ParSecureML: An Efficient Parallel Secure Machine Learning Framework on GPUs

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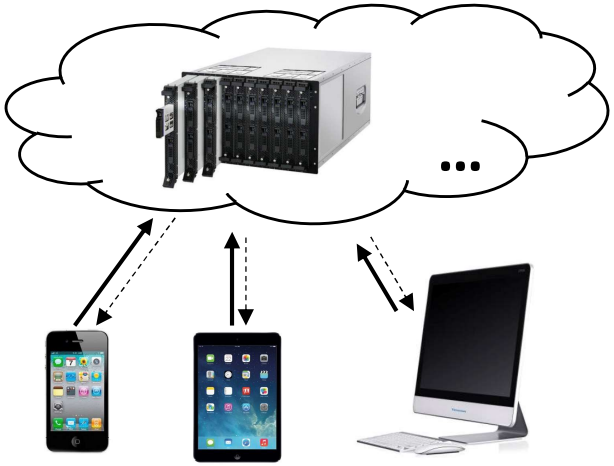
Outline

1. Background
2. Motivation
3. Basic Idea
4. Challenges
5. ParSecureML
6. Evaluation
7. Source Code at Github
8. Conclusion

1. Background

- Secure Machine Learning



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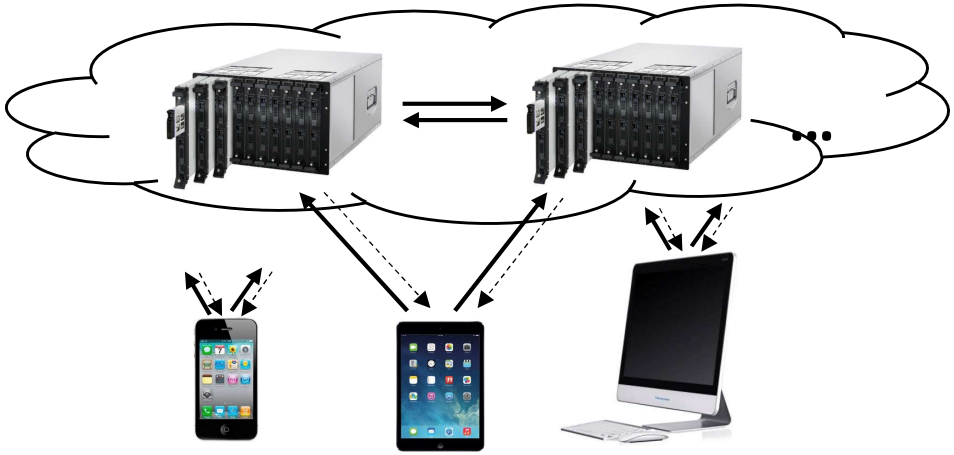

(b) Machine learning process with two-party computation.

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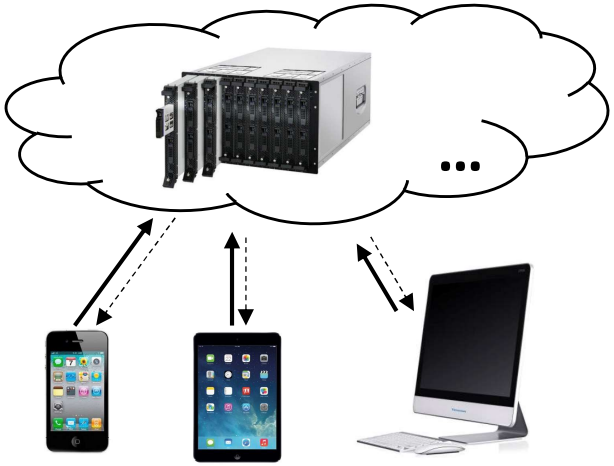

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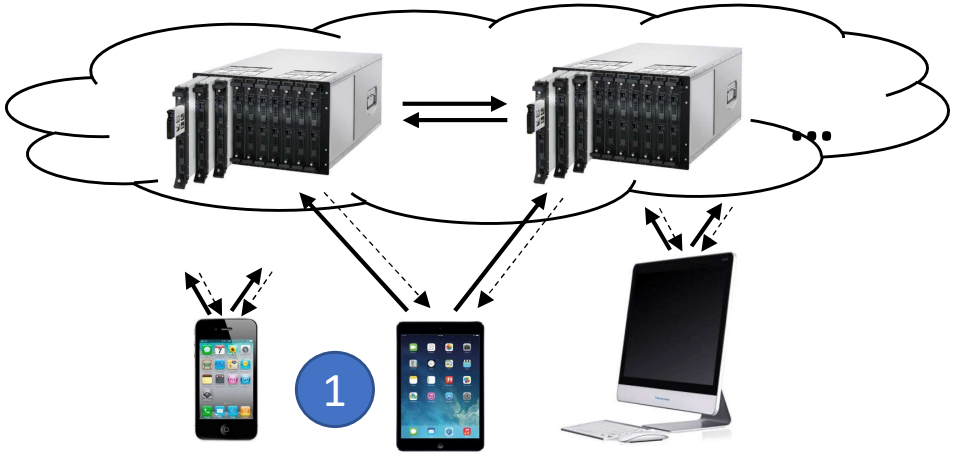

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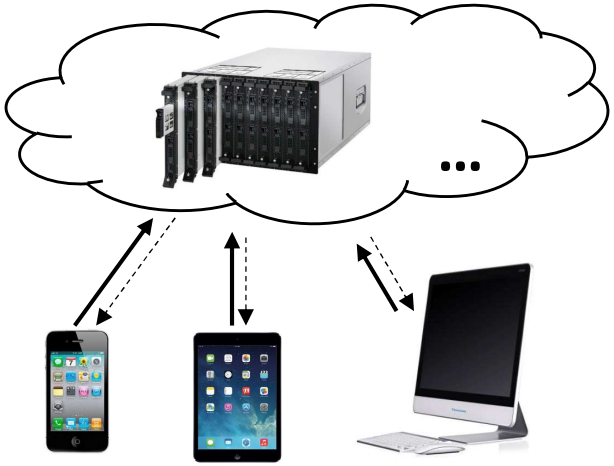

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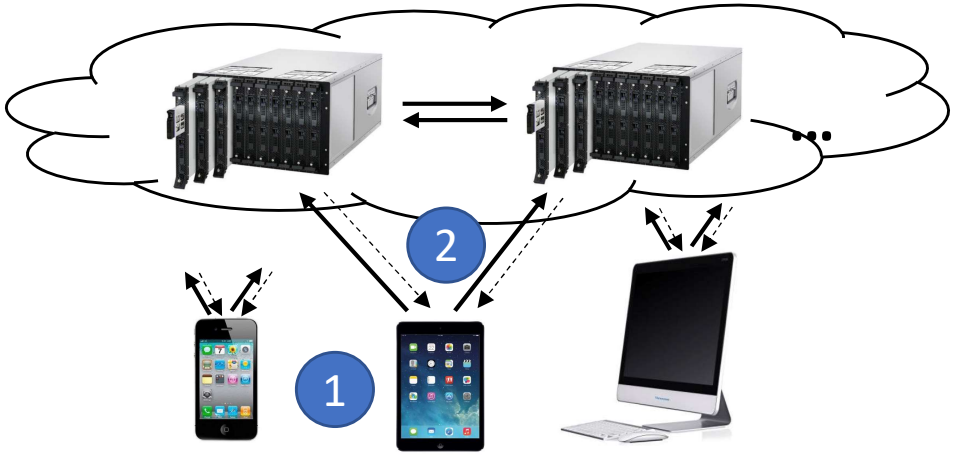

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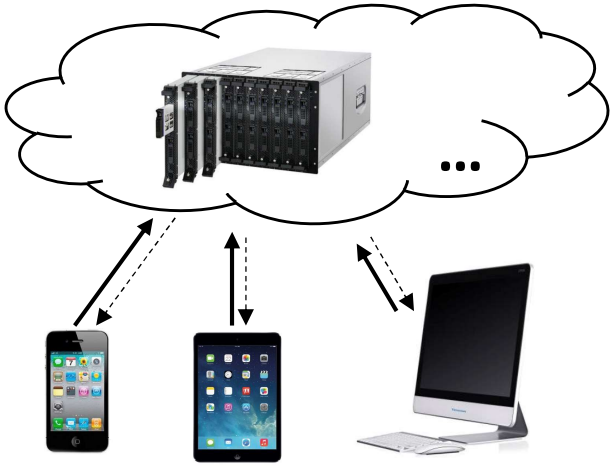

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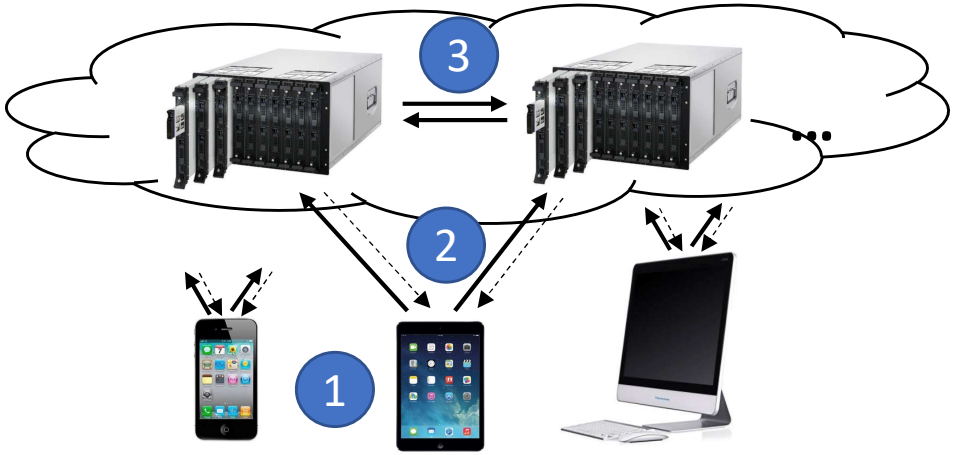

