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**Diversity-Preserving Horizontal Federated Reinforcement
Learning for Chess: A Clustered Approach to
Style-Preserving Multi-Agent Training**



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Abstract

Federated learning has emerged as a transformative paradigm for distributed machine learning, enabling collaborative model training without centralized data sharing. However, standard federated learning approaches, particularly Federated Averaging (FedAvg), employ homogenizing aggregation strategies that systematically eliminate client heterogeneity in pursuit of global model convergence. When applied to domains with inherent beneficial diversity, such as chess, where tactical, positional, and dynamic playing styles each offer unique strategic advantages, this homogenization destroys valuable specialization that has been recognized by domain experts for centuries.

This thesis introduces a novel diversity-preserving federated reinforcement learning framework specifically designed to maintain strategic heterogeneity while enabling collaborative learning. Applied to chess artificial intelligence, our approach clusters federated learning nodes by playing style, tactical/aggressive, positional/strategic, and dynamic/flexible, based on opening repertoire analysis grounded in grandmaster-maintained theoretical frameworks from the Encyclopedia of Chess Openings.

Our methodology employs a three-phase training approach: (1) individual style development through specialized self-play training, (2) intra-cluster federated learning that strengthens style-specific capabilities while preserving strategic identity, and (3) inter-cluster collaborative learning that shares universal chess knowledge while maintaining stylistic diversity. The approach leverages network analysis of chess opening relationships, validated through empirical studies of over 472,000 online games, to establish natural clustering boundaries that preserve beneficial heterogeneity.

Experimental evaluation demonstrates that diversity-preserving federated learning significantly outperforms traditional federated approaches in chess contexts. Our clustered federated engines maintain distinct playing styles while achieving superior adaptive performance against varied opponents compared to homoge-

nized baseline models. Statistical analysis reveals that preserved diversity leads to improved strategic flexibility, with tactical engines excelling in sharp positions, positional engines dominating closed structures, and dynamic engines adapting effectively to complex middlegame scenarios.

The research makes several novel contributions: (1) theoretical formalization of diversity-preserving federated learning with convergence guarantees, (2) integration of domain-specific expert knowledge with data-driven federated approaches, (3) demonstration that beneficial client heterogeneity can be maintained while achieving collaborative learning benefits, and (4) comprehensive evaluation framework for measuring both performance and diversity preservation in federated systems.

Results show that our diversity-preserving approach achieves comparable chess strength to traditional centralized training while maintaining the computational efficiency and privacy advantages of federated learning. Furthermore, the preserved stylistic diversity enables superior performance against human players and varied AI opponents, validating the importance of maintaining beneficial heterogeneity in collaborative learning systems. The framework’s principles demonstrate potential for generalization to other strategic domains where agent diversity provides complementary advantages.

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Chapter 1

Introduction

1.1 Research Background and Motivation

The advent of federated learning has revolutionized distributed machine learning by enabling collaborative model training without centralized data sharing [4]. Simultaneously, reinforcement learning has achieved remarkable success in complex strategic domains, most notably demonstrated by AlphaZero’s mastery of chess, shogi, and Go through self-play [5]. The intersection of these paradigms, federated reinforcement learning, presents unprecedented opportunities for developing distributed intelligent systems that can leverage collective experience while maintaining privacy and computational efficiency.

In the domain of chess artificial intelligence, the homogenization of playing styles represents a fundamental challenge that has received limited attention in current research. Traditional federated learning approaches, particularly Federated Averaging (FedAvg) [4], inherently drive participating models toward convergence, effectively eliminating the beneficial diversity that characterizes human chess expertise. This convergence tendency directly contradicts centuries of chess theory, which recognizes the existence of diverse playing styles such as tactical, positional, aggressive and dynamic approaches, each offering unique strategic advantages in different game contexts [3].

Recent empirical analysis has demonstrated that chess players naturally cluster by playing style preferences, with opening repertoire choices serving as reliable indicators of strategic inclinations [1]. This natural clustering suggests that beneficial heterogeneity exists in chess expertise and should be preserved rather than eliminated through homogenizing aggregation methods. The preservation of such diversity is not merely an academic curiosity but represents a fundamental requirement for developing chess AI systems that can adapt to varied opponents and game contexts.

The computational advantages of federated learning become particularly compelling when applied to chess engine development, where training state-of-the-art models requires substantial computational resources typically available only to major technology companies. By enabling distributed training across multiple nodes while preserving the strategic diversity that makes chess intellectually rich, federated chess learning could democratize access to advanced chess AI development while maintaining the game’s inherent complexity and appeal.

1.2 Problem Statement

Standard federated learning protocols, exemplified by Federated Averaging (FedAvg), employ homogenizing aggregation strategies that systematically eliminate client heterogeneity in pursuit of global model convergence [2]. When applied to chess reinforcement learning, this homogenization process destroys the beneficial diversity of playing styles that has been recognized as fundamental to chess mastery for centuries.

Specifically, the application of FedAvg to distributed chess engine training exhibits the following critical limitations:

Strategic Homogenization: Traditional federated aggregation forces diverse chess engines toward a uniform playing style that represents a statistical average of all participants, eliminating the tactical aggressiveness, positional depth, and dynamic flexibility that characterize distinct chess approaches.

Loss of Adaptive Capability: Homogenized models lose the ability to adapt

their playing style to different opponents or game situations, a capability that human chess masters employ to optimize their chances of success against varied competition.

Reduced Learning Efficiency: By forcing convergence toward a single strategic approach, traditional federated learning fails to leverage the complementary knowledge that different playing styles contribute to overall chess understanding.

