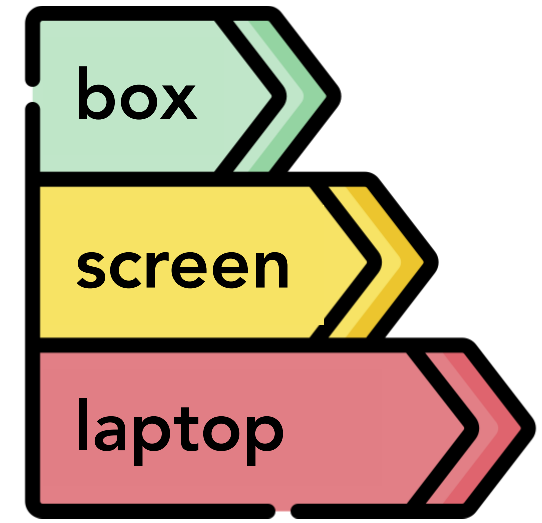
# BNS-GCN: Efficient Full-Graph Training of Graph Convolutional Networks with Partition-Parallelism and Random Boundary Node Sampling

**Cheng Wan***, **Youjie Li***, Ang Li, Nam Sung Kim, Yingyan Lin

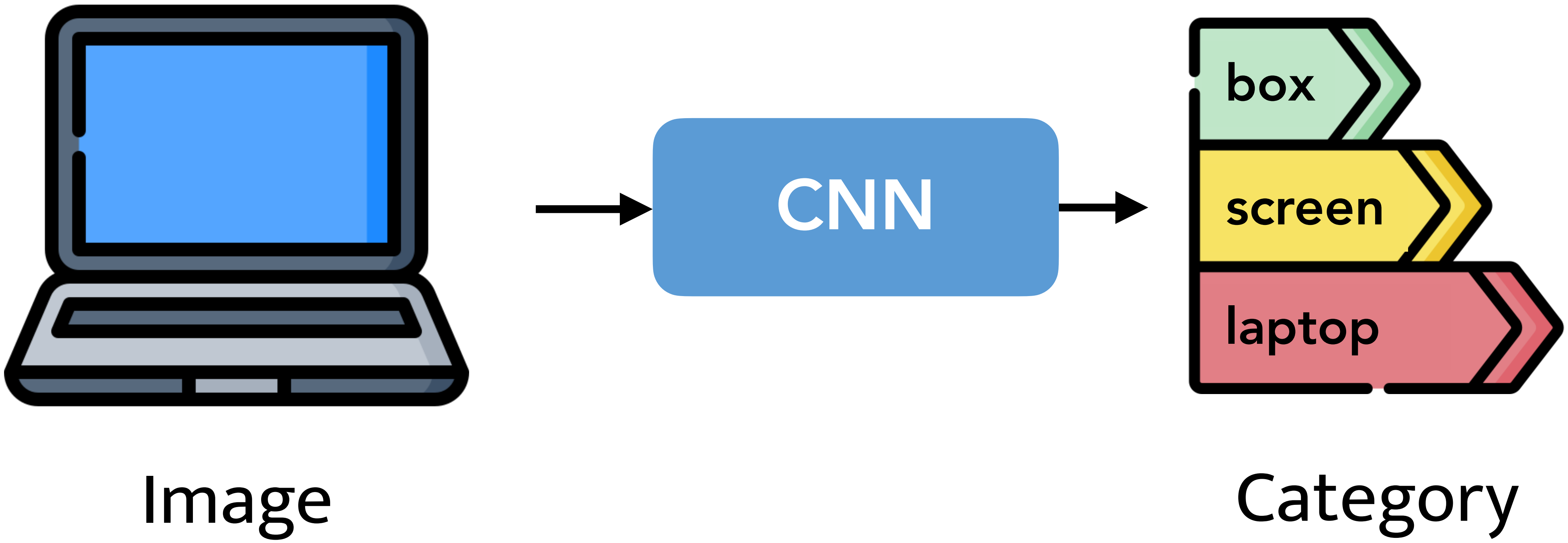