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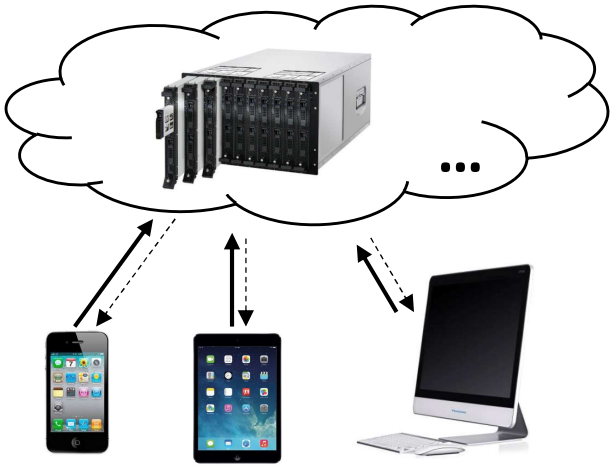

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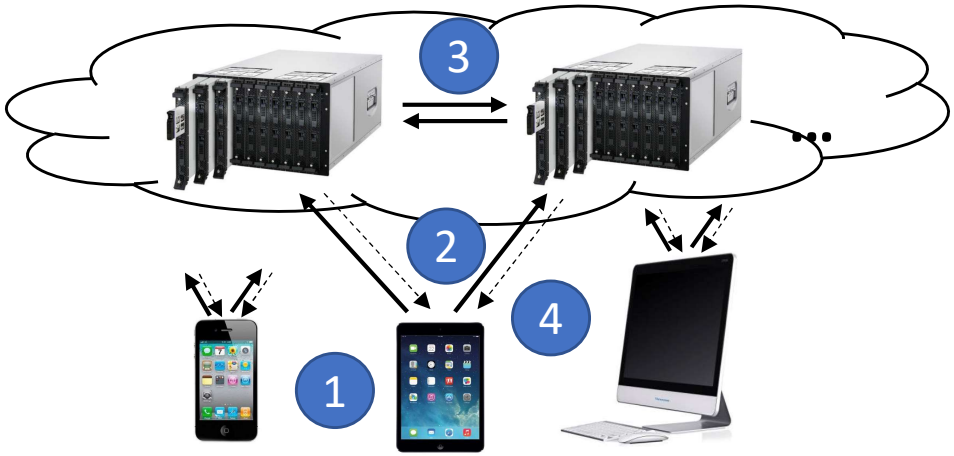

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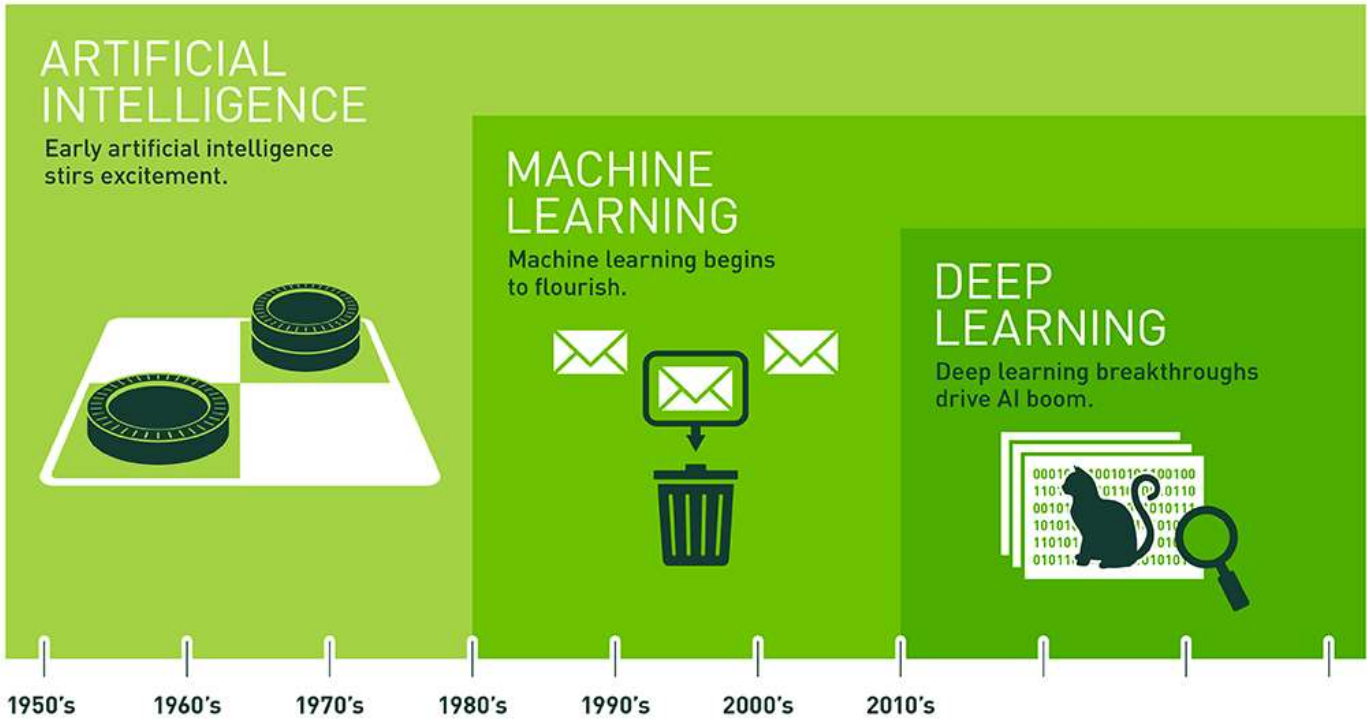
1. Background

