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该提案最初由李元健博士发起和撰写，旨在申请 Leverhulme Trust Early Career Fellowship。该提案已于2023年初提交至 Leverhulme Trust，尽管未被评审团选中，我保留对此提案所含内容的全部版权和知识产权。任何使用、复制或传播此提案或其任何部分的行为，须注明李元健博士为原作者。

Author’s Note on Proposal

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Quantum Federated Reinforcement Learning for 6G Wireless Systems

Background The sixth-generation (6G) wireless systems, inter alia, cell-free distributed multiple-input multiple-output (MIMO) networks, internet of everything (IoE), digital twin, e-finance and e-health, have been envisioned to be *artificial intelligence (AI)-native networks*, by industry, academia, and standardization bodies [1]. An AI-native wireless network is one in which the entire protocol stack, from the physical layer to the application layer, is designed using data-driven machine learning (ML) techniques. Radio resource management is one of the major building blocks for realizing agile and robust 6G networks, which would be designed using data-driven ML approaches. Deep reinforcement learning (DRL) is one well-known type of ML frameworks, which is the backbone enabling the mind-blowing AlphaGo and ChatGPT. Thanks to its adaptive and flexible decision-making ability via learning unknown environments in a model-free and trial-and-error manner [2], DRL is believed to be a competitive candidate to realize efficient and intelligent radio resource coordination for intelligent 6G systems. To enable the practically real-time application of AI-enabled solutions within extreme-large-scale and highly heterogeneous future 6G wireless systems, existing ML frameworks that are inherently based on centralized training inevitably suffer from inefficiency of scaling, e.g., significant latency and overhead for coordinating massive networks, not to mention that data privacy and security amid wireless transmissions among 6G transceivers fundamentally require to be taken more serious care of, e.g., genetic/biometric data, trade secret and marketing strategies. Among other ML techniques, federated learning (FL) is standing out to help deal with the key constraints of model scalability and data privacy, blessed by FL's nature of decentralized learning where distributed clients train their provincial models from locally collected data while the server trains the global model via aggregating model parameters extracted from distributed clients, rather than raw privacy-sensitive data. Recent advancements in quantum computing devices, e.g., quantum supremacy reported by IBM and Google, and the latest Nobel prize in Physics for ground-breaking experiments with quantum entangled particles, further reveal the promise and importance of quantum computing for leading the next industrial revolution. Besides, recent works on quantum machine learning (QML) showed that quantum computing is beneficial for improving efficiency [3] and enhancing generalization [4] for ML systems, e.g., comparable or better learning performance with much lighter parameter updating of quantum DRL algorithm has been reported in [5], compared to the conventional deep neural network (DNN)-based DRL. To leverage quantum advantages into decentralized privacy-preservative ML regime, a handful of related works in the interdisciplinary area of quantum FL (QFL) has emerged in recent years, e.g., FL-inspired variational quantum algorithm (VQA) with distributed data [6] and ML framework with federated training on hybrid quantum-classical learning models [7]. These works reported that QFL can help achieve favourable scalability and meanwhile safeguard privacy/security-sensitive data.

Motivation Unfortunately, there remains a research blank where quantum computing together with decentralized privacy-preservative ML and DRL is invoked to support 6G wireless systems. To fill this gap and thus pioneer this infant yet promising research direction, this project proposes *a novel interdisciplinary framework of QFL-aided DRL (QFRL) for intelligently allocating radio resources for future 6G wireless systems*, where distributed training, model scalability and data privacy/security will be achieved. *A fundamental question* here is whether one can build a novel QFRL framework that can be used to design AI-native 6G wireless systems, to achieve practical scalability and preserve data privacy with low latency and high reliability. *Another inherent challenge* is how to leverage quantum advantages to help deal with drawbacks or shortcomings of existing ML frameworks with federated training.

