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



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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, with comprehensive validation through a physical chess-playing robot system. 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 integrated with physical robotic demonstration: (1) individual style development through specialized self-play training, (2) intra-cluster federated learning that strengthens style-specific capabilities while preserving strategic identity, (3) inter-cluster collaborative learning that shares universal chess knowledge while maintaining stylistic diversity, and (4) physical robot deployment that enables human players to experience and learn from distinct AI playing styles through tangible chess gameplay.

The complete system integrates advanced computer vision for real-time chess board analysis, precise robotic manipulation for piece movement, and human-robot interaction protocols that allow users to select and play against different federated chess personalities. This physical demonstration validates that preserved diversity

in federated learning translates to genuinely distinguishable playing experiences, transforming abstract AI concepts into tangible educational interactions.

Experimental evaluation demonstrates that diversity-preserving federated learning significantly outperforms traditional federated approaches in both computational chess contexts and physical robot deployment. Our clustered federated engines maintain distinct playing styles while achieving superior adaptive performance against varied opponents compared to homogenized baseline models. The robotic system successfully executes moves with 98.7% precision while maintaining style-specific decision patterns that human players can reliably distinguish and learn from.

Statistical analysis reveals that preserved diversity leads to improved strategic flexibility across both digital and physical domains, with tactical engines excelling in sharp positions, positional engines dominating closed structures, and dynamic engines adapting effectively to complex middlegame scenarios. Human interaction studies demonstrate significant learning improvements when players engage with style-consistent robotic opponents compared to generic chess engines.

The research makes several novel contributions spanning artificial intelligence, robotics, and educational technology: (1) theoretical formalization of diversity-preserving federated learning with convergence guarantees, (2) integration of domain-specific expert knowledge with data-driven federated approaches, (3) first comprehensive physical chess robot system powered by federated learning, (4) demonstration that beneficial client heterogeneity can be maintained while achieving collaborative learning benefits, (5) complete human-robot chess interaction framework enabling style-based learning, and (6) comprehensive evaluation framework for measuring both performance and diversity preservation in federated systems deployed to physical robotics.

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. The integrated robotic system enables unprecedented educational applications, allowing human players to experience distinct AI personalities through physical gameplay while providing

quantifiable evidence that federated diversity preservation creates genuinely different and valuable playing experiences. The framework's principles demonstrate clear potential for generalization to other strategic domains where agent diversity provides complementary advantages, with immediate applications in educational robotics and human-AI collaborative learning systems.

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Chapter 1

Introduction

1.1 Research Background and Motivation

The convergence of federated learning, reinforcement learning, and educational robotics presents unprecedented opportunities for developing intelligent systems that preserve beneficial diversity while enabling tangible human interaction. The advent of federated learning has revolutionized distributed machine learning by enabling collaborative model training without centralized data sharing [1], while 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 [2]. Simultaneously, advances in educational robotics have created new possibilities for human-AI interaction that transform abstract computational concepts into concrete, experiential learning opportunities.

In the domain of chess artificial intelligence, the homogenization of playing styles represents a fundamental challenge that extends beyond computational efficiency to impact human learning and engagement. Traditional federated learning approaches, particularly Federated Averaging (FedAvg) [1], 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].

The motivation for this research stems from three critical observations that reveal significant gaps in current federated learning applications:

Loss of Strategic Diversity in AI Systems: 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 [4]. This natural clustering suggests that beneficial heterogeneity exists in chess expertise and should be preserved rather than eliminated through homogenizing aggregation methods. However, no existing federated learning framework specifically addresses the preservation of such strategic diversity while maintaining collaborative learning benefits.

Disconnect Between AI Capabilities and Human Learning: While modern chess engines achieve superhuman performance, they often provide generic, homogenized playing experiences that fail to offer the varied learning opportunities that human players need for skill development. Human chess improvement relies on exposure to different playing styles and strategic approaches, yet current AI systems increasingly converge toward similar patterns that, while optimal, provide limited educational value for human learners seeking to understand chess diversity.

Lack of Physical Validation for Federated Learning Diversity: Existing federated learning research predominantly focuses on computational metrics and algorithmic performance, with limited attention to whether preserved diversity translates into genuinely different and valuable user experiences. The field lacks comprehensive physical validation systems that can demonstrate whether theoretical diversity preservation creates meaningful real-world differences that humans can recognize, learn from, and benefit from in practical applications.

These observations led to the realization that chess represents an ideal domain for developing diversity-preserving federated learning approaches, with the additional opportunity to validate these approaches through physical robotic systems

that enable direct human interaction. 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, and by validating this diversity through physical robotic demonstration, federated chess learning could democratize access to advanced chess AI development while providing tangible proof of the educational value of preserved diversity.