- GPU Acceleration

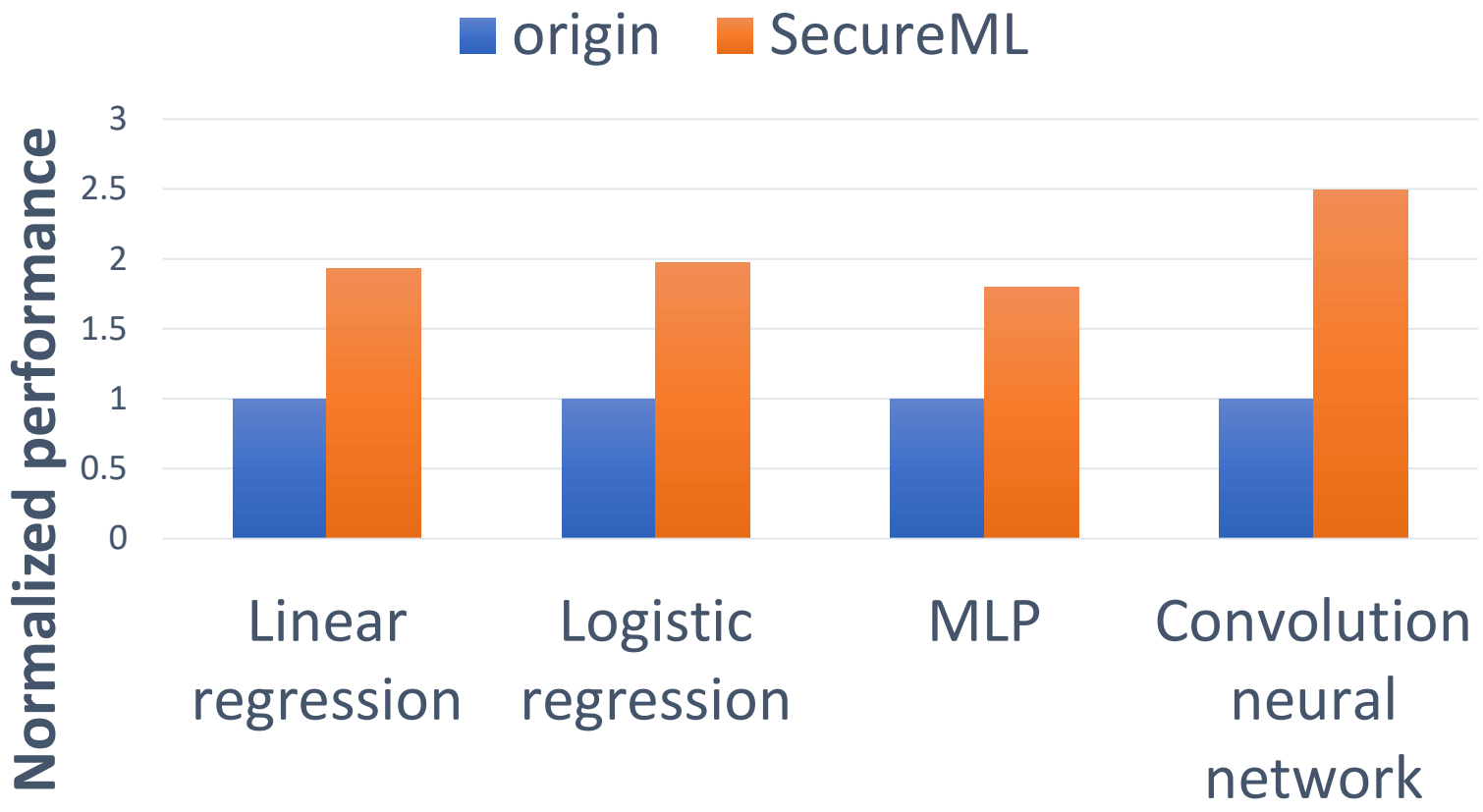


Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

https://developer.nvidia.com/deep-learning

2. Motivation

- Performance Degradation



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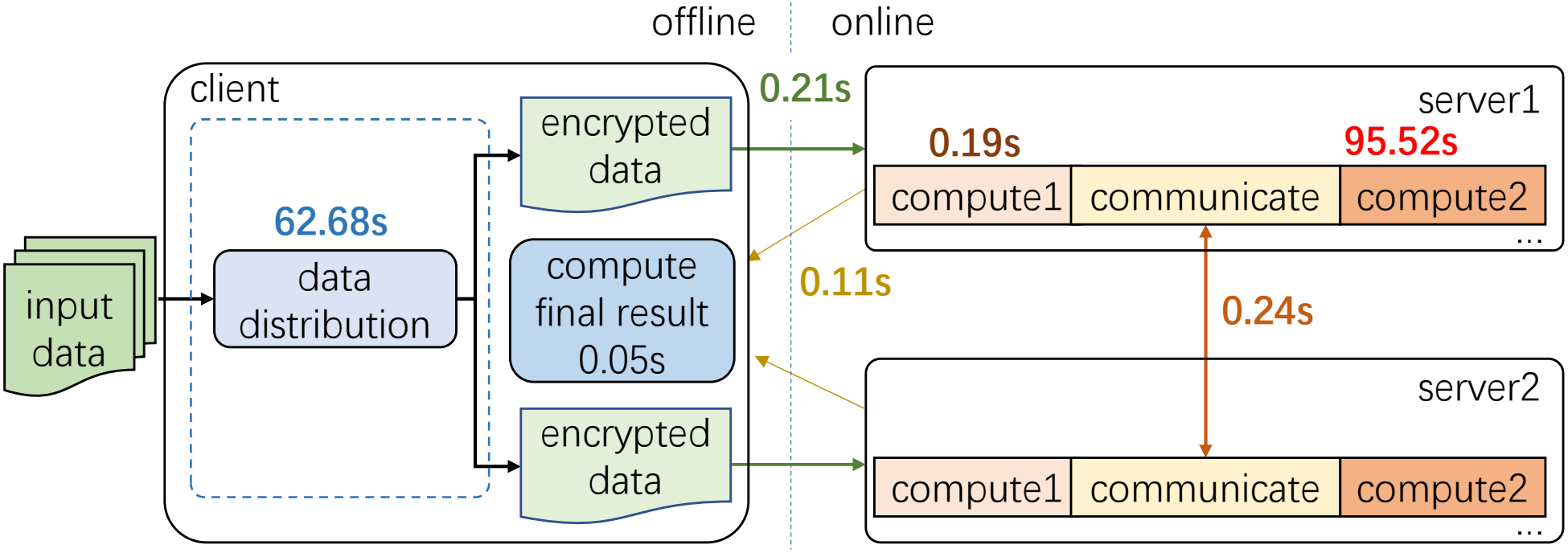
- Time Breakdown for two-party computation



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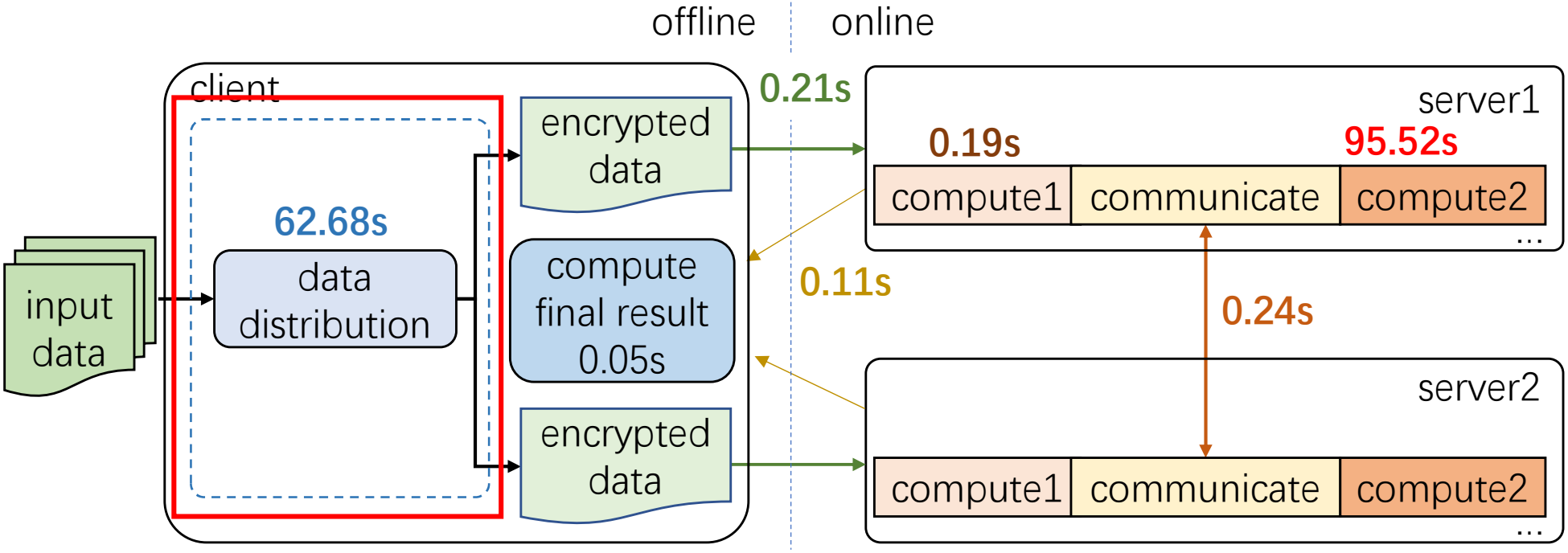

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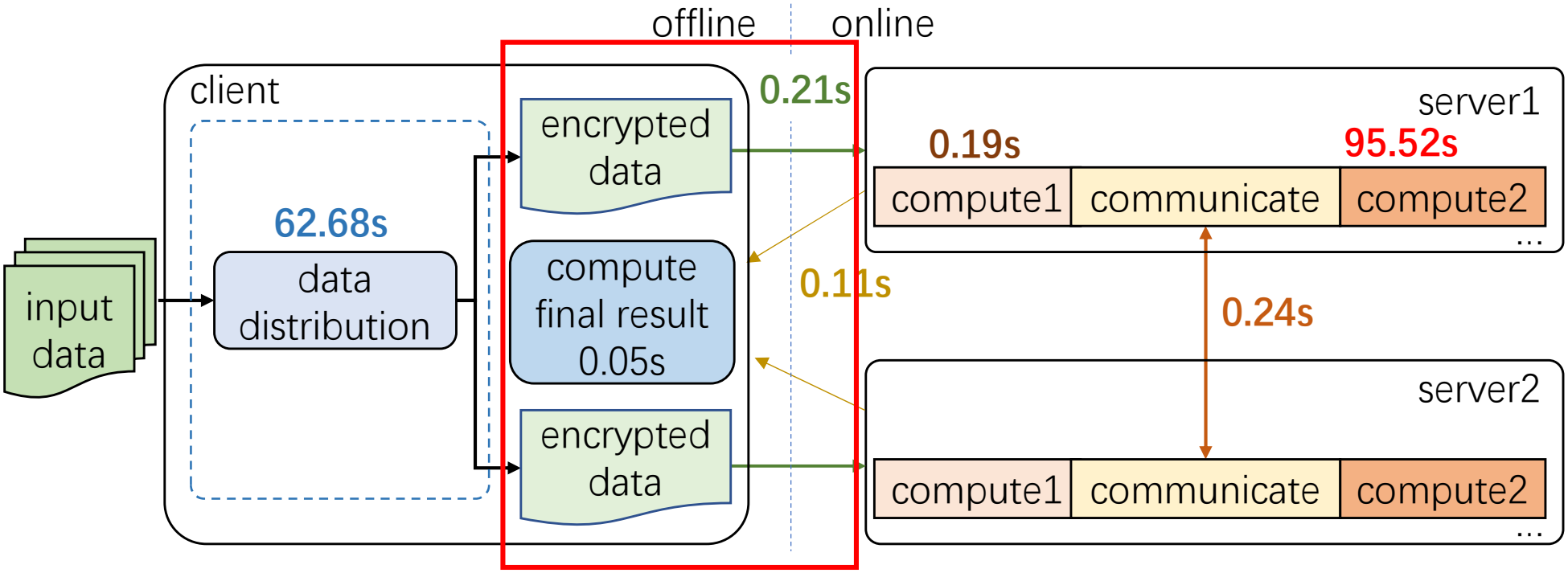

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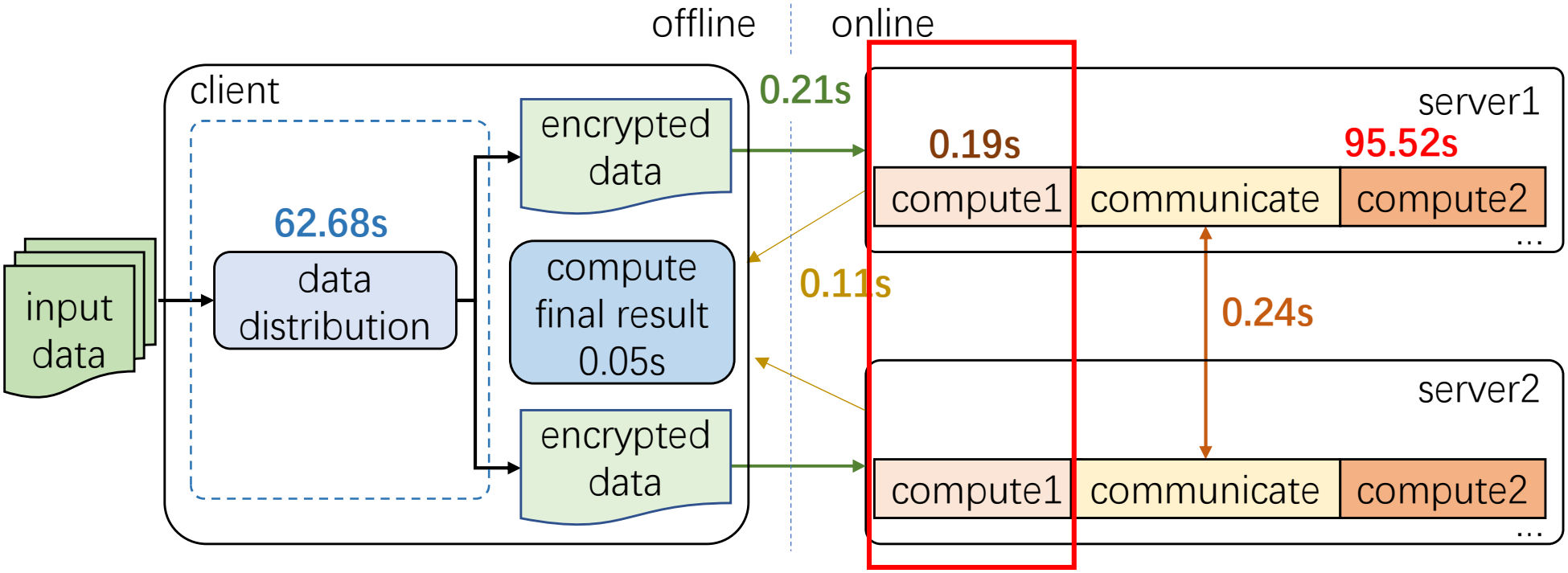