MLSys 2022

Image

→ Classify →

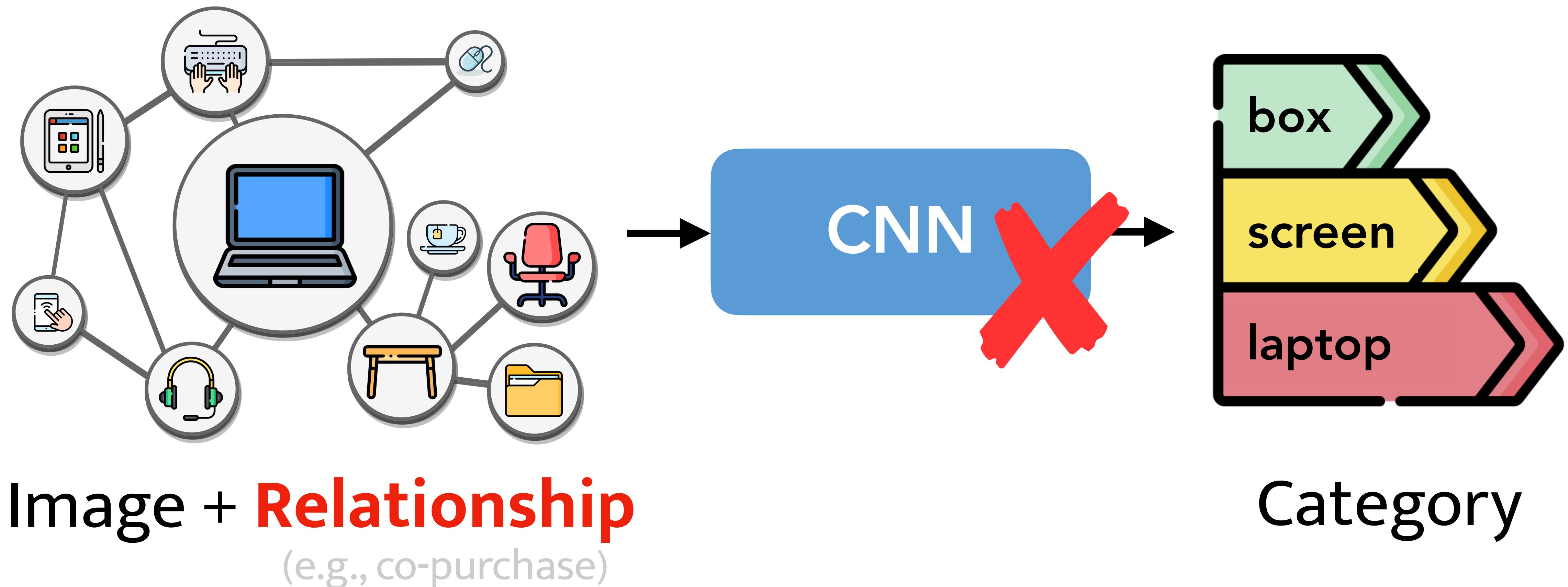



Category

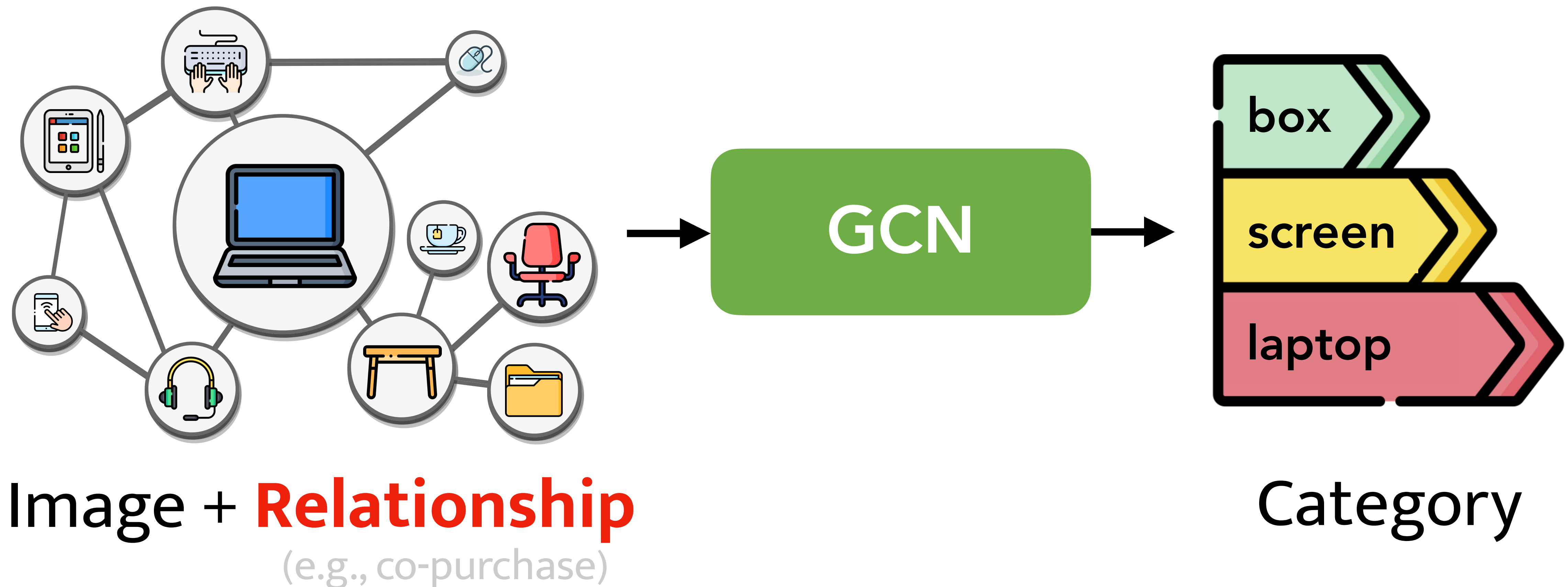



Convolutional Neural Networks (CNNs)

are powerful in image classification




How to incorporate **relationship** among data samples?



