

GPU Travelling

Efficient Confidential Collaborative Training with TEE-Enabled GPUs

Shixuan Zhao[†], Zhongshu Gu[‡], Salman Ahmed[‡], Enriquillo Valdez[‡], Hani Jamjoom[‡], Zhiqiang Lin[†]

[†]The Ohio State University [‡]IBM Research

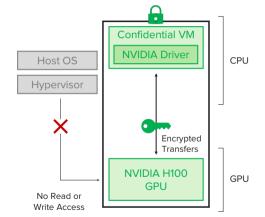




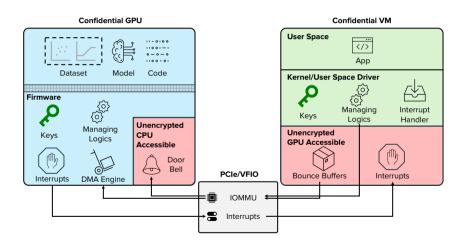
GPU TEEs

NVIDIA Confidential Computing

- Support added from Hopper (H100)
- No trust to the hypervisor
- Encrypt PCle communication via driver and firmware



GPU TEEs



Confidential collaborative training

What is

- Multiple data owners
- Mutually distrusted
- One model



Medical Industry



Media Industry

Existing solutions

Existing Solutions

- Share the datasets
- Share the model/gradients

Dataset



VS.

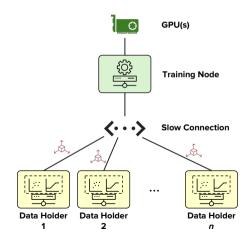


Model

Existing solutions

Sharing dataset

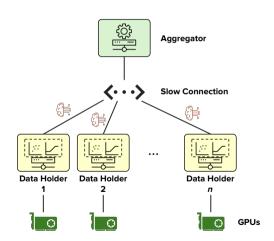
- Centralised training
- √ No model consolidation needed
- Large datasets go through slow connections
- × Sensitive datasets travel a long data path



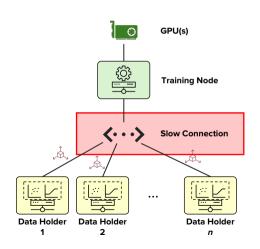
Existing solutions

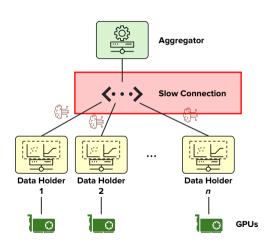
Sharing model/gradients

- E.g., federated learning
- Datasets don't travel a long data path
- Large model/gradients go through slow connections
- Extra overheads on model consolidation
- × Everyone needs enough GPUs



The common problem





The common problem

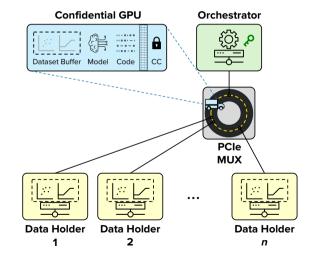


Can we just eliminate this?

Our solution

GPU Travelling

- An orchestrator
- Multiple Data Holders
- A Travelling GPU



Our solution

Physical Layer Travelling

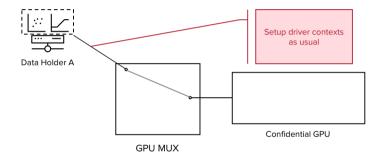


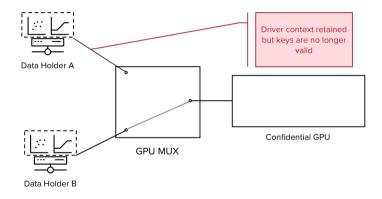
PCIe MUX: Routing a physical GPU to multiple VMs

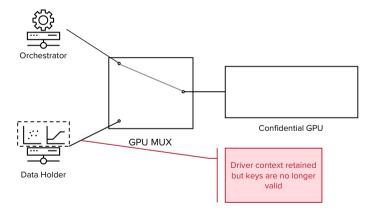


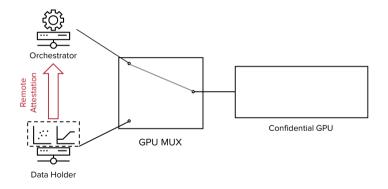
Encrypted transfer via PCle: Sharing the key = sharing the GPU

