Deep Learning and LLM Training: Quality & Reliability From the lenses of Distributed/Federated ML

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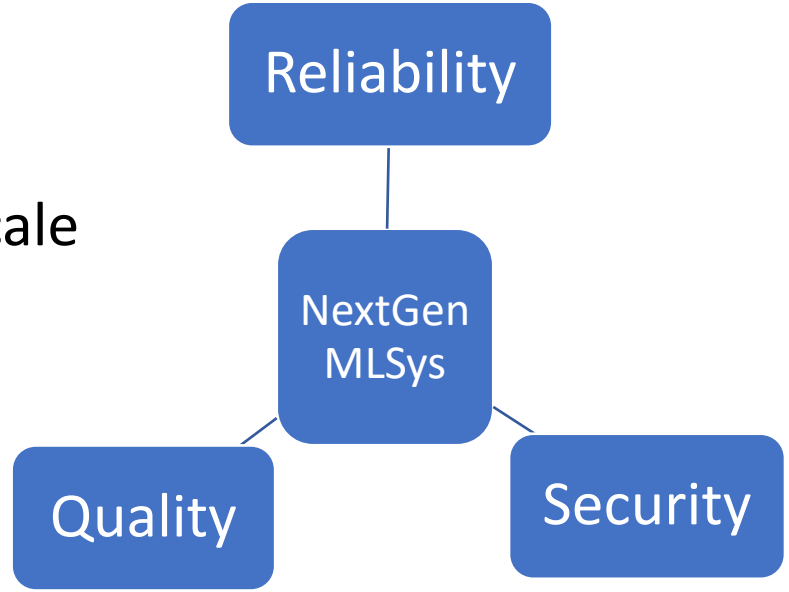
Current Objectives

Next Generations Machine Learning Systems require QRS

- Build the next generation architecture, techniques and methods for enabling high-**quality** machine learning at scale
- Democratize the access to efficient and **reliable** machine learning systems
- Responsible use of machine learning via **security** and privacy enhancing methods.

Sometimes these goals are at odds with each other



SAYED Systems Group (https://sayed-sys-lab.github.io)

- ML systems inc. Distributed and Federated Learning
- Performance evaluations and optimizations
- Distributed and Networked Architectures
- Cloud/Fog/Edge Computing