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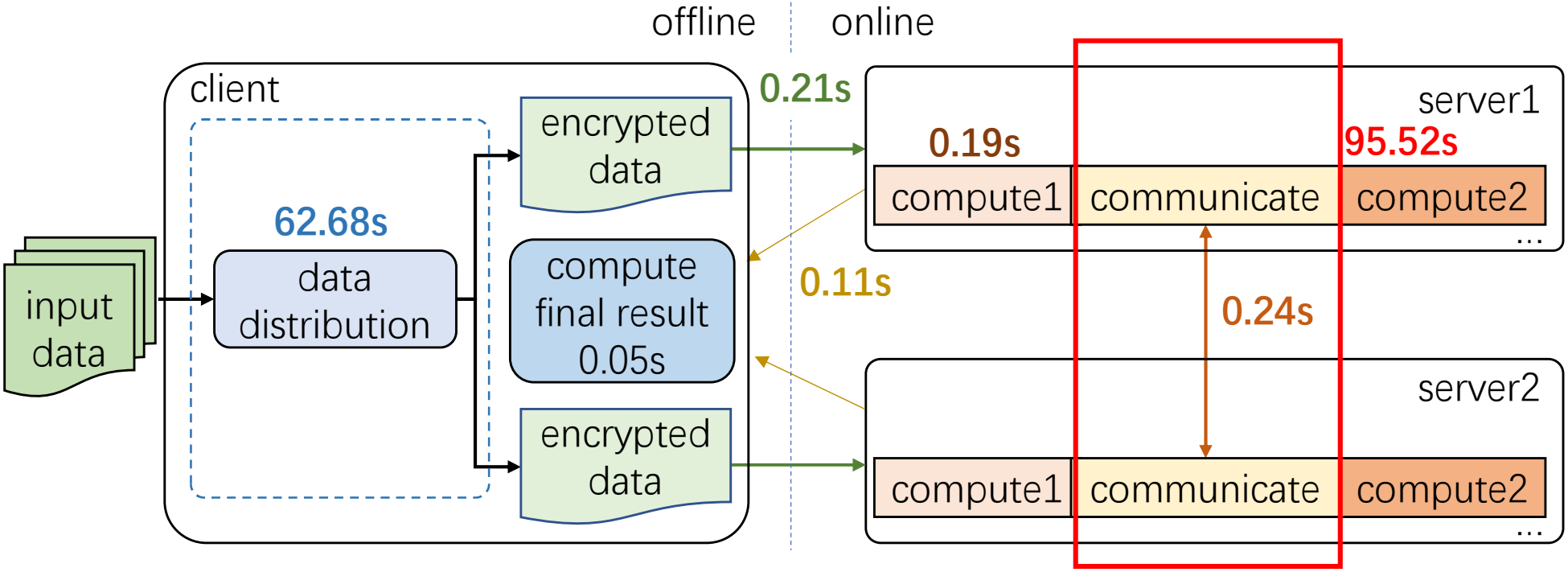

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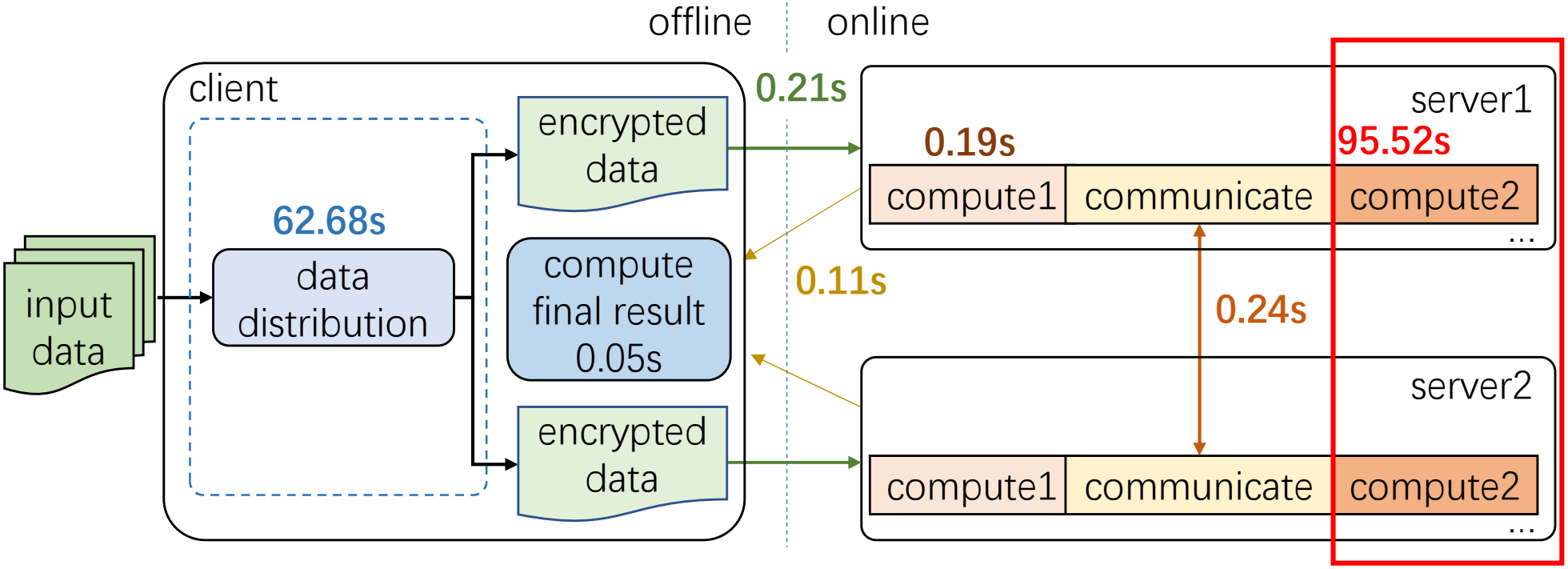

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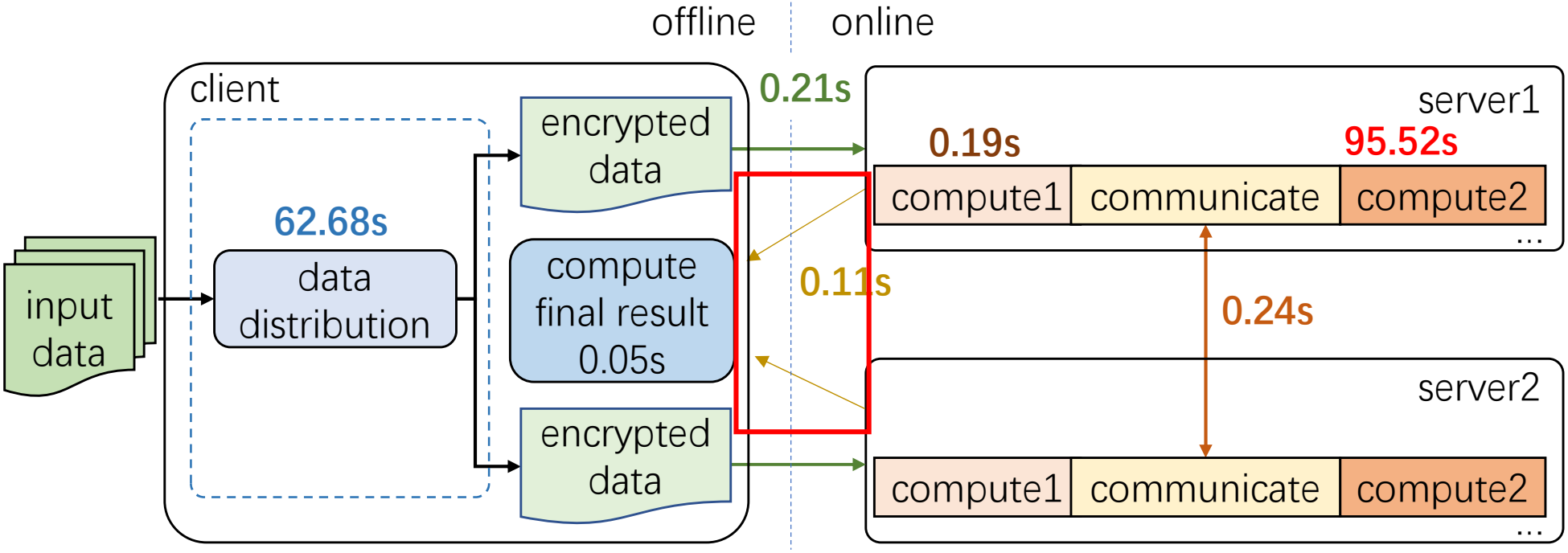


3. Basic Idea

- A GPU-based two-party computation that considers both the GPU characteristics and features of two-party computation shall have better performance acceleration effects.
- Challenges
  - Challenge 1: Complex triplet multiplication based computation patterns
  - Challenge 2: Frequent intra-node data transmission between CPU and GPU
  - Challenge 3: Complicated inter-node data dependence