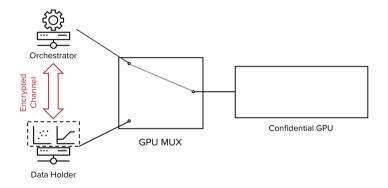
Security Layer Travelling



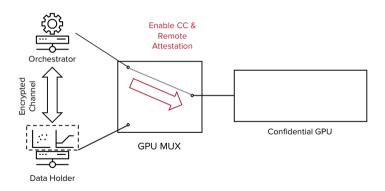




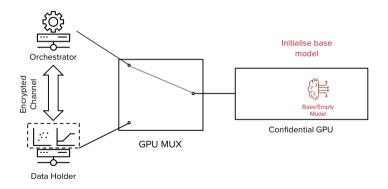




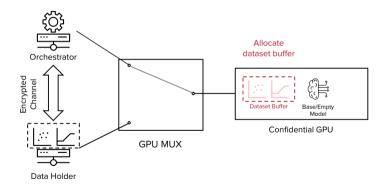
Setup



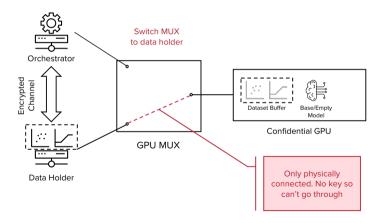
Setup



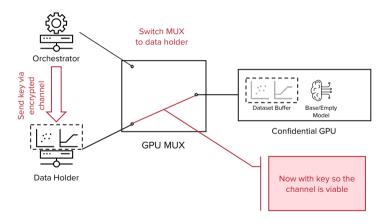
Setup



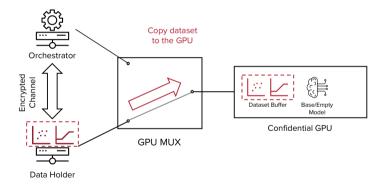
Physical layer travelling



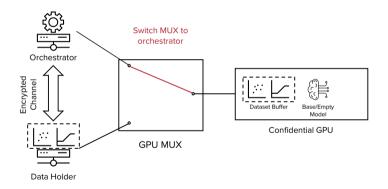
Security layer travelling



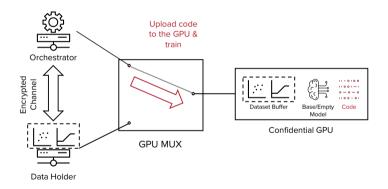
Data provisioning



Switch back

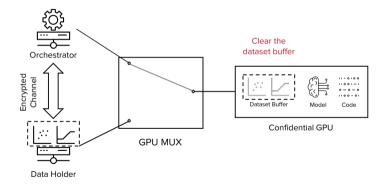


Training



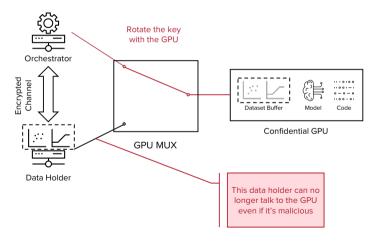
How it works - Epilogue

Dataset buffer clean up



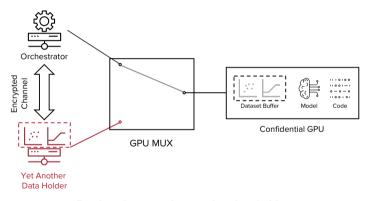
How it works - Epilogue

Key rotation



How it works - Epilogue

Ready for the next one



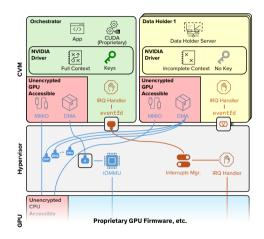
Ready to be passed to another data holder

Implementation

Requirement

No change to proprietary stuff

- Intel TDX
- NVIDIA H100
- VFIO-based MUX
- Modified NVIDIA driver
 - Key import/export
 - Context sync
 - Other magic chores

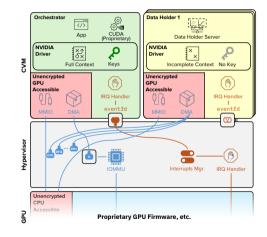


Implementation

- Total code changes: 4,746 LoC
- Artefacts available



https://zenodo.org/records/16899384

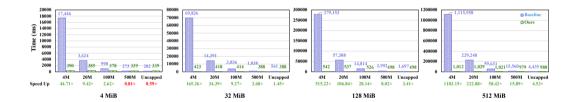


Evaluation

We've tried the real deal

- Ilm.c-based demo
- Showed significant efficiency improvement
- Demo artefacts also included

Data transfer overheads



The bigger the dataset buffer, the faster we are

Ilm.c comparison w/ GPT-2

- Save 7 seconds per 256 MiB transmission
- Fineweb is 44 TiB in size
- 1261568 s (14+ days) for the entire dataset

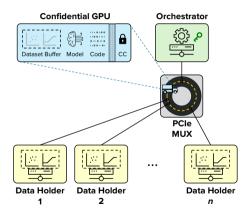
| | Baseline | | | Ours | | |
|----------|--------------|-----------|------------------|-----------------|-----------|------------------|
| | Training (s) | Tx (s) | Tx Percentage | Training (s) | Tx (s) | Tx Percentage |
| 4M | 1230.00 | 1115.88 | 47.568% | 1230.26 | 1.01 | 0.082% |
| 20M | 1231.39 | 230.84 | 15.787% | 1229.39 | 1.03 | 0.084% |
| 100M | 1231.17 | 60.36 | 4.674% | 1230.57 | 1.02 | 0.083% |
| 500M | 1230.73 | 15.86 | 1.272% | 1229.67 | 0.98 | 0.080% |
| Uncapped | 1229.36 | 7.34 | 0.594% | 1231.46 | 0.98 | 0.079% |

Conclusion



GPU Travelling significantly improved performance of confidential collaborative training

Eliminated transmission over slower channel by letting GPU to travel to the data holder to collect datasets directly



Artefacts



https://zenodo.org/records/16899384

Thank you





https://go.osu.edu/seclab

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