)
  - [5] Peer incentive reinforcement learning for cooperative multiagent games (Tianle Zhang, 2022) [View paper](#)
  - Action-Based Intrinsic Reward for Cooperative Behavior (1 papers)
  - [8] Action-Based Intrinsic Reward Design for Cooperative Behavior Acquisition in Multi-Agent Reinforcement Learning (Iori Takeuchi, 2025) [View paper](#)
  - GNN-Driven Intrinsic Rewards for Heterogeneous Cooperation (1 papers)
  - [4] Enhancing heterogeneous multi-agent cooperation in decentralized marl via GNN-driven intrinsic rewards (Jahir Sadik Monon, 2024) [View paper](#)
  - Potential-Based Reward Shaping with Reputation Filtering (1 papers)
  - [7] Reputation-Filtered Reward Reshaping: Encouraging Cooperation in High Dimensional Semi-Cooperative Multi-agent Settings (H Raissouni, 2025) [View paper](#)
- Information-Theoretic and Representation-Based Diversity Promotion
  - Mutual Information Maximization for Agent Diversity (1 papers)
  - [1] Celebrating diversity in shared multi-agent reinforcement learning (Li Chenghao, 2021) [View paper](#)
  - Explicit Diversity Control via Principled Measures (1 papers)
  - [9] Controlling Behavioral Diversity in Multi-Agent Reinforcement Learning (Bettini, 2024) [View paper](#)
- Population-Based and Multi-Policy Diversity Methods
  - Population-Based Exploration for Sparse Rewards (1 papers)
  - [2] Population-based diverse exploration for sparse-reward multi-agent tasks (Toby Walsh, 2024) [View paper](#)
  - Reward Randomization for Strategic Diversity Discovery (1 papers)

- [10] Discovering diverse multi-agent strategic behavior via reward randomization (Tang, 2021) [View paper](#)
- Leader-Collaborator Frameworks with Knowledge Distillation (1 papers)
- [12] Leaders and Collaborators: Addressing Sparse Reward Challenges in Multi-Agent Reinforcement Learning (Shaoqi Sun, 2024) [View paper](#)
- Distributed Task Allocation and Behavioral Heterogeneity
  - Game-Theoretic Distributed Task Assignment with Behavioral Entropy (1 papers)
  - [3] Behaviorally Heterogeneous Multi-Agent Exploration Using Distributed Task Allocation (Mandal, 2025) [View paper](#)
  - Reward Function Impact on Behavioral Diversity in Foraging (1 papers)
  - [11] Reward and diversity in multirobot foraging (Balch, 1999) [View paper](#)

## Narrative

Core task: reward design for behavioral diversity in cooperative multi-agent task allocation. The field addresses how to structure rewards so that multiple agents develop distinct yet complementary behaviors when solving shared tasks. The taxonomy reveals five main branches: theoretical foundations examining how reward curvature and aggregation operators shape emergent diversity; intrinsic reward mechanisms that provide agent-specific bonuses for novel or differentiated actions; information-theoretic approaches leveraging entropy or mutual information to promote representational diversity; population-based methods that maintain multiple policies or subpopulations with distinct strategies; and distributed task allocation frameworks emphasizing behavioral heterogeneity in decentralized settings. Early foundational work like Incentives to Help[6] and Multirobot Foraging Diversity[11] established the importance of incentive alignment, while recent efforts such as Celebrating Diversity[1] and Reward Randomization[10] explore how stochastic or structured reward perturbations can sustain varied agent roles.

Several active lines of work highlight key trade-offs between explicit diversity enforcement and emergent specialization. Population-based approaches like Population Diverse Exploration[2] and Heterogeneous Exploration[3] maintain ensembles of policies to cover diverse solution modes, whereas intrinsic reward methods such as GNN Intrinsic Rewards[4] and Action Intrinsic Reward[8] inject agent-specific bonuses to encourage differentiation without requiring separate policy populations. Peer-based mechanisms like Peer Incentive Learning[5] and Reputation Filtered Reshaping[7] dynamically adjust rewards based on inter-agent interactions, balancing cooperation with role diversity. The original paper, Diversity Rewarded[0], sits within the theoretical foundations branch, specifically analyzing reward curvature and aggregation operators—a perspective that complements the more mechanism-focused studies like Controlling Diversity[9] and Leaders and Collaborators[12]. By examining how mathematical properties of reward functions influence the stability and richness of emergent behavioral diversity, Diversity Rewarded[0] provides analytical grounding for the design choices explored empirically across neighboring branches.

## Related Works in Same Category

No sibling papers were found in the same taxonomy leaf. A taxonomy-subtopic-level comparison will be produced instead.

### Taxonomy-Level Summary

The original leaf focuses on mathematical analysis of reward aggregation operators (convexity, curvature) to understand when team heterogeneity improves performance in multi-agent task allocation. The sibling subtopic examines economic incentive design (principal-agent models, moral hazard) for eliciting cooperative helping behaviors. Both address reward mechanisms for cooperation, but differ fundamentally in methodology: one uses formal operator analysis while the other applies economic contract theory.

