

TANG ZICHEN

+86 15854550175 ztangap@connect.hkust-gz.edu.cn github.com/trl730109

Education

The Hong Kong University of Science and Technology (Guangzhou) <i>Master of Philosophy in Data Science and Analytics, GPA: 4.075/4.3</i>	Sep 2023 – Present <i>Guangzhou, China</i>
Korea Advanced Institute of Science and Technology <i>Exchange student in School of Computing</i>	Feb 2022 – Jun 2023 <i>Daejeon, Korea</i>
The Hong Kong University of Science and Technology <i>Bachelor of Engineering in Computer Science and Mathematics (Double Major)</i>	Sep 2019 – May 2023 <i>Hong Kong, China</i>

Award

HKSAR Government Scholarship Fund - Reaching Out Award	June 2022
---	------------------

Publications

Conference

- **Z. Tang**, J. Huang, R. Yan, Y. Wang, Z. Tang, S. Shi, A. Zhou, X. Chu. Bandwidth-Aware and Overlap-Weighted Compression for Communication-Efficient Federated Learning. In the 53rd International Conference on Parallel Processing (ICPP'24).
- Z. Tang*, **Z. Tang***, J. Huang, R. Yan, Y. Wang, A. Zhou, S. Shi, B. Li, X. Chu. DreamDDP: Accelerating Distributed Training with Layer-wise Partial Synchronization. In the IEEE International Conference on Computer Communications (INFOCOM'25). (Under Review) *These authors contributed equally to this work.
- J. Huang, **Z. Tang**, R. Yan, Y. Feng, Z. Li, Z. Tang, A. Zhou, Y. Liang, X. Chu. Stale Information Matters: Efficiently Tackling Data Heterogeneity in Asynchronous Federated Learning with Model Calibration. In the IEEE International Conference on Computer Communications (INFOCOM'25). (Under Review)
- Z. Tang, J. Huang, **Z. Tang**, X. Kang, Y. Wang, P. Dong, S. Shi, X. Chu, B. Li. Capturing and Mitigating Gradient Aggregation Errors for Fault-Tolerant Distributed Training. In the Thirteenth International Conference on Learning Representations (ICLR'25) (Under Review)

Research Interest

- Federated Learning
- Distributed ML Systems
- LLM

Research Experience

Federated Learning <i>Bandwidth-Aware and Overlap-Weighted Compression for Communication-Efficient Federated Learning</i>	Sep 2023 – Jan 2024 <i>Guangzhou, China</i>
---	---

- Proposed a new scheduling method to dynamically adjust compression ratios based on heterogeneous client bandwidth, aligning model update transmission times to tackle communication bottlenecks and bandwidth heterogeneity.
- Discovered the heterogeneous overlap pattern of clients' compressed parameters and proposed a novel averaging method that utilizes a parameter mask to adjust the model updates in the aggregation process based on their occurrence frequency across clients.

Federated Learning <i>Efficiently Tackling Data Heterogeneity in Asynchronous Federated Learning with Model Calibration</i>	Dec 2023 – June 2024
---	-----------------------------

- Developed a novel semi-asynchronous FL method, K-FedQue, that leverages a dynamic model queue on the server side to utilize stale information from historical updates for model calibration, mitigating client drift caused by asynchronous updates and data heterogeneity.
- Formulated and analytically demonstrated K-FedQue achieves standard SGD convergence in non-convex settings.
- Proposed and implemented a staleness-aware regularization term on the local sub-problem to further counteract the effects of client drift. Extensive experiments showed that K-FedQue improves training efficiency by up to 1.76 times compared to SOTA asynchronous FL algorithms.

Distributed ML Systems <i>DreamDDP: Accelerating Distributed Training with Layer-wise Partial Synchronization</i>	Feb 2024 – Aug 2024 <i>Guangzhou, China</i>
---	---

- Proposed partial synchronization that relaxes the strong synchronization in local SGD by layer-wisely decoupling model parameters into each iteration.
- Further introduced DreamDDP, which schedules synchronization according to the real-time profiled communication and computation time, maximizing communicated information with the minimal communication time by overlap.

- Theoretically proved that DreamDDP shows the same convergence rate as S-SGD by providing the convergence bounds. Experimental results tested on two GPU clusters with 32 GPUs demonstrated $1.49 - 3.91\times$ improvement over the SOTA algorithms, including local SGD and ASC-WFBP.

Distributed ML Systems

Aug 2024 – Oct 2024

Capturing and Mitigating Gradient Aggregation Errors for Fault-Tolerant Distributed Training

Guangzhou, China

- Mathematicall formulate and generalize the Silent Data Corruption (SDC) like bit corruption and communication noise to gradient inconsistency in Synchronous SGD.
- Theoretically analyze how gradient inconsistency leads to model divergence accumulated during training and the failed convergence.
- Design PAFT-Sync to mitigate model divergence by synchronizing model parameters every fix iterations. Then further design PAFT-Dyn to minimize synchronization overhead through dynamic training overlap and synchronization frequency scheduling based on profiled error degrees.
- PAFT is optimized to support popular optimizers, like SGD, SGD with momentum, Adam. Extensive experiments conducted on two GPU clusters with 32 GPUs demonstrated PAFT's resistance against gradient aggregation error while maintaining training performance.

Projects

Develop chatbots in Traditional Chinese Medicine domain | *Python*

Jan 2024 – Present

- Finetuned LLM with Non-IID data sources to improve TCM-related query handling via Federated Learning.
- Used RAG techniques to enhance the fine-tuned chatbot's response accuracy and relevance.

Skills

Professional Skills: Python, Pytorch, PyTorch Distributed, Horovod, Transformers

Language Profficiency: English(TOEFL-105) Chinese(Native), Cantonese(Elementary)

Examination Performance: GRE 324, Verbal 154, Quantitive 170, Writing 3.5