Furthermore, the integration of physical chess-playing robotics addresses a critical gap in human-AI interaction research. While significant advances have been made in developing chess AI systems and in building robotic manipulation systems, few attempts have been made to create comprehensive systems that bridge high-level strategic AI decision-making with precise physical execution, particularly in educational contexts where style diversity is crucial for effective learning.

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 [5]. When applied to chess reinforcement learning and deployed in physical robotic systems designed for human interaction, this homogenization process creates multiple interconnected problems that span computational efficiency, educational effectiveness, and human-robot interaction quality.

Specifically, the application of traditional federated learning to distributed chess engine training and physical robotic deployment exhibits the following critical limitations:

Strategic Homogenization in Distributed Training: Traditional federated aggregation forces diverse chess engines toward a uniform playing style that represents a statistical average of all participants, eliminating the tactical aggres-

siveness, positional depth, and dynamic flexibility that characterize distinct chess approaches. This homogenization not only reduces the computational diversity that could benefit distributed learning but also creates generic AI personalities that provide limited educational value when deployed in interactive systems.

Loss of Adaptive Capability in Physical Deployment: 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. When deployed in physical robotic systems designed for human interaction, this limitation becomes particularly problematic as human learners benefit from exposure to varied strategic approaches rather than encountering the same generic playing pattern regardless of the selected opponent or learning context.

Reduced Learning Efficiency in Collaborative Training: 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. This inefficiency is compounded when the trained models are deployed in educational robotic systems, as the lack of strategic diversity limits the range of learning experiences that can be provided to human users.

Inadequate Physical Validation of Diversity Preservation: Current federated learning research lacks comprehensive methods for validating whether theoretical diversity preservation translates into meaningful differences in real-world applications. The absence of physical validation systems means that claims about diversity preservation remain abstract and unverified, limiting confidence in the practical value of advanced federated learning approaches.

Limited Human-Robot Interaction Design for Educational Applications: Existing robotic chess systems focus primarily on mechanical execution rather than leveraging AI diversity for educational purposes. The lack of integration between advanced federated learning approaches and educational robotics represents a significant missed opportunity for creating more effective human-AI learning environments.

Theoretical Inconsistency with Domain Expertise: 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]. This inconsistency becomes particularly problematic when developing educational systems intended to teach chess concepts that depend on understanding strategic diversity.

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 enabling collaborative knowledge transfer across distributed training nodes, and how can this diversity be validated and utilized through physical robotic systems that provide meaningful educational experiences for human learners?*

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. Additionally, it requires creating comprehensive physical validation systems that demonstrate the practical value of preserved diversity through tangible human-robot interaction experiences that prove the educational and engagement benefits of maintaining strategic heterogeneity in federated learning systems.

1.3 Research Objectives and Questions

1.3.1 Primary Research Questions

This research addresses five primary questions that collectively examine the feasibility, effectiveness, and practical validation of diversity-preserving federated learning in chess through physical robotic demonstration:

RQ1: Diversity-Preserving Federated Learning Feasibility Can federated learning architectures be designed to preserve distinct chess playing styles while enabling collaborative learning across distributed nodes, and can this preservation be validated through measurable differences in decision-making patterns and

strategic approaches?

RQ2: Knowledge Transfer Optimization in Heterogeneous Systems What is the optimal balance between style-specific knowledge preservation and universal chess knowledge sharing in a federated learning context, and how can this balance be maintained when deploying trained models to physical robotic systems that interact with human learners?

RQ3: Performance vs. Diversity Trade-offs in Physical Deployment How do diversity-preserving federated chess engines perform compared to traditional homogenized federated models and individual engines trained in isolation, both in computational evaluations and when deployed in physical robotic systems that provide tangible gameplay experiences to human users?

RQ4: Clustering Strategy Effectiveness for Educational Applications Which clustering strategies most effectively group chess engines by playing style while maintaining intra-cluster learning benefits and inter-cluster knowledge transfer opportunities, and how do these clustering decisions impact the quality of educational experiences provided through physical robot deployment?

RQ5: Physical Validation and Human Learning Impact Can physical chess-playing robots powered by diversity-preserving federated learning provide distinguishable and educationally valuable experiences that demonstrate the practical benefits of maintaining strategic heterogeneity in distributed AI systems, and how do these experiences compare to traditional single-style chess AI interactions?

1.3.2 Secondary Research Questions

Supporting the primary research objectives, several secondary questions explore specific aspects of the integrated computational and physical system:

SQ1: Style Quantification and Physical Manifestation How can chess playing styles be quantitatively measured and validated using both computational metrics and physical behavioral analysis through robotic gameplay, and what are the most reliable indicators that preserved diversity translates to genuine strategic

differences in robot decision-making?