Scan for sample projects

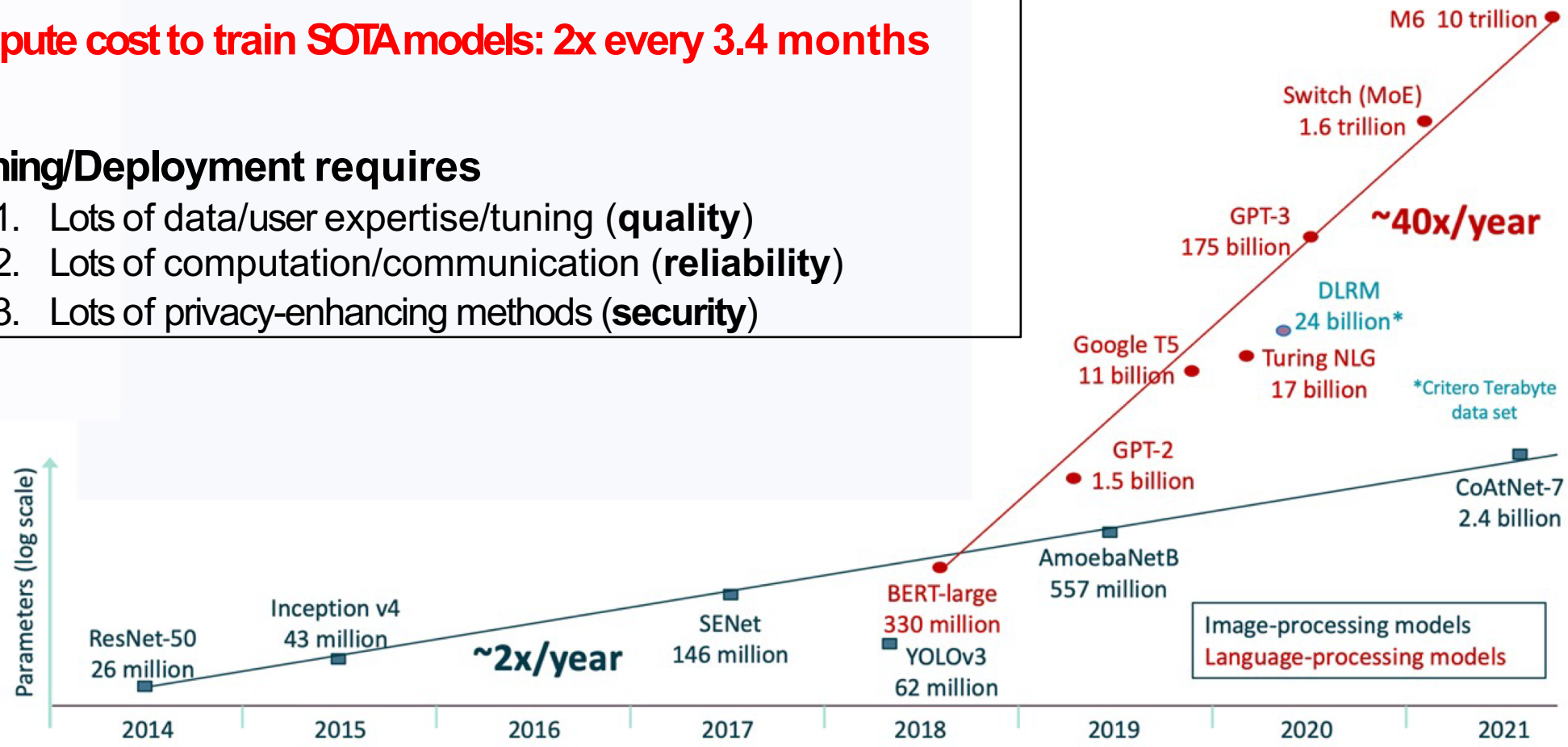
Deep Learning and LLMs are getting BIG FAST!

Growing model complexity & data size

Compute cost to train SOTA models: 2x every 3.4 months

Training/Deployment requires

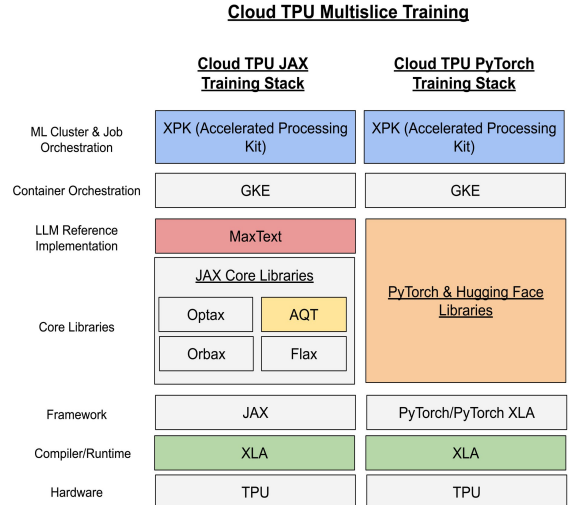
1. Lots of data/user expertise/tuning (**quality**)
2. Lots of computation/communication (**reliability**)
3. Lots of privacy-enhancing methods (**security**)



Source: Cadence, Linley Group

Scaling ML Systems to Enhance **Quality**

- The ML training needs to scale to have high quality deep learning models (or LLMs)
  - To crunch/train on larger datasets
  - To tune the training hyper-parameters
  - To frequently fine-tune or update the model
- Many HW/SW/Virt/Comm layers to optimize
  - Support for Distributed Training is a MUST
    - Data/Model/Pipeline Parallelism
  - Parameter-efficient training
    - Pruning/Sparsification or Quantization → impacts quality
    - Google achieved large-scale LLM training via INT8 Quant