4. Challenges

- Challenge 1: Complex triplet multiplication based computation patterns

$$C = A \times B \tag{1}$$

$$Z = U \times V \tag{2}$$

$$U = U_0 + U_1, V = V_0 + V_1, Z = Z_0 + Z_1 \tag{3}$$

$$E_i = A_i - U_i, F_i = B_i - V_i \tag{4}$$

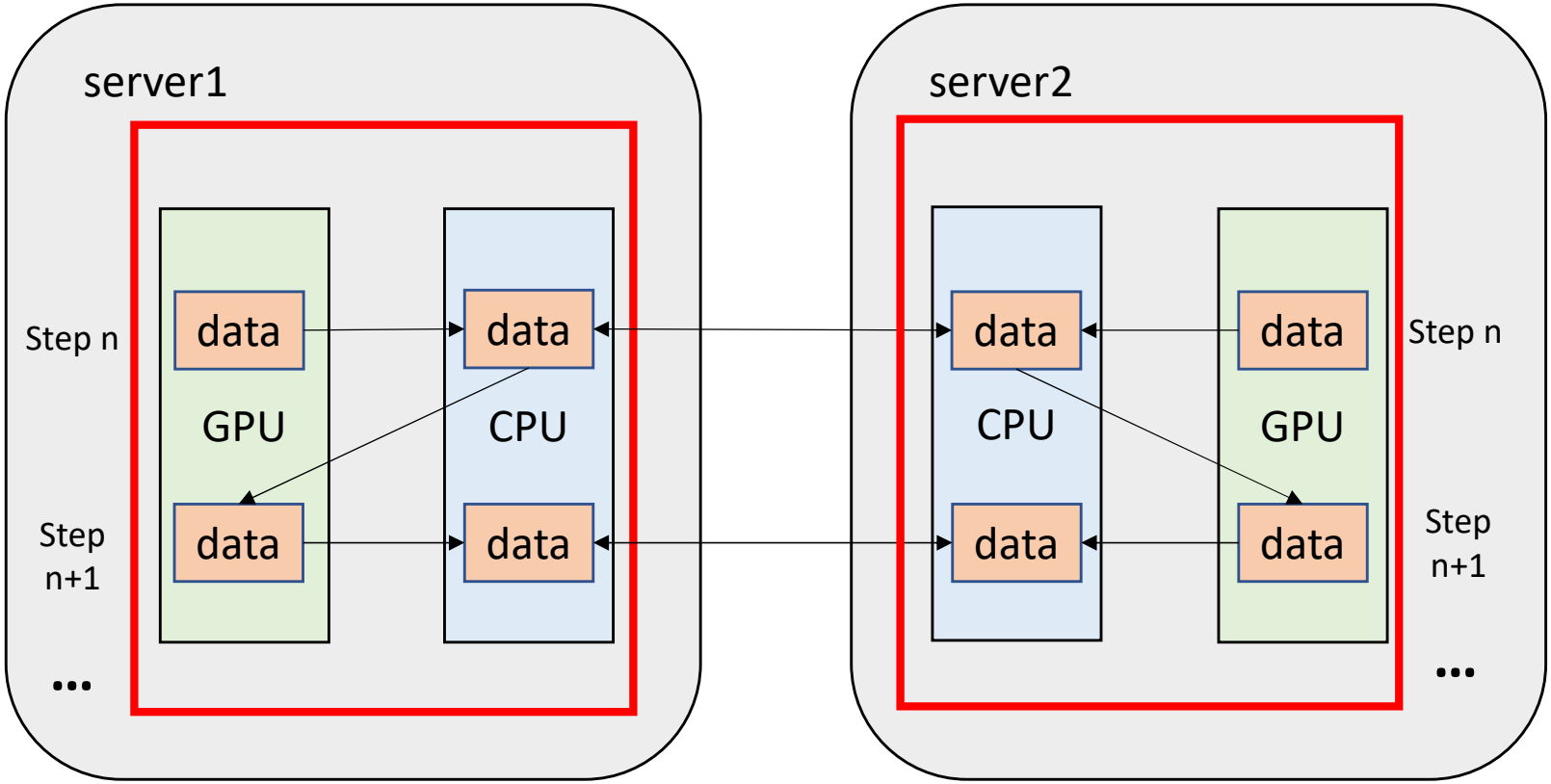
$$E = E_0 + E_1, F = F_0 + F_1 \tag{5}$$

$$C_i = (-i) \times E \times F + A_i \times F + E \times B_i + Z_i \tag{6}$$

... ...

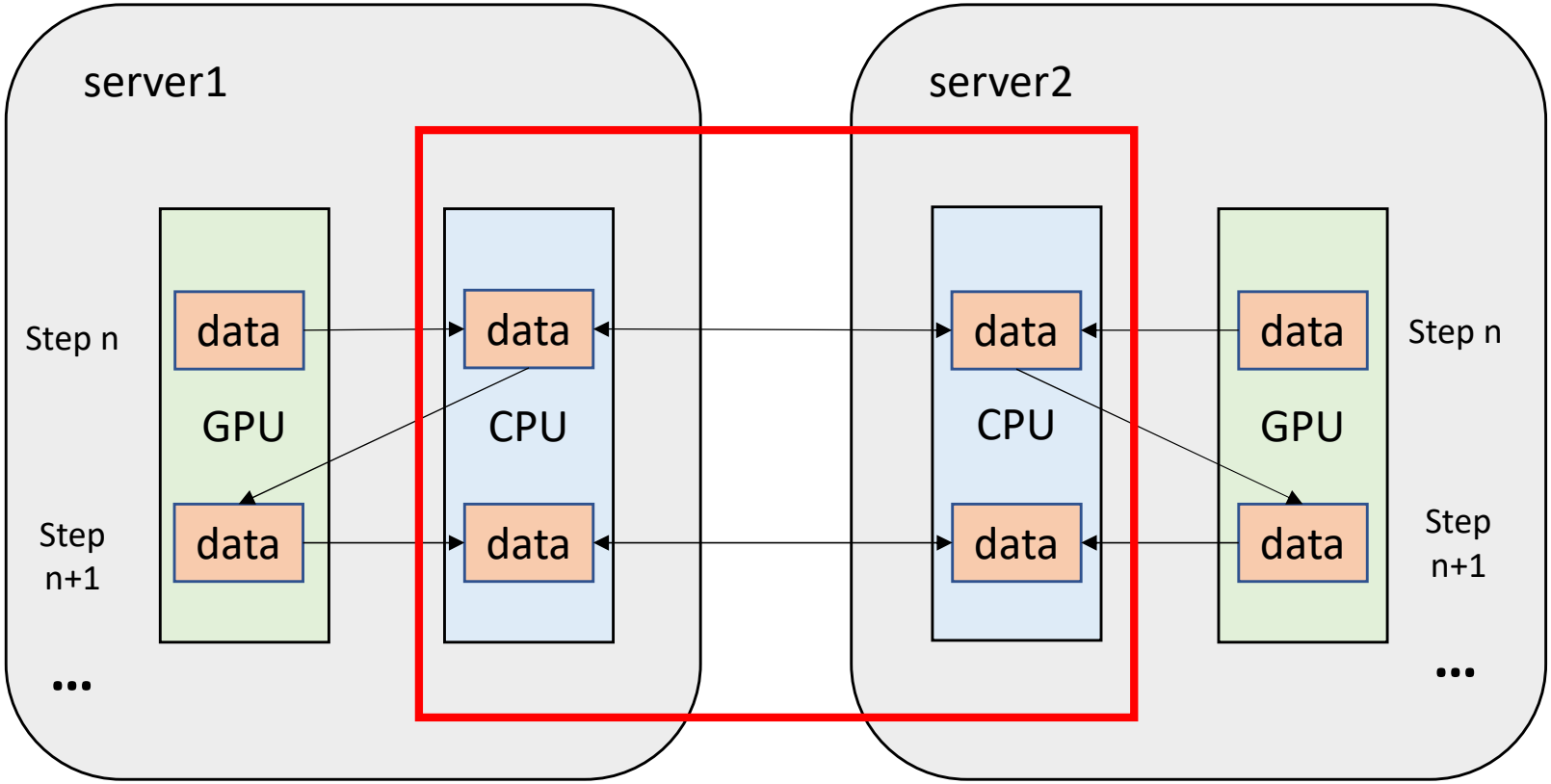
4. Challenges

- Challenge 2: Frequent intra-node data transmission between CPU and GPU



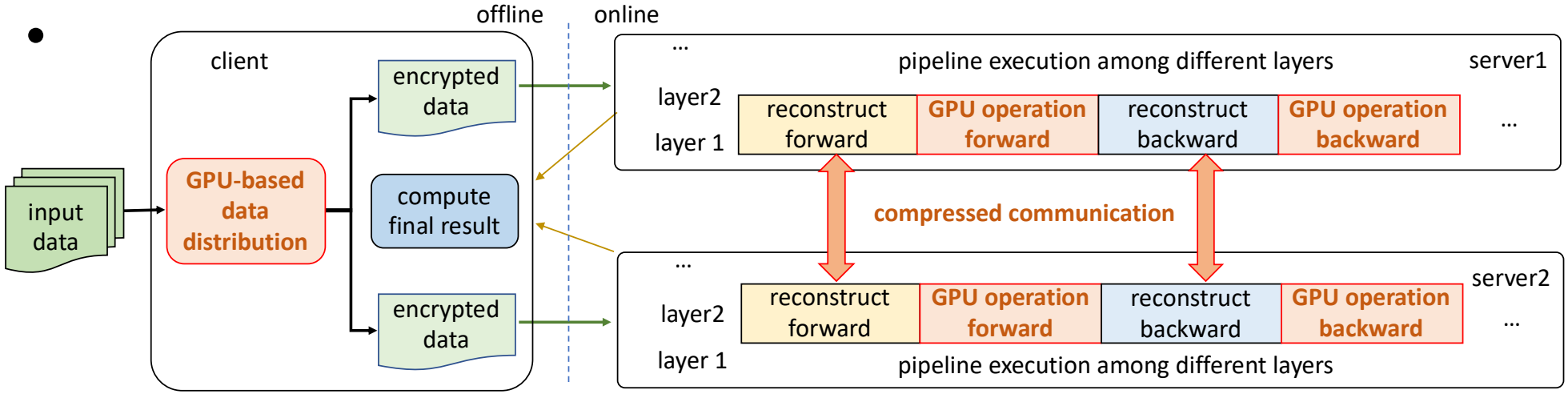
4. Challenges

- Challenge 3: Complicated inter-node data dependence



5. ParSecureML

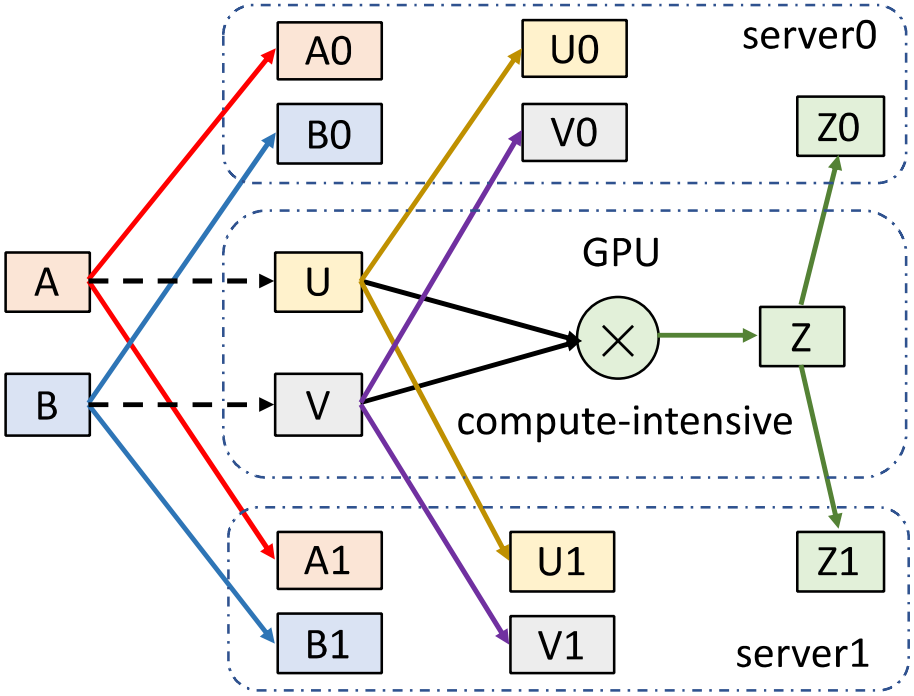
- Overview - ParSecureML consists of three major components:
  - Profiling-guided adaptive GPU utilization
  - Intra-node double pipeline
  - Inter-node compressed transmission communication
-