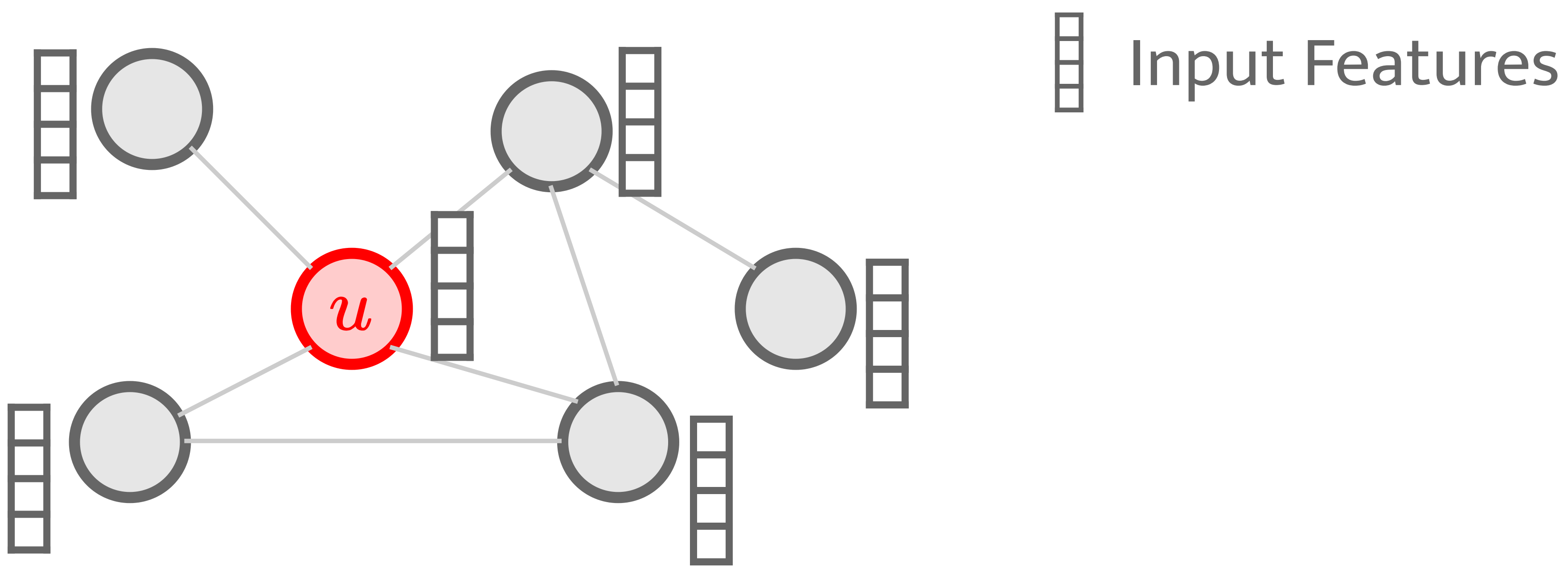

# Graph Convolutional Network (GCN)

the SOTA model for capturing **relationship**

[1] Kipf and Welling. Semi-supervised classification with graph convolutional networks. *ICLR'17*

# **Graph Convolutional Network** (GCN)

How to compute the embedding of node $u$?



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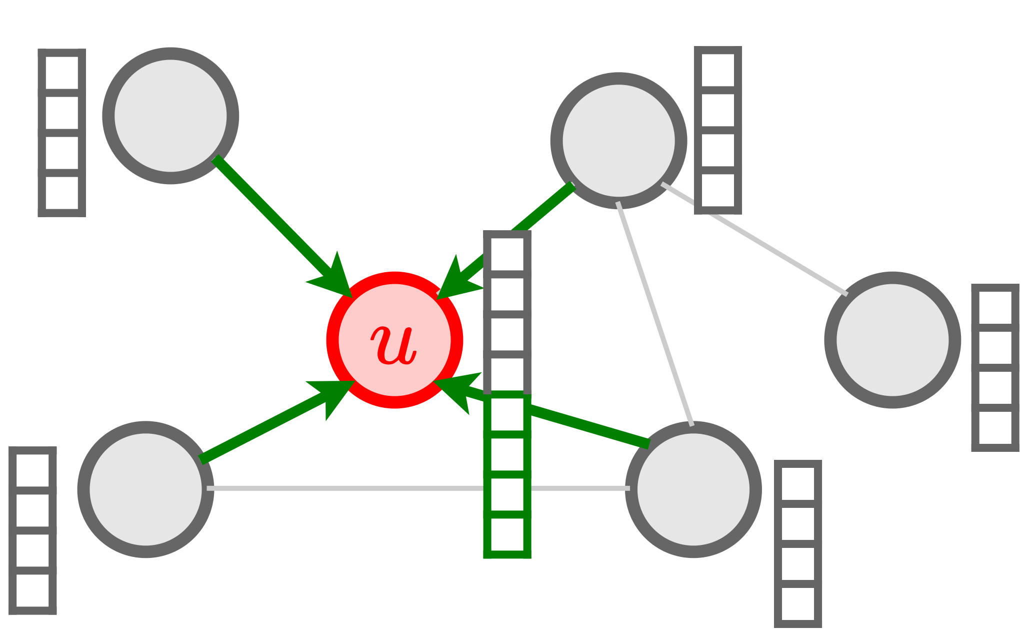