**Similarities:** - Both address reward design for cooperative multi-agent systems - Both consider how incentive structures influence collective performance - Both are concerned with optimizing team outcomes through reward mechanisms

**Differences:** - Original leaf analyzes mathematical properties of aggregation operators; sibling uses economic principal-agent frameworks - Original leaf focuses on heterogeneous vs. homogeneous team composition; sibling focuses on moral hazard and effort elicitation - Original leaf excludes empirical studies without formal analysis; sibling excludes reinforcement learning contexts - Original leaf studies reward curvature effects on diversity; sibling studies compensation schemes for helping behaviors

**Suggested Search Directions:** - Connections between aggregation operator curvature and economic utility functions in team incentive design - How principal-agent models could incorporate team heterogeneity and diversity metrics - Formal analysis of moral hazard under different reward aggregation schemes

### Sibling Subtopics

- **Economic Incentive Mechanisms for Cooperative Effort** (leaves: 1, papers: 1)
- Scope: Examines principal-agent compensation schemes and moral hazard in multi-agent cooperation with helping behaviors.
- Exclude: Excludes reinforcement learning contexts; see intrinsic reward methods or peer incentive approaches.

## Contributions Analysis

**Overall novelty summary.** The paper establishes a theoretical framework linking reward function curvature to the emergence of heterogeneous agent behaviors in multi-agent task allocation. It resides in the 'Reward Curvature and Aggregation Operator Analysis' leaf, which contains only this single paper within the broader 'Theoretical Foundations of Diversity and Reward Structure' branch. This positioning indicates a relatively sparse research direction: while the taxonomy includes twelve papers across thirteen leaf nodes addressing reward design for behavioral diversity, no other work directly analyzes aggregation operator properties to predict when heterogeneity outperforms homogeneity. The paper thus occupies a unique niche within the field's theoretical foundations.

The taxonomy reveals that neighboring branches focus on algorithmic mechanisms rather than mathematical characterization. The 'Intrinsic Reward and Incentive Mechanisms' branch (four papers) designs agent-specific bonuses to promote diversity, while 'Information-Theoretic and Representation-Based Diversity Promotion' (two papers) leverages mutual information maximization. The 'Population-Based and Multi-Policy Diversity Methods' branch (three papers) maintains multiple policies to discover diverse strategies. The original paper diverges by providing analytical conditions under which reward structure itself—independent of learning algorithms—favors heterogeneity. Its scope excludes empirical algorithm development, instead offering formal operator analysis that could inform the design choices explored in these neighboring branches.

Among seven candidates examined through limited semantic search, none clearly refutes the paper's three core contributions. The theoretical Schur-convexity characterization examined one candidate with no refutable overlap. The HetGPS algorithm examined four candidates, none providing prior implementations of this specific parameter search method. The connection between reward curvature theory and MARL validation examined two candidates without finding overlapping empirical frameworks. This absence of refutation within the examined scope suggests the work introduces novel theoretical machinery, though the small candidate pool (seven papers) means the search does not comprehensively cover all potential prior work in reward shaping or diversity promotion.

Given the limited search scope and the paper's position as the sole occupant of its taxonomy leaf, the work appears to introduce a distinct analytical perspective within a field otherwise dominated by algorithmic and empirical approaches. The theoretical characterization of reward curvature effects represents a methodological departure from neighboring intrinsic reward and population-based methods. However, the analysis is constrained to top-seven semantic matches and does not exhaustively survey adjacent areas such as game-

theoretic task allocation or broader reward shaping literature, leaving open the possibility of related mathematical frameworks in unexplored corners of the field.

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This paper presents **3 main contributions**, each analyzed against relevant prior work:

### **Contribution 1: Theoretical characterization of when heterogeneity increases reward via Schur-convexity**

**Description:** The authors establish a theoretical framework showing that the heterogeneity gain in multi-agent task allocation is determined by the Schur-convexity or Schur-concavity of inner and outer reward aggregation operators. They prove that Schur-convex inner aggregators and Schur-concave outer aggregators favor heterogeneous teams, while reversing these properties eliminates the advantage.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. Robust Equilibria in Shared Resource Allocation via Strengthening Border's Theorem**

URL: [View paper](#)

##### **Brief Assessment**

Robust Equilibria[15] focuses on repeated resource allocation with Schur-convexity used for proving properties of allocation mechanisms, not for characterizing heterogeneity gains in multi-agent task allocation. The candidate's Schur-convexity analysis concerns allocation probabilities and equilibrium robustness, while the original paper analyzes reward aggregation operators to determine when behavioral diversity is advantageous.

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### **Contribution 2: Heterogeneity Gain Parameter Search (HetGPS) algorithm**

**Description:** The authors develop HetGPS, a gradient-based bilevel optimization algorithm that automatically searches over differentiable environment parameters to discover configurations that maximize or minimize the empirical heterogeneity gain. This enables systematic exploration of when behavioral diversity is beneficial in MARL settings beyond the scope of their theoretical analysis.