Aim and Methodology The *aim of this project* is thus to lay the theoretical foundations of *distributed privacy-preservative* QFRL for optimizing transmission performance of AI-native 6G wireless systems and protocols. 1) A first key goal is to develop new QFRL algorithms tailored towards solving optimization problems in 6G networks with distributed wireless transceivers, in terms of radio resource coordination, e.g., beamforming design, spectrum access, resource (power, bandwidth) allocation, and energy efficiency. Hereby, QFRL solutions will be designed and developed. Specifically, decentralized RL clients will be redesigned with variational quantum circuit (VQC) including state encoding as well as parametric quantum circuit (PQC) and quantum measurements, while VQC-based server aggregates model parameters reported from clients to formulate the global model. Here, we will investigate the impact of various existing PQC ansatzes, and then design novel ansatzes that can better adapt to 6G transmission scenarios. Furthermore, we will investigate the signalling overhead and information sharing among distributed clients, and we will theoretically and empirically show how and when quantum designs can reduce such overhead, while identifying its impact on the learning in impactful use cases within 6G networks. Moreover, our designs will incorporate practical considerations on partial observability of complex 6G wireless environments. The application of VQC-aided training architecture for QFRL can significantly reduce the number of training parameters, which thus can potentially help overcome the scalability and latency challenges. Next, we will leverage promising techniques such as space compression, meta-learning and transfer learning to enhance the robustness and scalability of the proposed QFRL framework for large-scale and heterogeneous 6G networks. 2) Within practical 6G wireless systems, heterogenous and/or multi-modal clients' training data would not anymore be independent and identically distributed (non-i.i.d.), which could significantly deteriorate the learning performance of variants of classical FL. Therefore, we will investigate how skewed non-i.i.d. data affect the proposed QFRL framework, in terms of, e.g., learning efficiency and robustness, via both theoretical and numerical analyses. Then, we will focus to propose solutions to improve the proposed QFRL framework's trainability over non-i.i.d. wireless data, e.g., *data augmentation* via enabling clients to collectively train a generative model and then augment their local data towards achieving i.i.d. dataset, *multi-task learning* and *knowledge distillation*. 3) In the current noise intermediate-scale quantum (NISQ) era, quantum errors caused by quantum decoherence and imprecision of quantum gates will inevitably jeopardize the learning performance of VQC-based schemes. Hence, we will explicitly investigate the *fundamental effects of quantum noise on our QFRL* solutions, and we will propose efficient strategies to counter this shortcoming, including hybrid optimization, ensemble learning, and use of kernel matrices. 4) To make the proposed QFRL solution more communication-efficient when coping with time-varying 6G wireless channels, we will study the depth-manageable architecture of VQC over its depth-fixed counterpart. Inspired by the slimmable FL (SFL) technique, we aim to initiate entangled slimmable PQC with multiple depths to rebuild the proposed QFRL framework as entangled silimmable QFRL. Herein, the clients of entangled silimmable QFRL will communicate superposition-coded parameters to realize federated training. Then, we will aim to develop an optimal power allocation strategy for superposition coding which is used to encode clients' model parameters. However, entangled slimmable PQC may lead entangled silimmable QFRL to be less trainable, as significant entanglement entropy and inter-depth interference would be inevitably introduced. We will thus try to tackle this challenge by adopting advanced techniques from quantum computing, e.g., entanglement controlled universal gates and in-place fidelity distillation regularizer.

Outcomes The proposed research will *contribute simultaneously to AI, machine learning, quantum computing, and 6G wireless systems* thus providing scientific foundations for pioneering the emerging yet promising interdisciplinary area of QFRL applied to 6G wireless systems. We plan to submit high-impact papers to leading communications (e.g., IEEE Transactions on Wireless Communications), AI (e.g., IEEE Transactions on Pattern Analysis and Machine Intelligence), and quantum (e.g., Quantum Information Processing) venues, while regularly publishing in top-tier international conferences, e.g., IEEE GLOBECOM, IEEE ICC, NeurIPS and ICML. Besides, this project's scientific outcomes can potentially contribute to the development of future 6G standards, by introducing quantum to aid the AI-native nature of 6G networks.

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量子联邦强化学习在6G无线系统中的应用

背景 第六代（6G）无线系统，包括分布式无蜂窝多输入多输出（MIMO）网络、万物互联（IoE）、数字孪生、电子金融和电子健康等，已被业界、学术界和标准化机构视为原生人工智能（AI）网络 [1]。原生AI无线网络是指整个协议栈，从物理层到应用层，均采用数据驱动的机器学习（ML）技术设计的网络。无线资源管理是实现灵活且稳健的 6G 网络的关键组成部分，这将通过数据驱动的机器学习方法设计。深度强化学习（DRL）是众所周知的一类机器学习框架，是支撑震撼全球的AlphaGo和ChatGPT的核心。由于其通过在未知环境中进行无模型和试错的方式，具备自适应和灵活决策的能力 [2]，DRL 被认为是帮助实现智能 6G 系统高效无线资源协调的有力候选方案。为使 AI 驱动的解决方案能够在未来超大规模和高度异构的 6G 无线系统中实现几乎实时的应用，现有基于集中训练的机器学习框架不可避免地面临扩展效率的不足，如协调大规模网络时产生的显著延迟和开销，更不用说在6G收发器之间的无线传输过程中，数据隐私和安全（如基因/生物识别数据、商业机密和市场策略）需要得到更严密的保护。在众多机器学习技术中，联邦学习（FL）由于其分布式学习的特性，脱颖而出，帮助解决模型可扩展性和数据隐私的关键限制。在联邦学习中，分布式客户端基于本地收集的数据训练它们的本地模型，而服务器通过聚合客户端提取的模型参数来训练全局模型，而不是直接传输隐私敏感的原始数据。量子计算设备的最新进展，如 IBM 和谷歌报告的量子霸权，以及因对量子纠缠粒子的突破性实验而获得的诺贝尔物理学奖，进一步揭示了量子计算对引领下一次工业革命的承诺和重要性。此外，关于量子机器学习（QML）的最新研究表明，量子计算有助于提高机器学习系统的效率 [3] 和泛化能力 [4]，例如，与传统的基于深度神经网络（DNN）的 DRL 算法相比，量子 DRL 算法在参数更新量显著减少的情况下，仍能获得可比或更好的学习性能 [5]。为了将量子优势融入到去中心化的隐私保护机器学习范畴，近年来在量子联邦学习（QFL）这个交叉学科领域出现了一些相关工作，例如基于FL的变分量子算法（VQA）与分布式数据结合 [6] 和基于量子-经典混合学习模型的联邦训练框架 [7]。这些工作报告指出，QFL能够在实现可扩展性的同时，保护隐私和安全敏感的数据。