Input Features

① Neighbor Aggregation
(e.g., average pooling)

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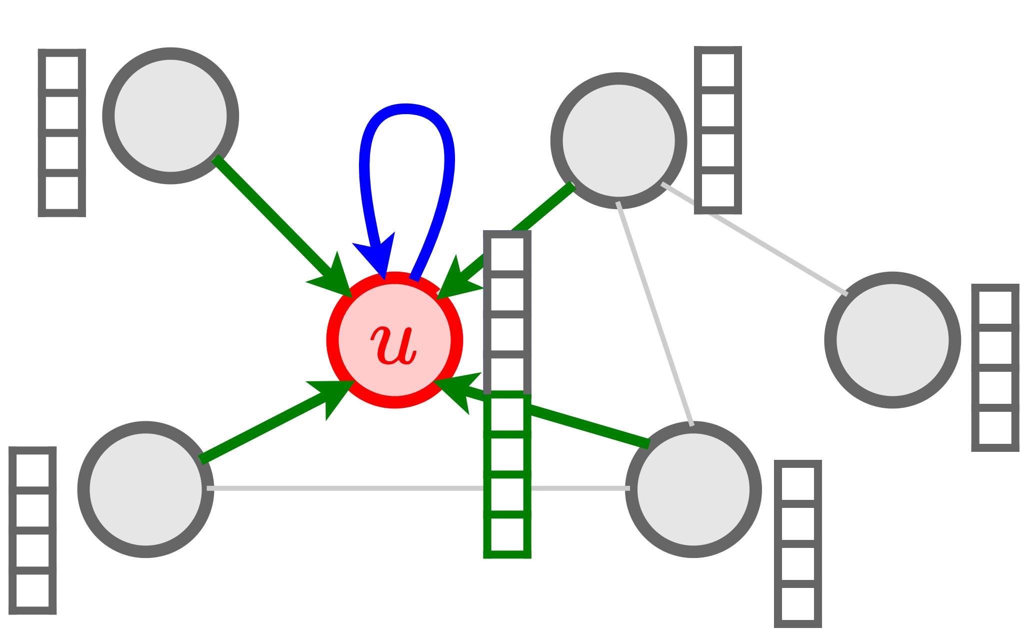


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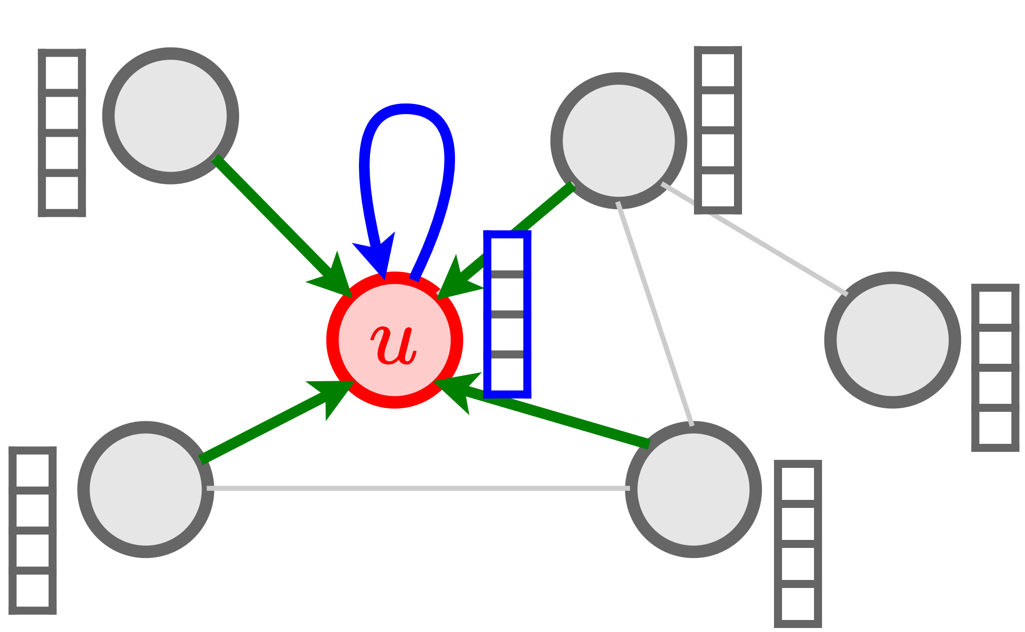
② Feature Update
(e.g., MLP)

# **Graph Convolutional Network** (GCN)

How to compute the embedding of node $u$?