5. ParSecureML

- Profiling-Guided Adaptive GPU Utilization

Offline acceleration design



Online acceleration design

$$CPU: \quad E_i = E_0 + E_1 \quad F = F_0 + F_1$$

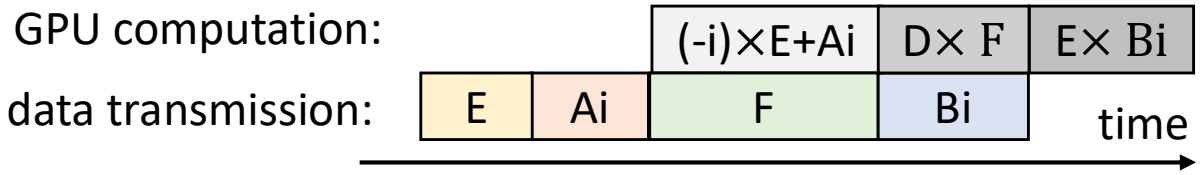
$$GPU: \quad Ci = (-i) \times E \times F + Ai \times F + E \times Bi + Zi$$

$$C_i = \begin{pmatrix} (-i) \times E & A_i & E \end{pmatrix} \times \begin{pmatrix} F \\ F \\ B_i \end{pmatrix} + Z_i, i \in 0, 1$$

$$C_i = \begin{pmatrix} (-i) \times E + A_i & E \end{pmatrix} \times \begin{pmatrix} F \\ B_i \end{pmatrix} + Z_i, i \in 0, 1$$

5. ParSecureML

- Double Pipeline for Intra-Node CPU-GPU Fine-Grained Cooperation
  - Pipeline 1 to overlap PCIe data transmission and GPU computation.



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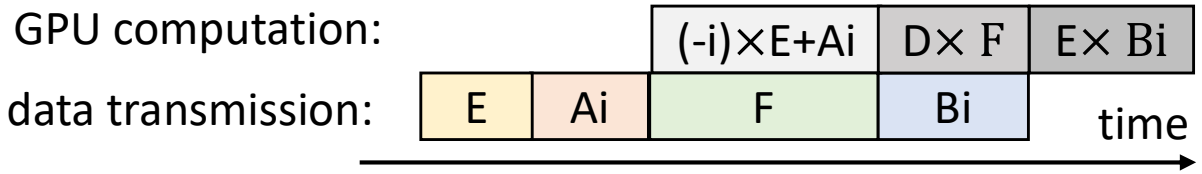
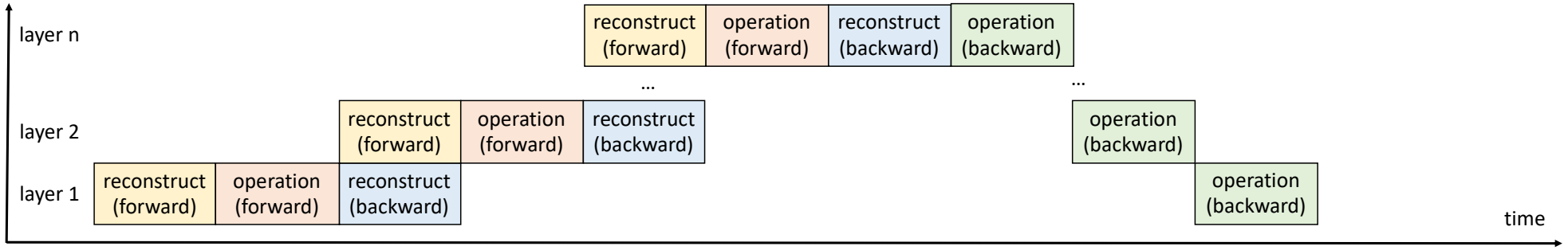
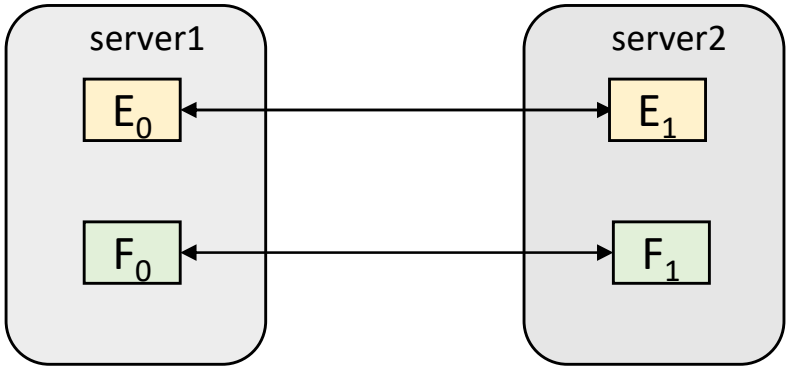


  - Pipeline 2 to overlap operations



5. ParSecureML

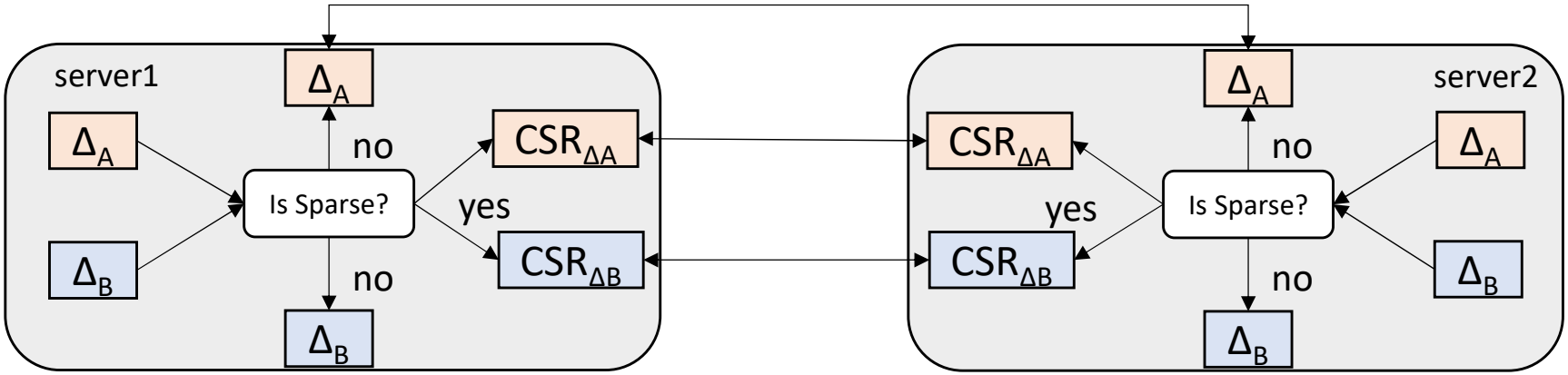
- Compressed Transmission for Inter-Node Communication