Theoretical Inconsistency: The homogenization approach contradicts established chess theoretical frameworks maintained by grandmaster authorities, which recognize tactical, positional, and dynamic approaches as equally valid but strategically distinct paradigms [3, 6].

The central research problem addressed in this thesis is: *How can federated learning be adapted to preserve beneficial strategic diversity in chess reinforcement learning while still enabling collaborative knowledge transfer across distributed training nodes?*

This problem requires developing novel aggregation mechanisms that maintain the distinct strategic identities of different chess playing styles while facilitating the sharing of universal chess knowledge such as tactical motifs, endgame principles, and fundamental strategic concepts.

1.3 Research Objectives and Questions

1.3.1 Primary Research Questions

This research addresses four primary questions that collectively examine the feasibility and effectiveness of diversity-preserving federated learning in chess:

RQ1: Style Preservation Feasibility Can federated learning architectures be designed to preserve distinct chess playing styles while enabling collaborative learning across distributed nodes?

RQ2: Knowledge Transfer Optimization What is the optimal balance between style-specific knowledge preservation and universal chess knowledge sharing

in a federated learning context?

RQ3: Performance vs. Diversity Trade-offs How do diversity-preserving federated chess engines perform compared to traditional homogenized federated models and individual engines trained in isolation?

RQ4: Clustering Strategy Effectiveness Which clustering strategies most effectively group chess engines by playing style while maintaining intra-cluster learning benefits and inter-cluster knowledge transfer opportunities?

1.3.2 Secondary Research Questions

Supporting the primary research objectives, several secondary questions explore specific aspects of the proposed approach:

SQ1: Style Quantification Methods How can chess playing styles be quantitatively measured and validated using both computational metrics and chess theoretical frameworks?

SQ2: Communication Efficiency What are the communication overhead implications of clustered federated learning compared to standard federated approaches in chess training contexts?

SQ3: Scalability Considerations How does the proposed diversity-preserving approach scale with increasing numbers of participating nodes and playing style categories?

SQ4: Generalization Beyond Chess To what extent can the diversity-preserving federated learning principles identified in chess be generalized to other strategic domains with inherent style diversity?

SQ5: Human-AI Style Similarity How closely do the preserved chess playing styles in federated engines correspond to recognized human playing style categories?

1.4 Research Contributions

This thesis makes several novel contributions to the intersection of federated learning and reinforcement learning, with specific applications to chess artificial intelligence:

Theoretical Contributions:

- Development of a formal framework for diversity-preserving federated reinforcement learning that balances style preservation with collaborative learning
- Mathematical formalization of style-based clustering criteria for strategic domains with inherent player diversity
- Theoretical analysis of convergence properties in heterogeneous federated reinforcement learning systems

Methodological Contributions:

- Novel clustering-based federated learning architecture that preserves beneficial client heterogeneity
- Integration of domain-specific expert knowledge (grandmaster chess theory) with data-driven federated learning approaches
- Adaptive aggregation mechanisms that enable selective knowledge transfer while maintaining strategic diversity
- Comprehensive evaluation framework for measuring both performance and diversity preservation in federated learning systems

Empirical Contributions:

- First large-scale empirical study of diversity-preserving federated learning applied to chess reinforcement learning
- Demonstration that distinct chess playing styles can be maintained while achieving collaborative learning benefits

- Validation that preserved diversity leads to superior adaptive performance against varied opponents
- Comprehensive comparison of diversity-preserving approaches against traditional federated learning baselines

Practical Contributions:

- Open-source implementation of diversity-preserving federated chess learning system
- Reproducible experimental framework for evaluating federated learning in strategic domains
- Practical guidelines for applying diversity-preserving federated learning to other domains with inherent agent heterogeneity
- Chess education applications enabling human players to train against AI opponents with distinct, consistent playing styles

1.5 Thesis Structure

This thesis is organized into eight chapters that progress from theoretical foundations through implementation and evaluation to conclusions and future work:

Chapter 2: Literature Review and Related Work provides comprehensive coverage of relevant research in federated learning, reinforcement learning, and chess artificial intelligence. Special attention is given to personalized and clustered federated learning approaches, horizontal federated reinforcement learning frameworks, and the theoretical foundations of chess playing style diversity.

Chapter 3: Methodology establishes the epistemological foundation for treating grandmaster-maintained chess knowledge as authoritative academic sources, develops the chess playing style classification framework, and details the federated node clustering strategy. This chapter also specifies the individual node architecture, federated learning protocols, and comprehensive evaluation framework.

Chapter 4: System Implementation documents the technical architecture and software implementation of the diversity-preserving federated chess learning system. Detailed descriptions of chess engine implementation, federated learning infrastructure, and evaluation tools provide the foundation for experimental reproducibility.

Chapter 5: Experimental Design and Setup defines the experimental objectives, dataset construction, and baseline establishment procedures. Comprehensive specification of experimental configurations and controlled variables ensures rigorous evaluation of the proposed approach.

Chapter 6: Results and Analysis presents empirical findings from the three-phase training methodology, including individual style development, intra-cluster federated learning, and inter-cluster collaborative learning results. Comprehensive performance evaluation, ablation studies, and statistical significance testing validate the research hypotheses.

Chapter 7: Discussion interprets the empirical findings within the broader context of federated learning and chess AI research. Theoretical implications, practical applications, methodology evaluation, and comparison with existing approaches provide comprehensive analysis of the research contributions.

Chapter 8: Conclusions and Future Work summarizes the research conclusions, contributions to knowledge, and limitations of the current work. Detailed future research directions and interdisciplinary applications suggest avenues for extending the diversity-preserving federated learning paradigm.

The thesis is supported by comprehensive appendices providing implementation details, additional results, and reproducibility guidelines to enable future research building upon these foundations.

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