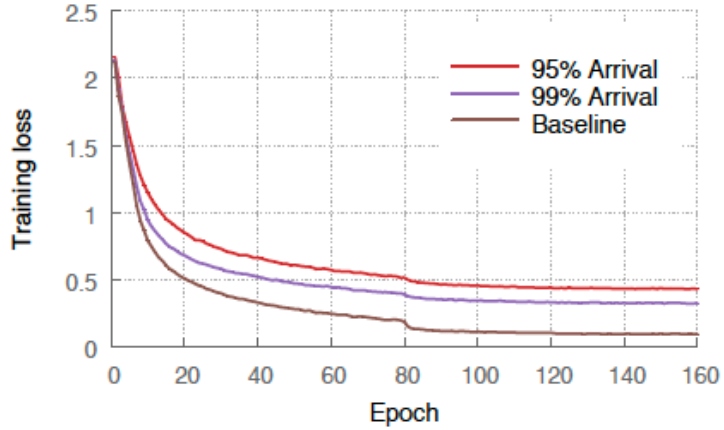


MaxText LLM Training Results

BF16/INT8 Training	parameters	TPU v5e pods	TPU v5e chips	Observed Perf/chip	Total observed Perf	EMFU
BF16	16B	1	256	120 TFLOP/s	0.03 exa-FLOP/s	61.10%
BF16	16B	16	4096	111 TFLOP/s	0.46 exa-FLOP/s	56.56%
BF16	32B	1	256	132 TFLOP/s	0.03 exa-FLOP/s	66.86%
BF16	32B	16	4096	123 TFLOP/s	0.50 exa-FLOP/s	62.26%
BF16	64B	1	256	118 TFLOP/s	0.03 exa-FLOP/s	59.90%
BF16	64B	16	4096	105 TFLOP/s	0.43 exa-FLOP/s	53.29%
BF16	128B	1	256	110 TFLOP/s	0.03 exa-FLOP/s	56.06%
BF16	128B	16	4096	100 TFLOP/s	0.41 exa-FLOP/s	50.86%
BF16	32B	199	50944	88 TFLOP/s	4.48 exa-FLOP/s	44.67%
INT8 Quant	**32B**	**199**	**50944**	**104.4 TOP/s**	**5.32 exa-OP/s**	**52.99%**

Large-Scale ML Systems require **Reliability**

- Large number of **computation** nodes (servers, edge/mobile devices)
  - The devices are prone-to-failure at any time (dropouts)
  - The devices are heterogenous in configs (stragglers)
- Nodes are connected via **communication** links
  - The communication can be become noisy/unreliable
  - Networks are volatile and gets congested
- How can we minimize their impact (reliability?)
  - MLSys configs need to be auto-tuned
    - Tuning should be system informed (not arbitrary) to guarantee job completion
    - MLSys need to be adaptive to varying conditions



***ResNet20 – CIFAR10**

*Tang, Hanlin, Chen Yu, Cédric Renggli, Simon Kassing, Ankit Singla, Dan Alistarh, Ji Liu and Ce Zhang. “Distributed Learning over Unreliable Networks.”, ICML (2018).

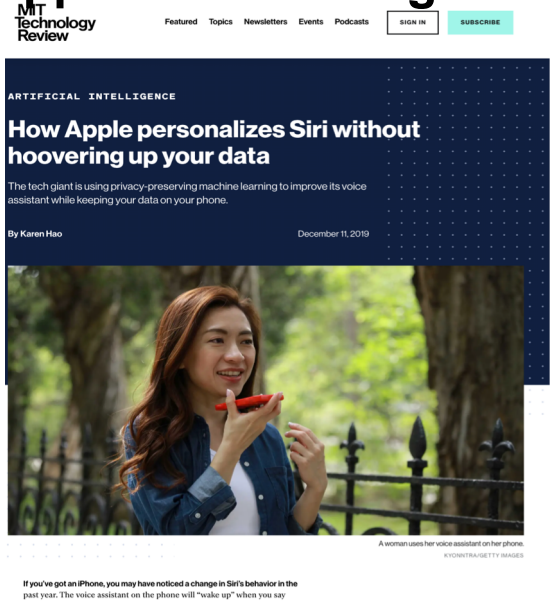
WHAT WE HAVE BEEN DOING?

New distributed methods evolved → Federated ML

User Data is Distributed at Edge!