$$E_i = Ai - Ui \qquad F_i = Bi - Vi$$

$$A_{i\ j\ +\ 1} = A_{i\ j} + \Delta^A{}_{ij}$$

$$B'_{i,\ j\ +\ 1} = B'_{i,\ j} + \Delta^B{}_{ij}$$



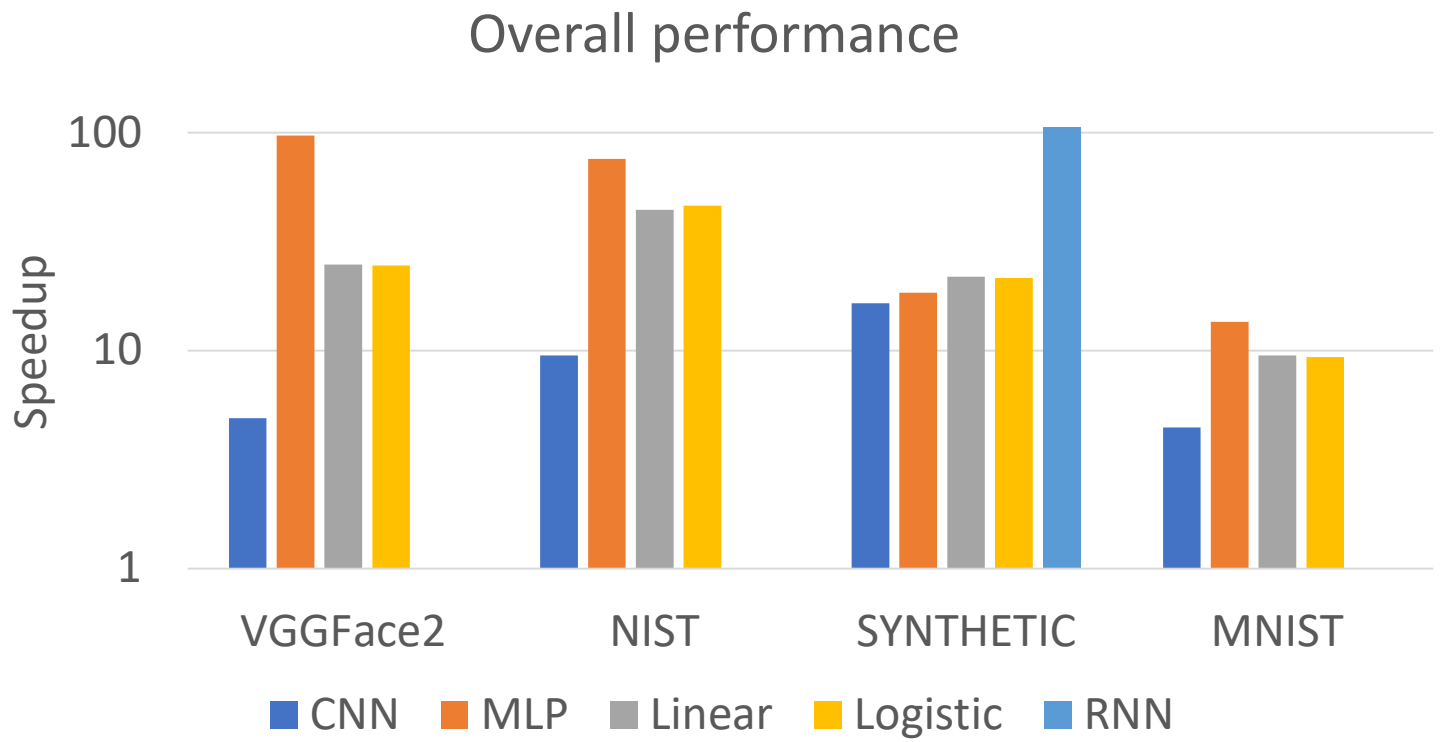
6. Evaluation

- Baseline: SecureML[1]
- Benchmarks
  - Convolution neural network (CNN)
  - Multilayer Perceptron (MLP).
  - Recurrent neural network (RNN)
  - Linear regression
  - Logistic regression
- Datasets - VGGFace2/NIST/SYNTHETIC/MNIST
- HPC Cluster
  - Intel(R) Xeon(R) CPU E5-2670 v3
  - Nvidia Tesla V100

[1] Mohassel P, Zhang Y. Secureml: A system for scalable privacy preserving machine learning[C]//2017 IEEE Symposium on Security and Privacy (SP). IEEE, 2017: 19-38

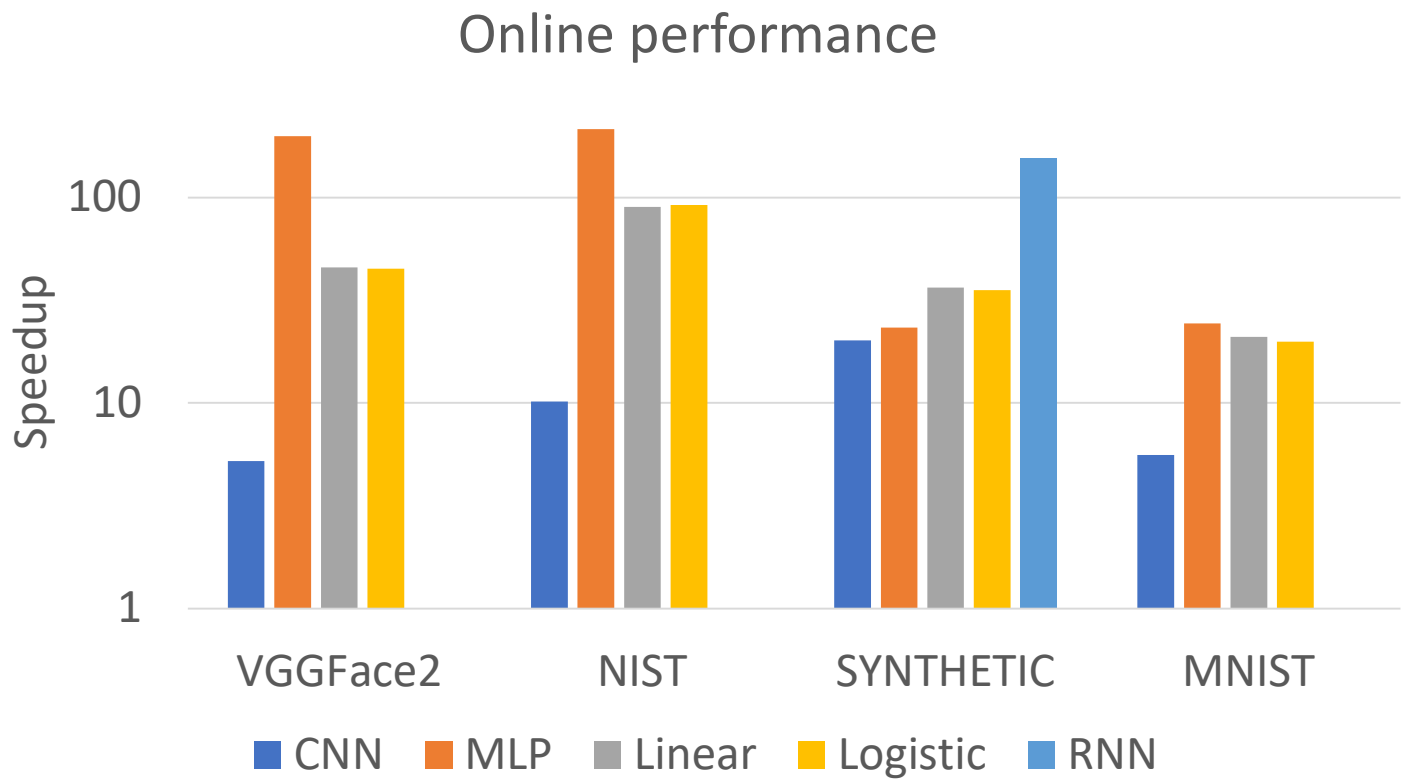
6. Evaluation

- Overall speedups. On average, ParSecureML achieves an average speedup of 32.2x over the SecureML.



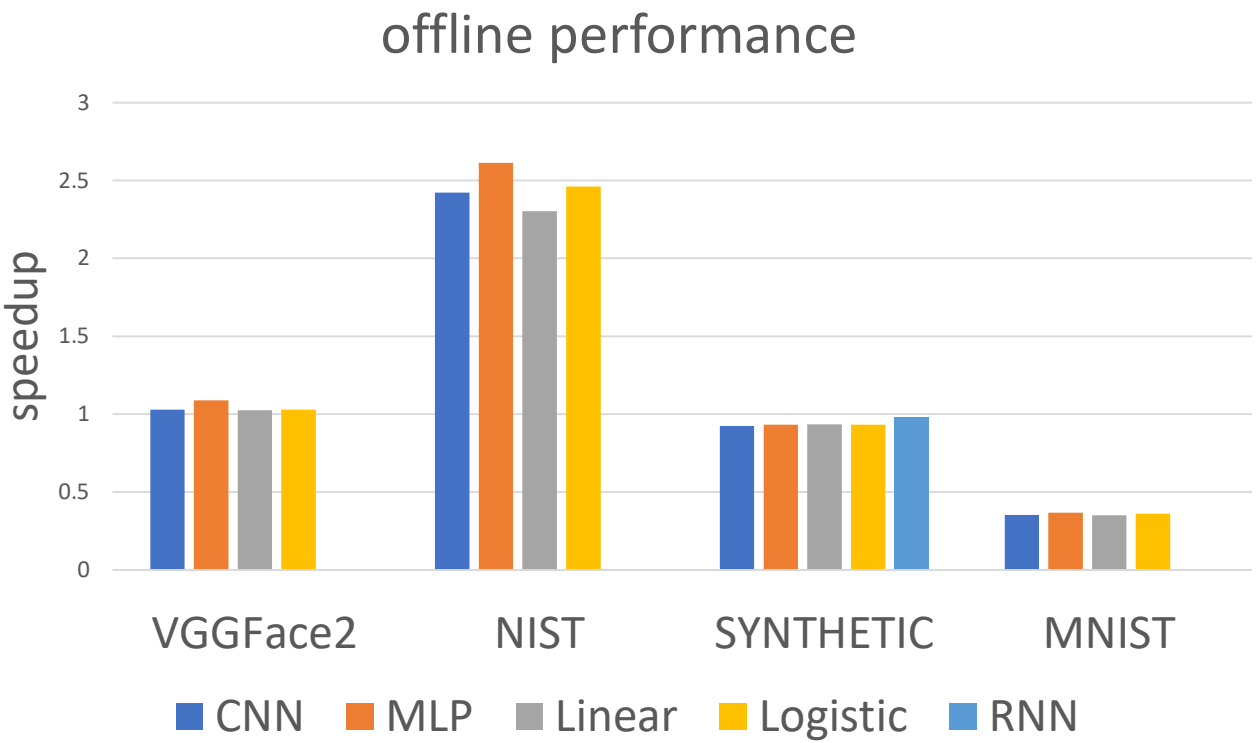
6. Evaluation

- Online speedups. The average online performance speedup is 61.4x (even higher than the overall speedup).