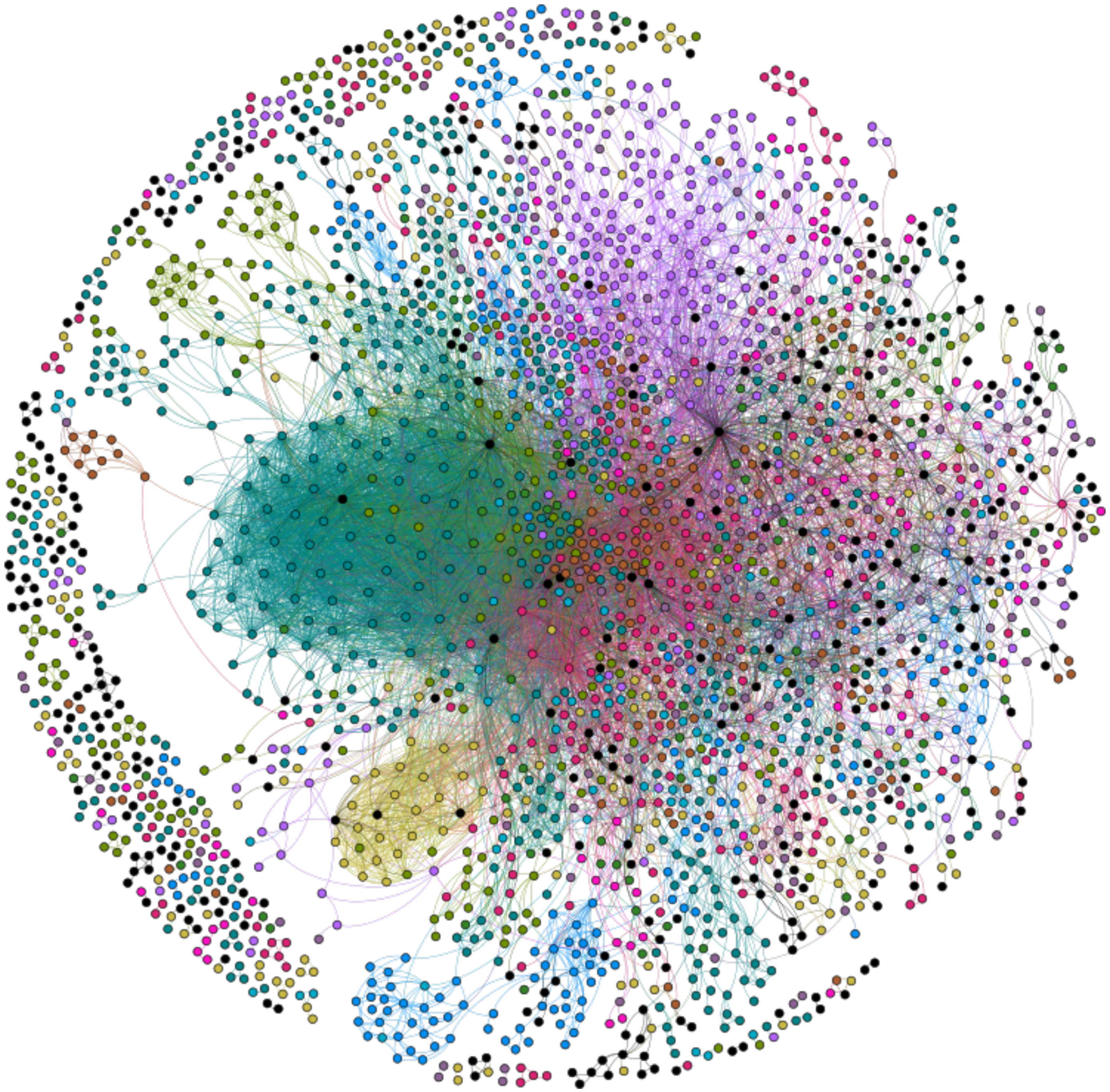

Input Features

① Neighbor Aggregation
(e.g., average pooling)

② Feature Update
(e.g., MLP)

Output embedding can be fed to the next GCN layer
or be used to downstream tasks
(e.g., node classification)