动机 遗憾的是，尚无研究探讨如何利用量子计算与去中心化隐私保护的机器学习和深度强化学习结合起来，以支持6G无线系统。为填补这一空白，并开创这一尚处于初期但前景广阔的研究方向，本项目提出了一种新的跨学科框架——QFL辅助DRL（QFRL），用于智能分配未来6G无线系统的无线资源，实现分布式训练、模型可扩展性和数据隐私/安全保护。这里一个基本问题是，能否构建一个全新的 QFRL 框架，用于设计原生 AI 6G 无线系统，以实现实际的可扩展性和数据隐私保护，并具备低延迟和高可靠性。此外，另一个固有挑战是如何利用量子优势来应对联邦训练的机器学习框架的不足或短板。

目标与方法 因此，本项目的目标是为分布式隐私保护的 QFRL 奠定理论基础，以优化原生 AI 6G 无线系统和协议的传输性能。1）第一个关键目标是开发新的 QFRL 算法，专门解决 6G 网络中分布式无线收发器的优化问题，涉及无线资源协调，如波束成形设计、频谱接入、资源（功率、带宽）分配和能效优化。为此，我们将设计和开发QFRL解决方案。具体而言，去中心化的RL客户端将通过变分量子电路（VQC）重新设计，包括状态编码以及参数量子电路（PQC）和量子测量，而基于 VQC 的服务器将通过聚合客户端报告的模型参数来构建全局模型。在此过程中，我们将研究现有 PQC 的不同结构，并设计新的适应 6G 传输场景的结构。此外，我们将研究分布式客户端之间的信令开销和信息共享，并在理论和实验上展示量子设计如何以及何时能减少此类开销，同时识别其对 6G 网络中重要应用场景的学习影响。我们的设计还将考虑 6G 复杂无线环境的部分可观测性问题。通过应用 VQC 辅助的训练架构，QFRL 可以显著减少训练参数的数量，从而有望克服扩展性和延迟的挑战。接下来，我们将利用诸如空间压缩、元学习和迁移学习等有前景的技术，来增强所提出的 QFRL 框架在大规模和异构 6G 网络中的鲁棒性和可扩展性。2）在实际的 6G 无线系统中，异构客户端的训练数据将不再是独立同分布（non-i.i.d.）的，这可能会显著降低无量子辅助的 FL 变体的学习性能。因此，我们将研究在提出的 QFRL 框架中，non-i.i.d.问题是否仍然存在，结合理论和数值分析。接着，借助局部密度估计器，我们旨在从理论上证明，全球 QFRL 模型可以被精确分解为由每个客户端维护的本地 QFRL 模型，从而证明所提出的 QFRL 算法在

non-i.i.d.数据下依然表现良好。3）在当前的噪声中间规模量子（NISQ）时代，量子退相干和量子门不精确引发的量子错误将不可避免地损害基于 VQC 方案的学习性能。因此，我们将明确研究量子噪声对我们 QFRL 解决方案的基本影响，并提出有效策略来应对这一不足，包括混合优化、集成学习和使用核矩阵。4）为了使所提出的 QFRL 解决方案在应对时变 6G 传输信道时更具通信效率，我们将研究 VQC 的深度可管理架构，以替代其固定深度的架构。受可缩放 FL（SFL）技术的启发，我们旨在发起量子纠缠的可缩放 PQC，并利用多个深度重构所提出的 QFRL 框架，使其成为量子纠缠的可缩放 QFRL。在此框架下，量子纠缠的可缩放 QFRL 客户端将通过叠加编码的参数进行通信，实现联邦训练。然后，我们将开发一个最优的功率分配策略用于叠加编码。然而，量子纠缠的可缩放 PQC 可能会使量子纠缠的可缩放 QFRL 训练难度增加，因为不可避免地会引入显著的纠缠熵和深度间干扰。为此，我们将尝试通过采用量子计算的先进技术来解决这一挑战，例如纠缠控制通用门和原地保真蒸馏正则化器。

预期成果 该研究将同时为人工智能、机器学习、量子计算和 6G 无线系统做出贡献，为在 6G 无线系统中应用 QFRL 这一新兴且前景广阔的跨学科领域奠定科学基础。我们计划向领先的通信（如 IEEE Transactions on Wireless Communications）、AI（如 IEEE Transactions on Pattern Analysis and Machine Intelligence）和量子（如 Quantum Information Processing）期刊提交高影响力的论文，并定期在顶级国际会议上发表成果，如 IEEE GLOBECOM、IEEE ICC、NeurIPS 和 ICML。此外，本项目的科学成果有望通过引入量子技术以辅助 6G 网络的原生 AI 特性，为未来 6G 标准的发展做出贡献。

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