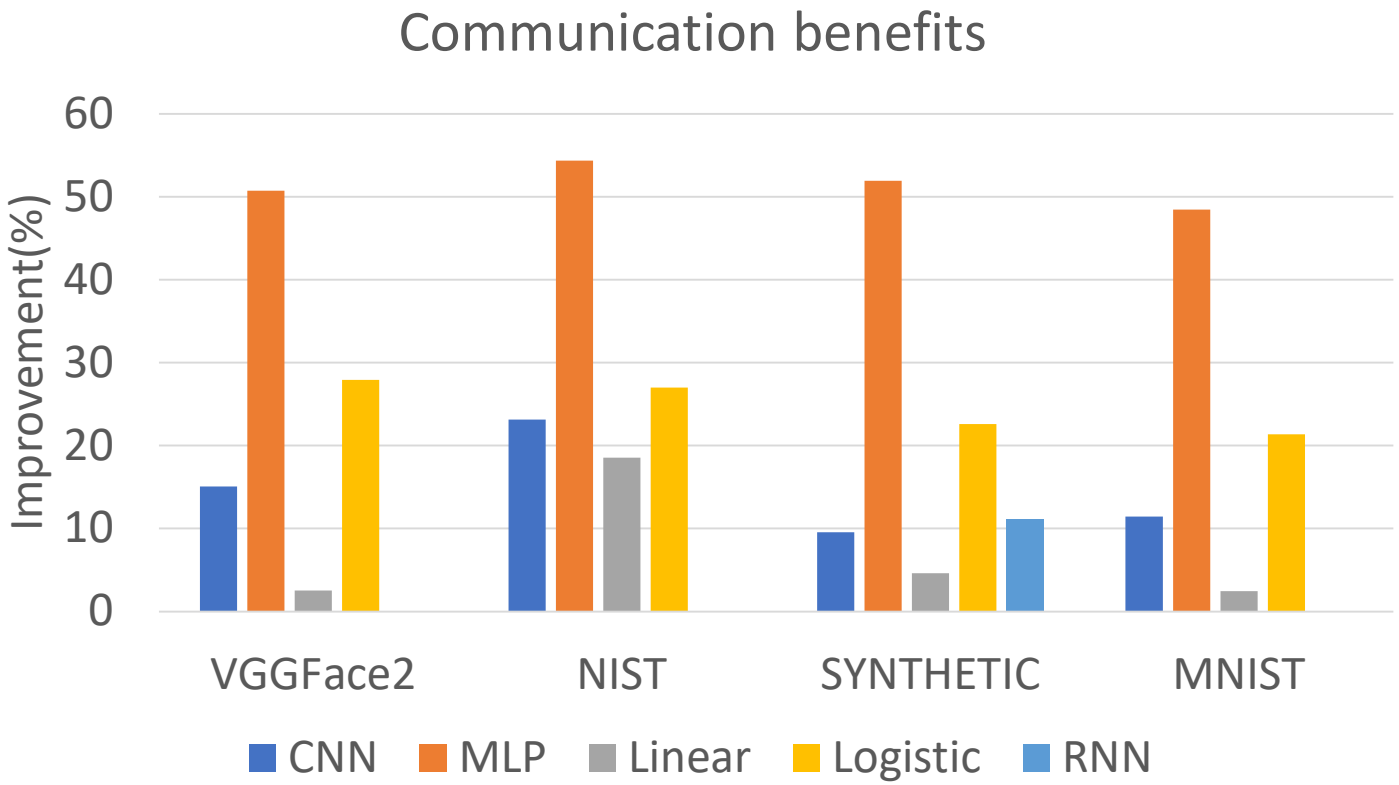
6. Evaluation

- Offline speedups. Applying GPUs in the offline phase brings 1.2x performance benefits.



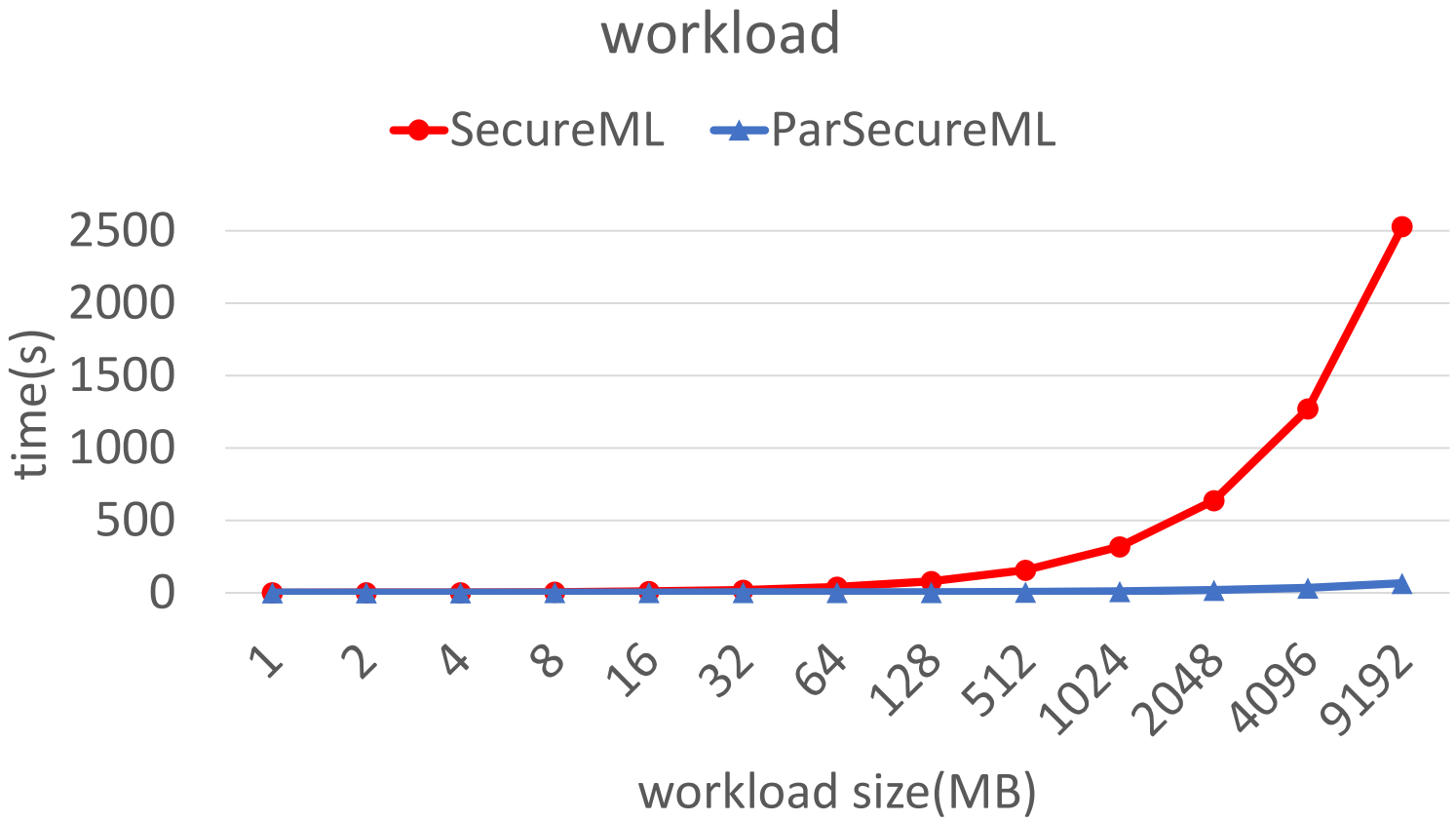
6. Evaluation

- Communication benefits - On average, ParSecureML reduces 23.7% communication overhead.



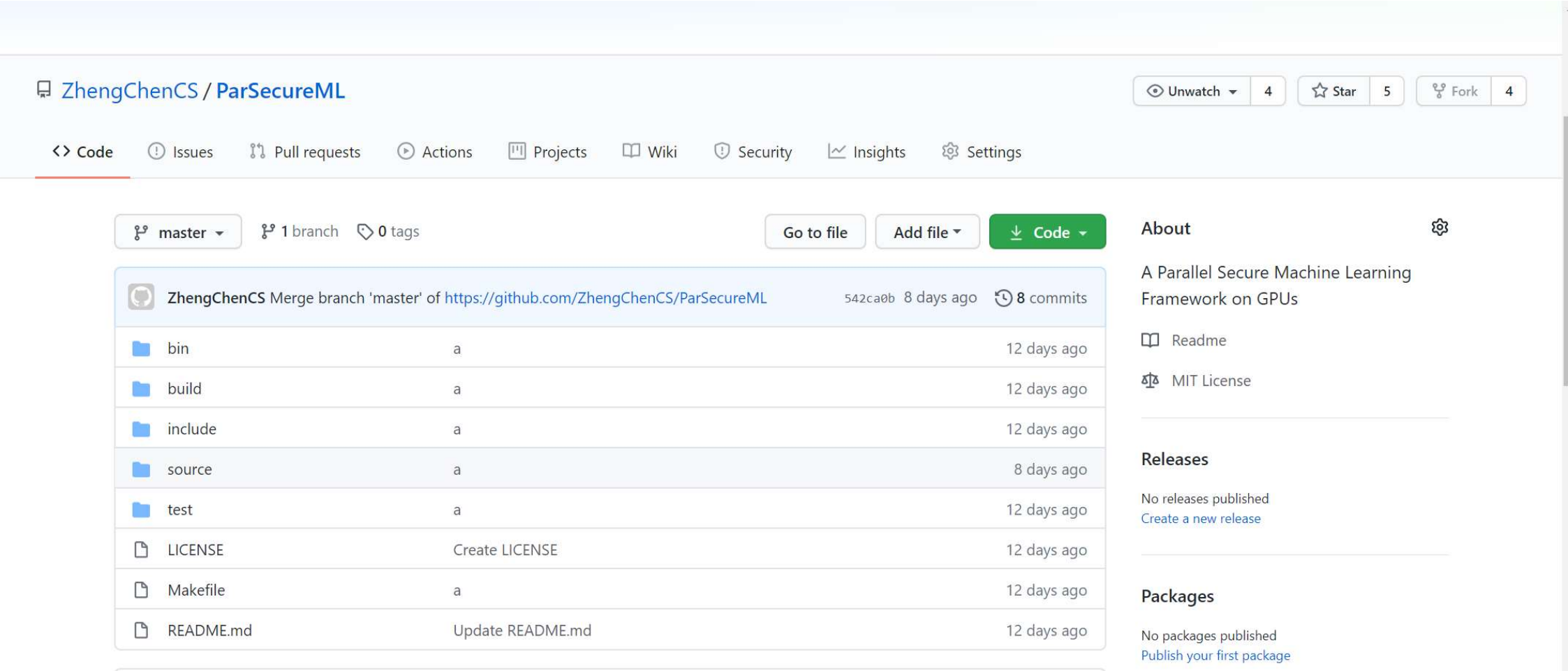
6. Evaluation

- Influence of workload size



6. Source Code at Github

- https://github.com/ZhengChenCS/ParSecureML



7. Conclusion

- We exhibit our observations and insights in SecureML acceleration.
- We develop ParSecureML, the first parallel secure machine learning framework on GPUs.
- We demonstrate the benefits of ParSecureML over the state-of-the-art secure machine learning framework.

Thank you!

- Any questions?

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GitHub https://github.com/ZhengChenCS/ParSecureML