This contribution was assessed against **4 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. A stochastic linearized augmented lagrangian method for decentralized bilevel optimization**

URL: [View paper](#)

##### **Brief Assessment**

Stochastic Linearized Lagrangian[18] addresses decentralized bilevel optimization for multi-agent reinforcement learning with consensus constraints, not gradient-based environment parameter search to maximize heterogeneity gain in task allocation settings.

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#### **2. Self-Reflective Multi-Agent Reinforcement Architecture for Autonomous Recommendation Policy Evolution**

URL: [View paper](#)

##### **Brief Assessment**

Self-Reflective Architecture[16] describes a bi-level learning process with alternating gradient ascent on policy parameters, but focuses on autonomous recommendation policy evolution rather than environment parameter optimization for heterogeneity gain maximization in MARL settings.

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#### **3. Policy Optimization for Continuous-time Linear-Quadratic Graphon Mean Field Games**

URL: [View paper](#)

##### **Brief Assessment**

Graphon Mean Field[17] focuses on policy optimization for continuous-time linear-quadratic graphon mean field games using bilevel optimization to find Nash equilibria. The original paper's HetGPS uses bilevel optimization to search environment parameters that maximize heterogeneity gain in multi-agent task allocation settings. These are fundamentally different objectives and problem domains.

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#### **4. Bi-Level Multi-Agent Reinforcement Learning for Intervening in Intertemporal Social Dilemmas**

URL: [View paper](#)

##### **Brief Assessment**

Intertemporal Social Dilemmas[19] focuses on bi-level optimization for intervening in social dilemmas with temporal dynamics, not on gradient-based environment parameter search to maximize heterogeneity gain in multi-agent task allocation settings. The provided candidate text fragments are insufficient to establish any methodological overlap with HetGPS.

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### **Contribution 3: Connection between reward curvature theory and MARL through empirical validation**

**Description:** The authors empirically demonstrate across multiple environments (matrix games, multi-goal-capture, tag, football) that their theoretical predictions about reward curvature transfer to embodied, time-extended MARL settings. They show HetGPS independently rediscovers the theoretically optimal reward structures, validating both the algorithm and the practical applicability of their curvature theory.

This contribution was assessed against **2 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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#### **1. Adaptive curvature exploration geometric graph neural network**

URL: [View paper](#)

##### **Brief Assessment**

Adaptive Curvature GNN[13] focuses on geometric graph neural networks with learnable curvature for graph representation, not on reward curvature theory in multi-agent reinforcement learning task allocation settings.

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#### **2. The Topological Filter: Curvature-Constrained Resonance and Self-Stabilizing Alignment in Symbolic Persona Coding (SPC v3)**

URL: [View paper](#)

##### **Brief Assessment**

Topological Filter[14] mentions 'reward curvature' only in passing and focuses on topological filtering and symbolic persona coding rather than empirical validation of reward curvature theory in multi-agent reinforcement learning settings.

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## Appendix: Text Similarity Detection

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No high-similarity text segments were detected across any compared papers.

## References

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- [0] When Is Diversity Rewarded in Cooperative Multi-Agent Learning? [View paper](#)
- [1] Celebrating diversity in shared multi-agent reinforcement learning [View paper](#)
- [2] Population-based diverse exploration for sparse-reward multi-agent tasks [View paper](#)
- [3] Behaviorally Heterogeneous Multi-Agent Exploration Using Distributed Task Allocation [View paper](#)
- [4] Enhancing heterogeneous multi-agent cooperation in decentralized marl via GNN-driven intrinsic rewards [View paper](#)
- [5] Peer incentive reinforcement learning for cooperative multiagent games [View paper](#)
- [6] Incentives to help in multi-agent situations [View paper](#)
- [7] Reputation-Filtered Reward Reshaping: Encouraging Cooperation in High Dimensional Semi-Cooperative Multi-agent Settings [View paper](#)
- [8] Action-Based Intrinsic Reward Design for Cooperative Behavior Acquisition in Multi-Agent Reinforcement Learning [View paper](#)
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- [11] Reward and diversity in multirobot foraging [View paper](#)
- [12] Leaders and Collaborators: Addressing Sparse Reward Challenges in Multi-Agent Reinforcement Learning [View paper](#)
- [13] Adaptive curvature exploration geometric graph neural network [View paper](#)
- [14] The Topological Filter: Curvature-Constrained Resonance and Self-Stabilizing Alignment in Symbolic Persona Coding (SPC v3) [View paper](#)
- [15] Robust Equilibria in Shared Resource Allocation via Strengthening Border's Theorem [View paper](#)
- [16] Self-Reflective Multi-Agent Reinforcement Architecture for Autonomous Recommendation Policy Evolution [View paper](#)
- [17] Policy Optimization for Continuous-time Linear-Quadratic Graphon Mean Field Games [View paper](#)
- [18] A stochastic linearized augmented lagrangian method for decentralized bilevel optimization [View paper](#)
- [19] Bi-Level Multi-Agent Reinforcement Learning for Intervening in Intertemporal Social Dilemmas [View paper](#)