- Internet of Things (IoT)
- Healthcare
- Finance
- Industry
- Smart-city/grid
- Telecommunications
- Self-driving vehicles
- ….

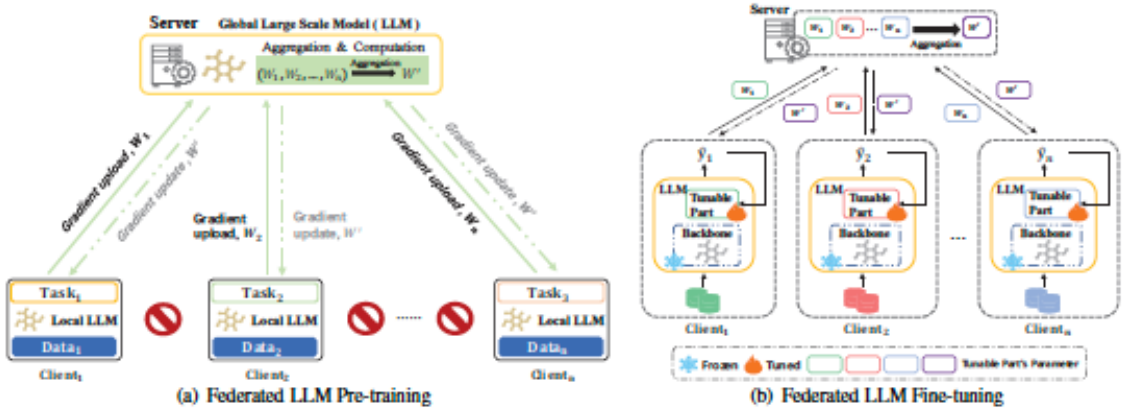
Apple: Voice recognition



Gboard next-word prediction

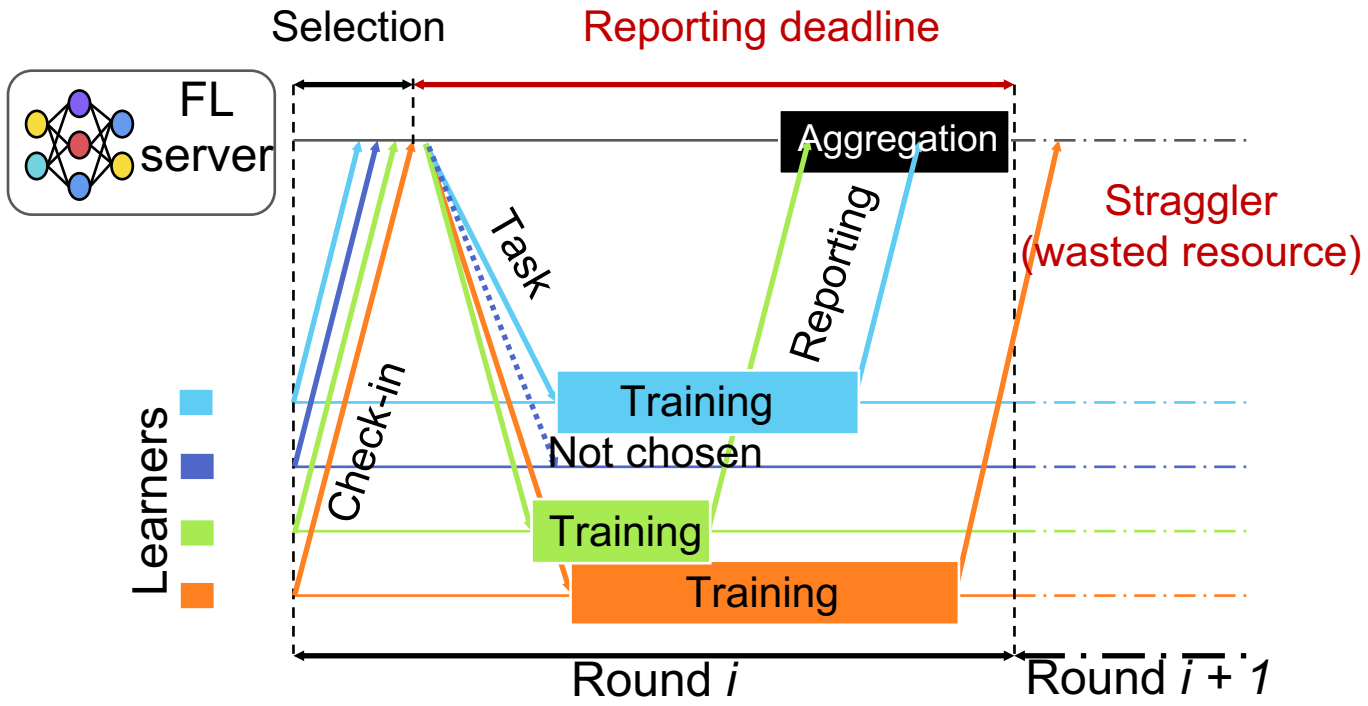
Using FL, better next-word predict accuracy: +24%