# Challenge: **Giant** Graphs for GCNs

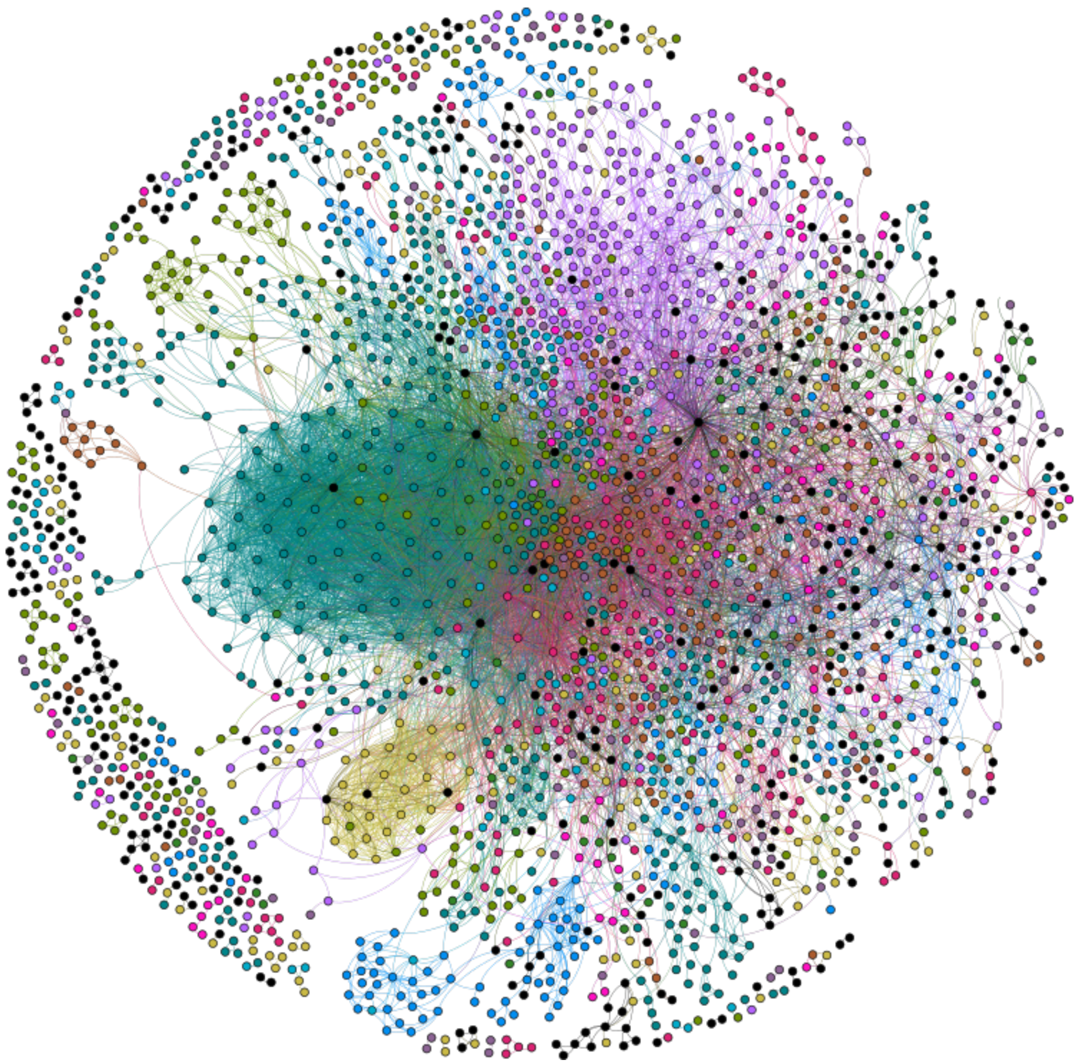


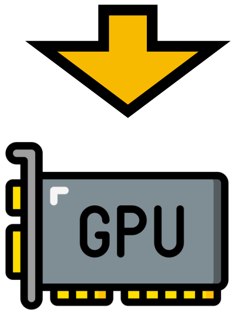
Amazon Co-Purchase Dataset [1,2]

- **9.4M** nodes
- **231M** edges
- **>100GB memory for a 3-layer GCN**

[1] Backman, Evans and Girke. Large-scale Bioactivity Analysis of the Small-molecule Assayed Proteome. *PLoS ONE'17*.
[2] McAuley et al. Image-based Recommendations on Styles and Substitutes. *SIGIR'15*.