SQ2: Communication Efficiency in Distributed Physical Systems What are the communication overhead implications of clustered federated learning compared to standard federated approaches in chess training contexts, and how do these overheads impact real-time performance when models are deployed to physical robotic systems requiring responsive gameplay?

SQ3: Scalability Considerations for Educational Deployment How does the proposed diversity-preserving approach scale with increasing numbers of participating nodes and playing style categories, and what are the practical limitations for deploying such systems in educational environments with multiple physical robots serving diverse learning needs?

SQ4: Human-Robot Interaction Quality and Style Recognition How effectively can human players distinguish between different federated chess styles when interacting with physical robotic opponents, and what aspects of robot behavior most clearly communicate strategic differences to human learners across different skill levels?

SQ5: Educational Effectiveness and Learning Outcomes What measurable improvements in chess understanding and strategic thinking do human learners demonstrate when exposed to diverse federated chess styles through physical robot interaction compared to traditional chess learning methods or single-style AI opponents?

SQ6: Generalization Beyond Chess and Educational Applications To what extent can the diversity-preserving federated learning principles identified in chess be generalized to other strategic domains with inherent style diversity, and how can physical validation approaches be adapted for different human-robot interaction contexts in educational and training applications?

1.4 Research Contributions

This thesis makes several novel contributions that span artificial intelligence, federated learning theory, educational robotics, and human-computer interaction, establishing new paradigms for preserving beneficial diversity in distributed learning systems while providing tangible validation through physical deployment:

Theoretical Contributions:

- Development of a formal framework for diversity-preserving federated reinforcement learning that balances style preservation with collaborative learning, including mathematical convergence guarantees for heterogeneous multi-agent systems
- Mathematical formalization of style-based clustering criteria for strategic domains with inherent player diversity, with specific application to chess opening theory and strategic classification systems
- Theoretical analysis of convergence properties in heterogeneous federated reinforcement learning systems, demonstrating that beneficial diversity can be maintained without sacrificing learning effectiveness
- Novel theoretical bridge between federated learning optimization and educational robotics applications, establishing formal foundations for diversity-preserving AI in human-interactive systems

Methodological Contributions:

- Novel clustering-based federated learning architecture that preserves beneficial client heterogeneity while enabling selective knowledge transfer across strategically distinct agents
- Integration of domain-specific expert knowledge (grandmaster chess theory) with data-driven federated learning approaches, demonstrating how authoritative domain expertise can guide machine learning system design
- Adaptive aggregation mechanisms that enable selective knowledge transfer while maintaining strategic diversity, with specific protocols for balancing

universal knowledge sharing with style-specific preservation

- Comprehensive three-phase training methodology (individual development, intra-cluster collaboration, inter-cluster knowledge transfer) that systematically builds and preserves strategic diversity
- Complete physical validation framework that bridges theoretical diversity preservation with tangible human-interactive demonstration through robotic systems

Empirical Contributions:

- First large-scale empirical study of diversity-preserving federated learning applied to chess reinforcement learning, with comprehensive validation across multiple playing styles and strategic approaches
- Demonstration that distinct chess playing styles can be maintained during federated training while achieving collaborative learning benefits that exceed isolated training approaches
- Validation that preserved diversity leads to superior adaptive performance against varied opponents, with statistical significance across multiple evaluation metrics
- Comprehensive comparison of diversity-preserving approaches against traditional federated learning baselines, individual training methods, and centralized training approaches
- First empirical validation of federated learning diversity through physical robotic deployment, providing concrete evidence that theoretical diversity preservation translates to meaningful real-world differences
- Human interaction studies demonstrating measurable learning improvements when engaging with diverse AI styles compared to homogenized chess engines

Technical and System Contributions:

- Complete implementation of diversity-preserving federated chess learning

system with open-source availability for research community adoption and extension

- First comprehensive physical chess robot system powered by federated learning, integrating computer vision, robotic manipulation, and human-interactive gameplay
- Advanced computer vision system for real-time chess board analysis and move recognition with 98.7% accuracy in dynamic gameplay conditions
- Robust robotic control system for precise chess piece manipulation with integrated safety protocols for human-robot interaction
- Novel human-robot interaction protocols that enable style selection and educational feedback, transforming abstract AI concepts into tangible learning experiences
- Complete system integration framework that bridges high-level AI decision-making with low-level robotic control for seamless human-interactive gameplay

Educational and Practical Contributions:

- Reproducible experimental framework for evaluating federated learning in strategic domains with validation through physical deployment
- Practical guidelines for applying diversity-preserving federated learning to other domains with inherent agent heterogeneity, supported by concrete implementation examples
- Chess education applications enabling human players to train against AI opponents with distinct, consistent playing styles that provide varied learning experiences
- Demonstration of educational robotics applications that leverage AI diversity for enhanced learning outcomes, with measurable improvements in human chess understanding

- Complete open-source implementation enabling other researchers to build upon the diversity-preserving federated learning paradigm in both computational and physical contexts
- Practical framework for deploying diversity-aware AI systems in educational environments, with guidelines for human-robot interaction design and educational effectiveness measurement

Interdisciplinary Contributions:

- First comprehensive bridge between federated learning theory and educational robotics applications, establishing new research directions at the intersection of distributed AI and human-interactive systems
- Novel validation methodology that transforms abstract machine learning concepts into tangible, measurable human experiences through physical robot interaction
- Integration of chess domain expertise with cutting-edge AI research, demonstrating how traditional human knowledge can enhance modern machine learning approaches
- Establishment of new evaluation paradigms for federated learning that incorporate human-centered metrics alongside traditional computational performance measures

1.5 Thesis Structure

This thesis is organized into eight chapters that progress from theoretical foundations through implementation and physical validation to conclusions and future work, with integrated coverage of both computational federated learning advances and physical robotic demonstration:

Chapter 2: Literature Review and Related Work provides comprehensive coverage of relevant research spanning federated learning, reinforcement learning, chess artificial intelligence, and educational robotics. Special attention is given

to personalized and clustered federated learning approaches, horizontal federated reinforcement learning frameworks, the theoretical foundations of chess playing style diversity, and existing physical chess-playing robotic systems. The chapter establishes the interdisciplinary foundation necessary for understanding the integration of diversity-preserving federated learning with educational robotics applications.

Chapter 3: Methodology establishes the epistemological foundation for treating grandmaster-maintained chess knowledge as authoritative academic sources, develops the chess playing style classification framework grounded in opening theory analysis, and details the federated node clustering strategy. The chapter specifies the individual node architecture, federated learning protocols, and comprehensive evaluation framework. Additionally, it presents the complete methodology for physical chess robot integration, including computer vision systems, robotic control protocols, and human-robot interaction design that enables tangible validation of diversity preservation.

Chapter 4: System Implementation documents the technical architecture and software implementation of both the diversity-preserving federated chess learning system and the integrated physical robotic demonstration platform. Detailed descriptions of chess engine implementation, federated learning infrastructure, computer vision systems, robotic control software, and human-robot interaction protocols provide the foundation for experimental reproducibility and system deployment in educational contexts.

Chapter 5: Experimental Design and Setup defines the experimental objectives for both computational validation and physical robotic demonstration, dataset construction procedures, and baseline establishment protocols. Comprehensive specification of experimental configurations for federated learning, robotic system performance evaluation, and human interaction studies ensures rigorous evaluation of the proposed approach across both computational and physical validation domains.

Chapter 6: Results and Analysis presents empirical findings from the three-phase computational training methodology and comprehensive physical validation

through robotic demonstration. Results include individual style development outcomes, intra-cluster and inter-cluster federated learning performance, robotic system execution accuracy, and human interaction study findings. Comprehensive performance evaluation, ablation studies, and statistical significance testing validate the research hypotheses across both computational and physical deployment contexts.

Chapter 7: Discussion interprets the empirical findings within the broader context of federated learning research, chess AI development, and educational robotics applications. The chapter analyzes theoretical implications for distributed learning systems, practical applications for educational technology, methodology evaluation across computational and physical domains, and integration challenges encountered when bridging AI research with robotic implementation. Comparison with existing approaches demonstrates the advantages and limitations of the diversity-preserving federated learning paradigm.

Chapter 8: Conclusions and Future Work summarizes the research conclusions, contributions to knowledge spanning multiple disciplines, and limitations of the current work. Detailed future research directions encompass both computational extensions to the federated learning framework and advanced applications in educational robotics, with specific attention to commercial deployment possibilities and interdisciplinary applications that suggest avenues for extending the diversity-preserving federated learning paradigm to other domains requiring human-interactive AI systems.

The thesis is supported by comprehensive appendices providing implementation details for both computational and robotic systems, additional results from human interaction studies, complete source code for reproducibility, and detailed documentation for physical robot assembly and deployment. These resources enable future research building upon the integrated computational and physical foundations established by this work, facilitating both theoretical advances in federated learning and practical applications in educational robotics.

Chapter 2

Literature Review and Related Work

2.1 Literature Review Methodology

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