A. Hard, et al. Federated Learning for Mobile Keyboard Prediction. arXiv:1811.03604



Chen et. al., Federated Large Language Model: A Position Paper, arXiv:2307.08925

Federated Model Training

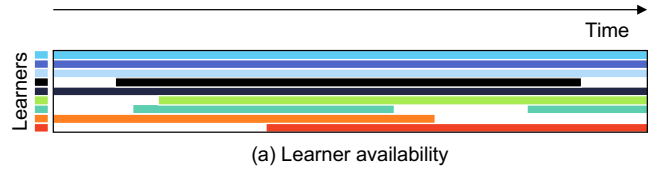


Heterogeneity in FL impacts QRS!

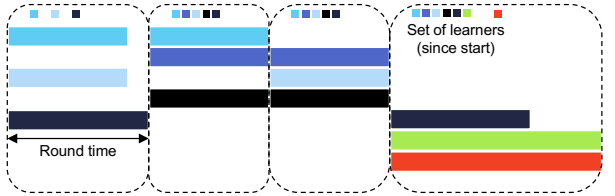
- Heterogenous data distributions → non-IID setting (**quality**)
- Diverse hardware and network capabilities → stragglers (**reliability**)
- Clients are not always available/fail → fault-tolerance is hard (**quality/reliability**)
- Clients are not always faithful → combating adversaries (**quality/security**)

Data/Resource Efficiency (**Quality**)

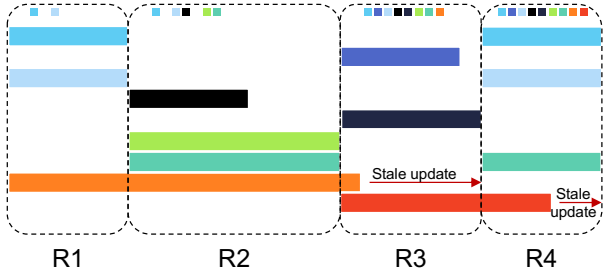
- Data/Resource diversity vs efficiency tradeoff
  - Diversity → improve clients' inclusion (i.e., data)
  - Efficiency → reduce compute/comm consumed
- REFL: Resource-efficient FL framework
  - Intelligent selection to maximize diversity
  - Novel stale aggregation to improve efficiency
  - >2X quality improvement over SOTA methods
- Published in ACM EuroSys'23
  - https://dl.acm.org/doi/abs/10.1145/3552326.3567485
  - Evaluated by ACM AE https://github.com/ahmedcs/REFL