# Challenge: **Giant** Graphs for GCNs






>100GB training

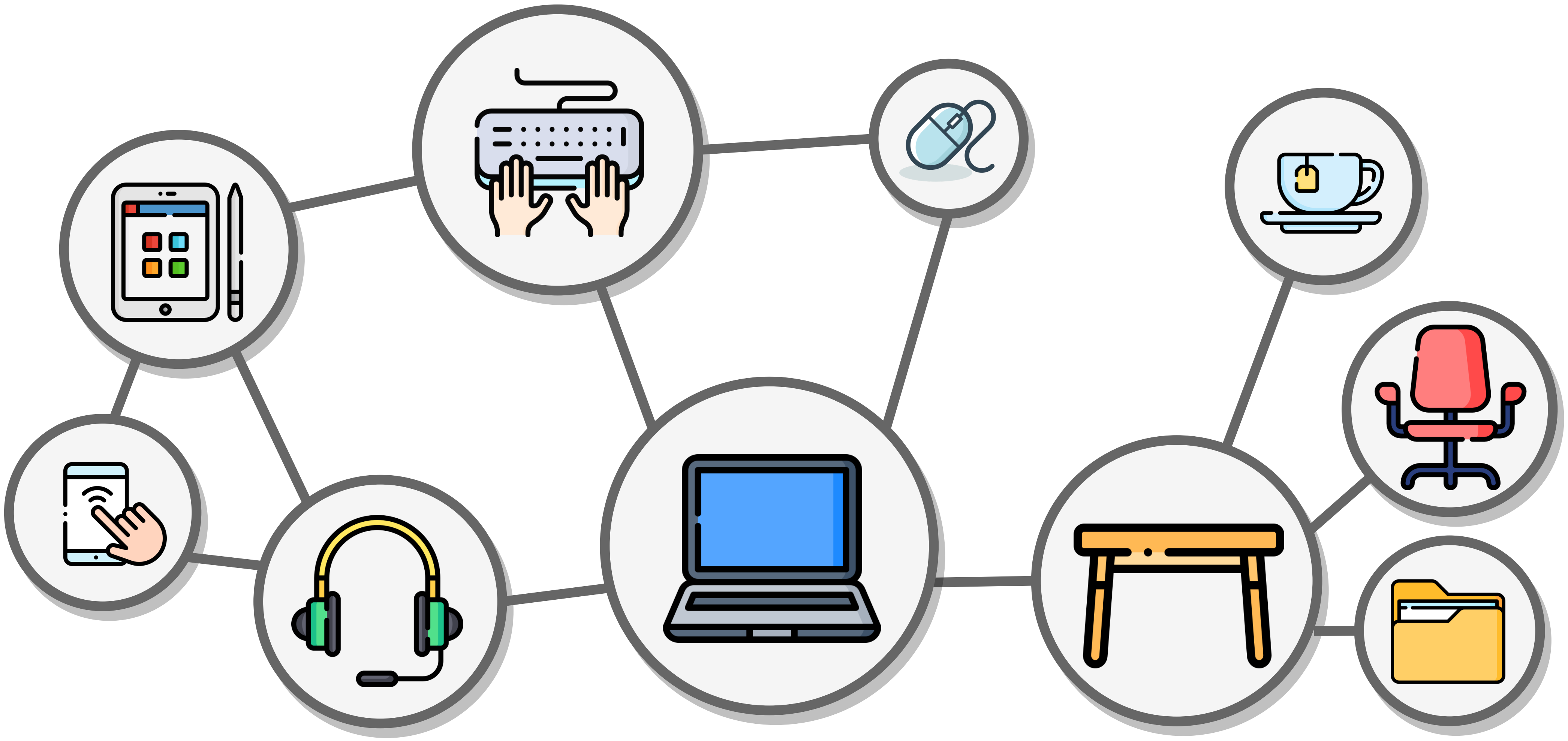
NOT fit

16GB V100

How to train a GCN at scale? Efficiently?

