Full Name (English):	（中英文）**Yinglei Teng 滕颖蕾**	
Affiliated Institution and Title (English):	（中英文）**Beijing University of Posts and Telecommunications 北京邮电大学**	

Biography

(Please provide in paragraph form within 500 words.)（中英文）

Yinglei Teng, a professor at Beijing University of Posts and Telecommunications, specializes in wireless communications, stochastic optimization, and edge intelligence. She received funding from renowned programs, including the NSFC, National Key R&D Young Scientist Project, Huawei, and China Mobile, etc.. She has authored over 30 high-quality SCI papers, holds more than 80 invention patents, and has contributed to 8 industry standards. She has been recognized with honors such as the China Association for Science and Technology Special Award and the Beijing Science and Technology Award. Her recent research focuses on edge intelligence, ML/AI for PHY, and millimeter-wave technologies, etc.

Speech Title (English):（中英文）

边缘异构联邦学习：从数据多样性到模型优化

Heterogeneous Federated Learning at the Edge: From Data Diversity to Model Optimization

Speech Abstract

(Please provide in paragraph form within 500 words.)（中英文）

With the evolution of 6G and large-scale edge intelligence, wireless networks are increasingly required to support distributed learning under strongly constraints on bandwidth, latency, energy, and device heterogeneity. Federated learning has emerged as a key technology for communication-efficient and privacy-preserving intelligence at the network edge; however, its performance is fundamentally limited by non-IID data distributions, heterogenous device capabilities. This talk presents recent advances in communication- and computation-aware federated edge intelligence from three tightly coupled perspectives: data augmentation, model compression and fine tuning for heterogenous edge networks.

From data augmentation perspective, a clustered data sharing framework is introduced that exploit sidelink-assisted communications to reduce data heterogeneity while controlling communication cost. By aligning data distribution with wireless connectivity and trust contains, this method significantly accelerated convergence and improve the FL model performance with non-IID data. From the model compress perspective, heterogeneous federated pruning techniques enable personal model compression while preserving aggregation compatibility. By incorporating curvature-aware pruning and reconstruction, clients with diverse computation and communication budgets can transmit compact updates without degrading convergence stability, achieving a favorable accuracy-communication tradeoff in resource-constrained edge networks. Moving beyond conventional edge models, federated fine-tuning of foundation models is explorable over heterogeneous wireless edge systems. A sparse Mixture-of-Experts (MoE)-based federated fine-tuning framework is introduced that replaces parameter-efficient fine tuning with adaptive expert activation, allowing each device to dynamically balance computation, communication load, and adaptation capability. Meanwhile, a heterogeneity-aware load-balancing mechanism is devised to stabilize routing and improve robustness under severe non-IID data and device diversity, making large-scale foundation models feasible in resource-limited federated networks.

随着 6G 技术的发展以及大规模边缘智能的兴起，无线网络正逐步承担起在带宽、时延、能耗以及设备异构性等多重强约束条件下支持分布式学习的重要任务。联邦学习（Federated Learning, FL）作为一种兼顾通信效率与隐私保护的关键技术，为边缘侧协同智能提供了有效解决方案。然而，在实际部署中，联邦学习的性能仍然受到非独立同分布（non-IID）数据以及终端设备能力差异等因素的根本性制约。

本报告围绕通信与计算感知的联邦边缘智能，从三个紧密关联的角度系统介绍相关研究进展，分别是：数据增强、模型压缩，以及面向异构边缘网络的模型微调方法。

在数据增强方面，我们提出了一种基于聚类的数据共享框架，通过引入侧链路辅助通信（sidelink-assisted communications），在控制通信开销的同时有效缓解数据分布异构问题。该方法将数据共享机制与无线连接关系及信任约

束相结合，在 non-IID 场景下显著加快了联邦学习的收敛速度，并提升了整体模型性能。在模型压缩方面，我们研究了异构联邦剪枝技术，该方法支持终端进行个性化模型压缩，同时保持模型聚合过程的结构兼容性。通过引入曲率感知的剪枝与重构机制，不同计算与通信能力的设备能够上传更加紧凑的模型更新，而不会破坏联邦优化的收敛稳定性，从而在资源受限的边缘网络中实现更优的精度与通信开销权衡。我们进一步将研究扩展至异构无线边缘环境中的基座模型联邦微调问题。针对传统参数高效微调方法在异构场景下的局限性，提出了一种基于稀疏混合专家（Mixture-of-Experts, MoE）的联邦微调框架。该框架通过自适应专家激活机制，使终端能够根据自身资源条件灵活调节计算负载、通信开销与模型适配能力。同时，引入的异构感知负载均衡机制有效缓解了专家路由失衡问题，在严重 non-IID 数据和设备异构条件下显著提升了系统鲁棒性，使大规模基础模型在资源受限的联邦网