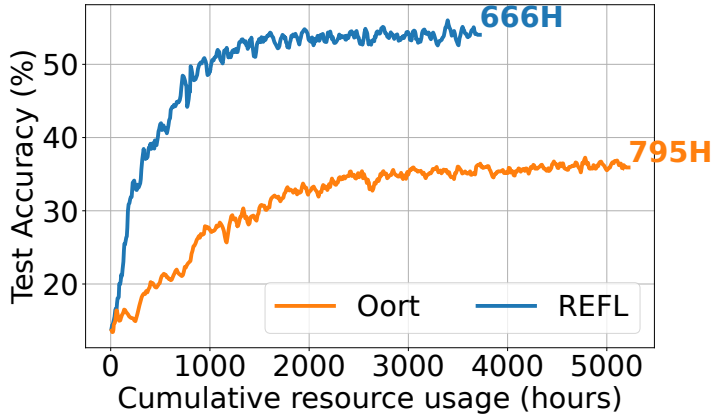
(a) Learner availability



(b) Oort – Sampled learners: 7

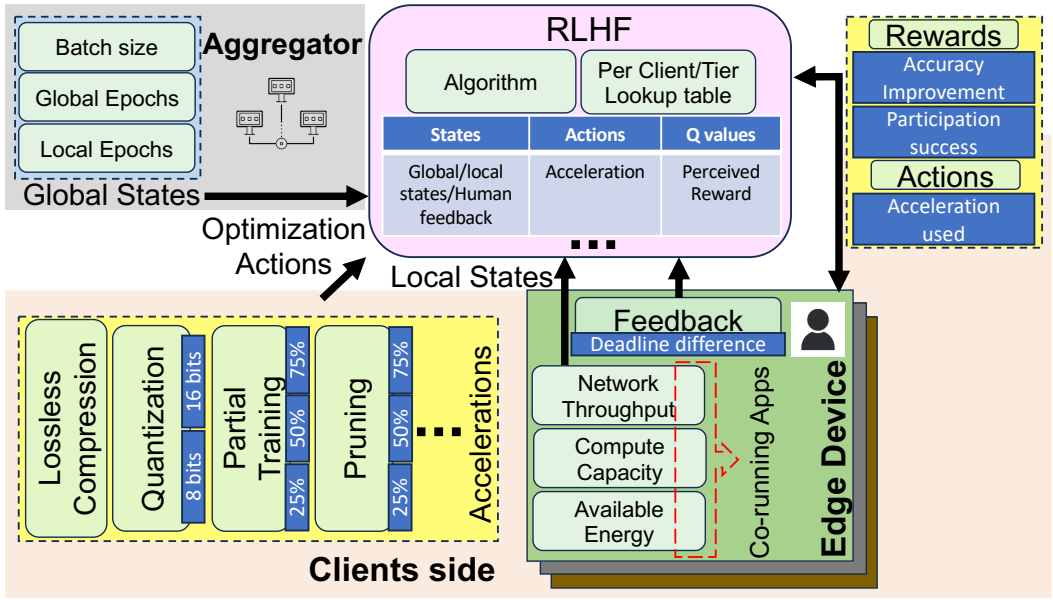


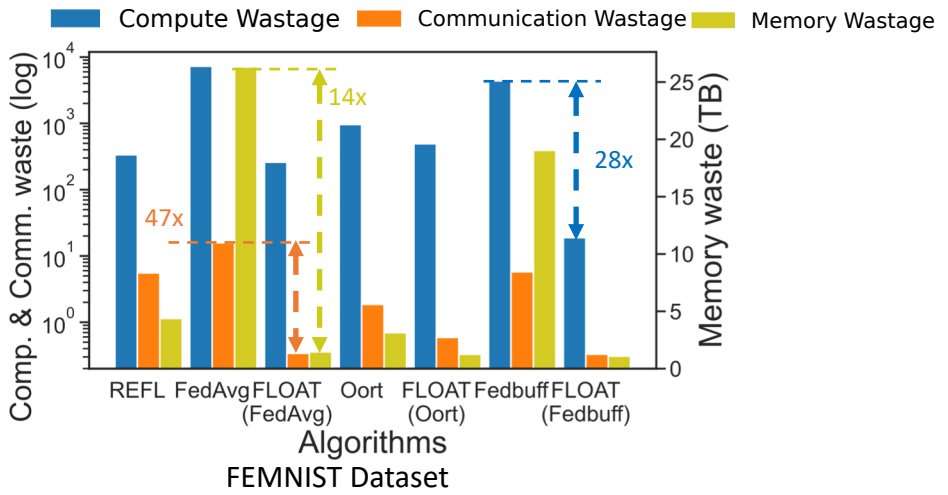
(c) REFL – Sampled learners: 9



Auto-tuning FL (**Reliability**)

- Auto-Tuning in FL is difficult problem
  - How to choose the right acceleration and configuration for thousands of devices?
  - Dynamic environment -> infinite possible system conditions unknown by the server.
- FLOAT: Auto-tuning for FL Systems
  - Reinforcement Learning with Human Feedback
  - Up to 53% better reliability over SOTA methods
- Published in ACM EuroSys'24
  - https://dl.acm.org/doi/abs/10.1145/3627703.3650081
  - Evaluated by ACM AE https://github.com/AFKD98/FLOAT

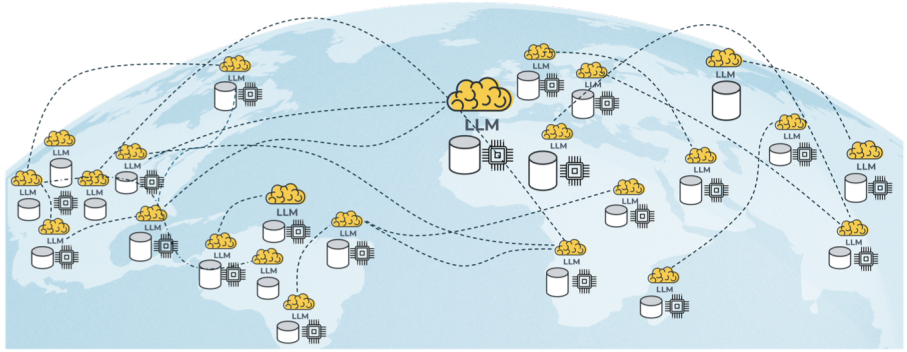




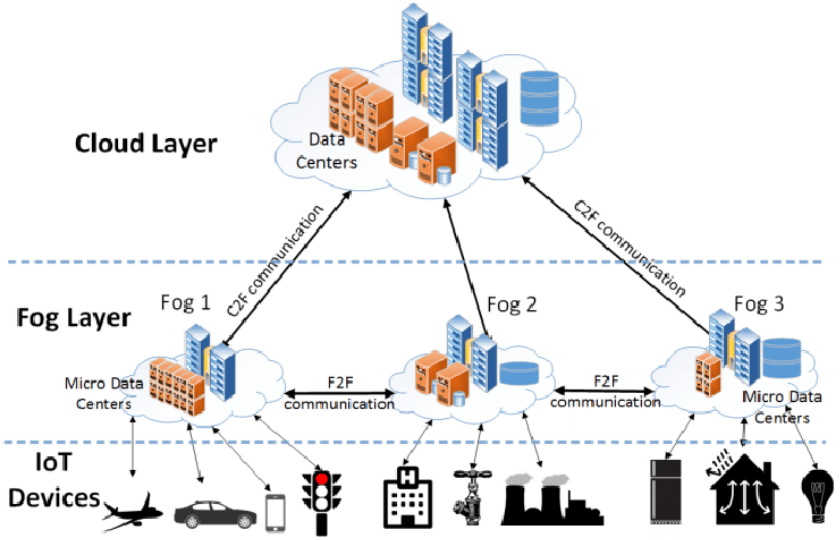
WHAT IS NEXT?

How about the Future?!

- The future for Deep Learning & LLMs is **Federated**
  - FL can help leverage planet's unutilized data and computational resources, for LLM training.
  - Federated LLM training can be done with affordable hardware configurations
  - *Federated LLM training offers competitive performance with centralized training.
- Leveraging the **Edge-to-Cloud Continuum**
  - Scalable MLSys via multi-tiered approach
  - Support of system architectures and protocols
    - Don't forget about **privacy and security**
  - Consider the capacity vs latency trade-offs
    - Cloud is resourceful but has high latency
    - Edge has low-latency but is limited in resources



*Large Language Model Pre-training will be Federated in future



Most importantly, as a community we need to make our solutions **Open-Source**

*Lorenzo Sani et. al.. "The Future of Large Language Model Pre-training is Federated.", Arxiv 2405.10853 (2024).

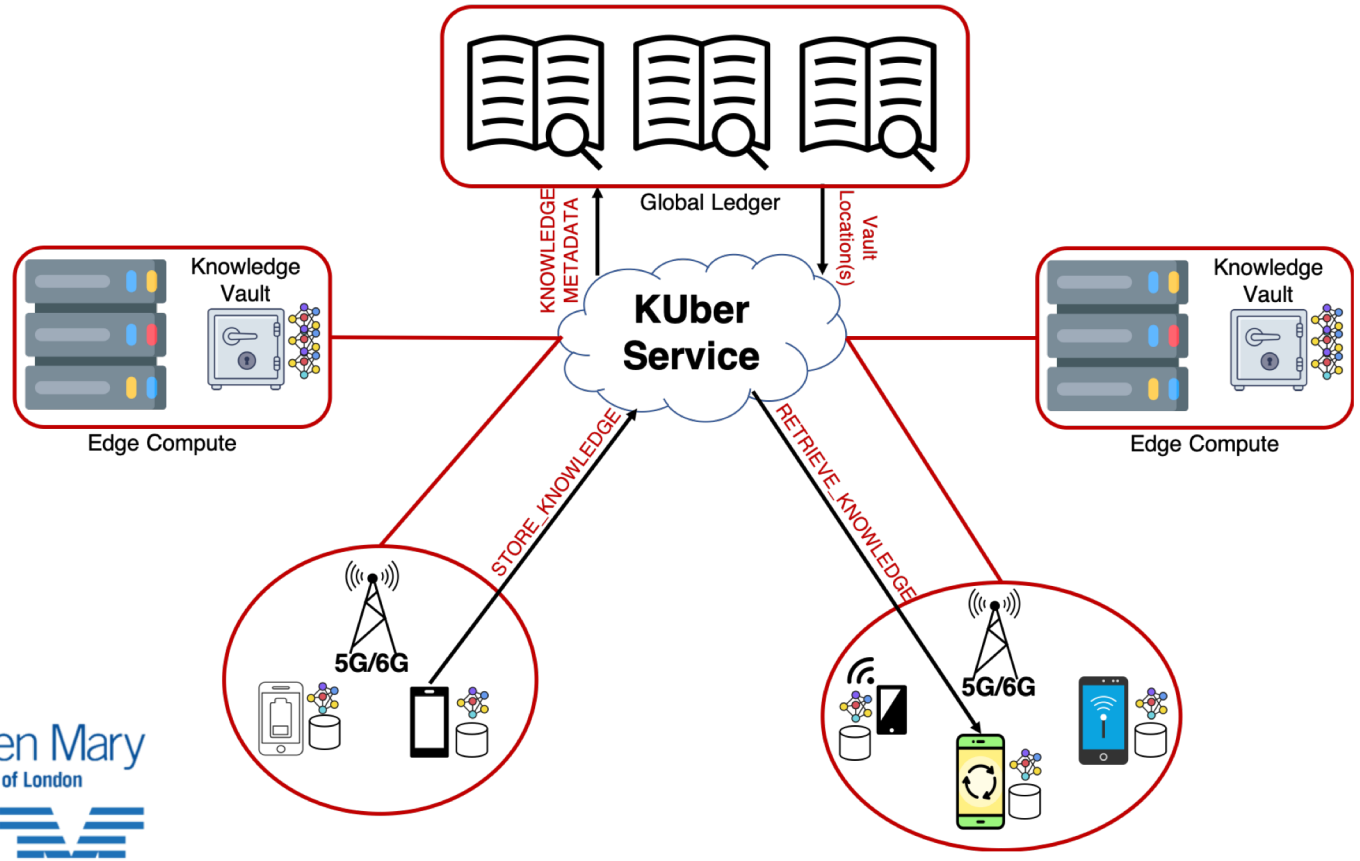
How can we enable this?

NextGen MLSys should be

Efficient → Produce high **Quality** models in reasonable cost/time via knowledge exchange
Scalable → **Reliably** support large number of distributed & dynamic learners
Privacy → **Security**/privacy of user data

KUber: Knowledge Delivery System for ML at Scale

https://kuber.org.uk



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IBM

Thanks

To follow-up, please reach me at ahmed.sayed@qmul.ac.uk

If you are intrigued by these problems,
Please reach out to collaborate with us

https://sayed-sys-lab.github.io