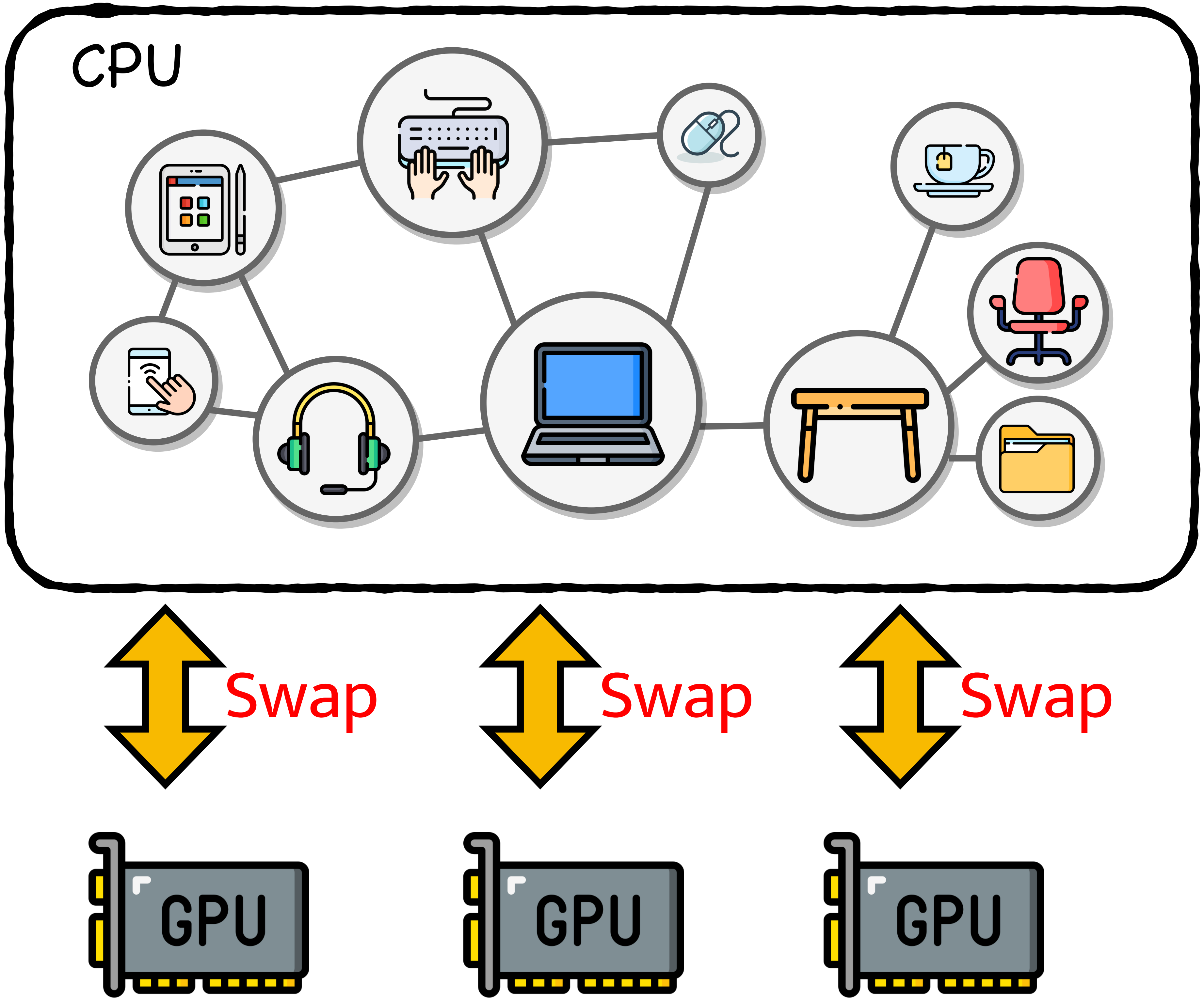
🤔

# Category I

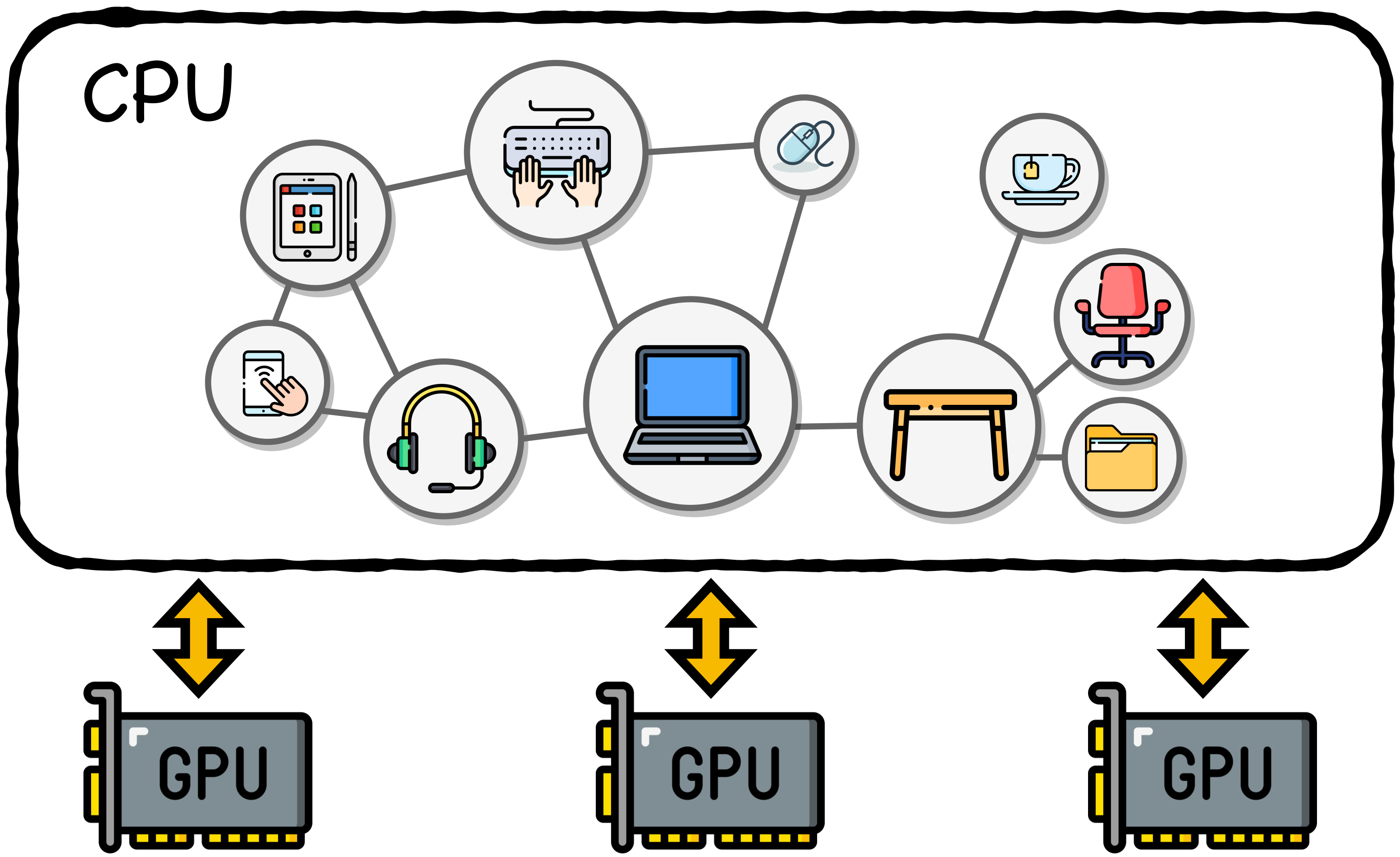


Storage in CPU

Training in GPU



# Category I: Swap-Based Methods

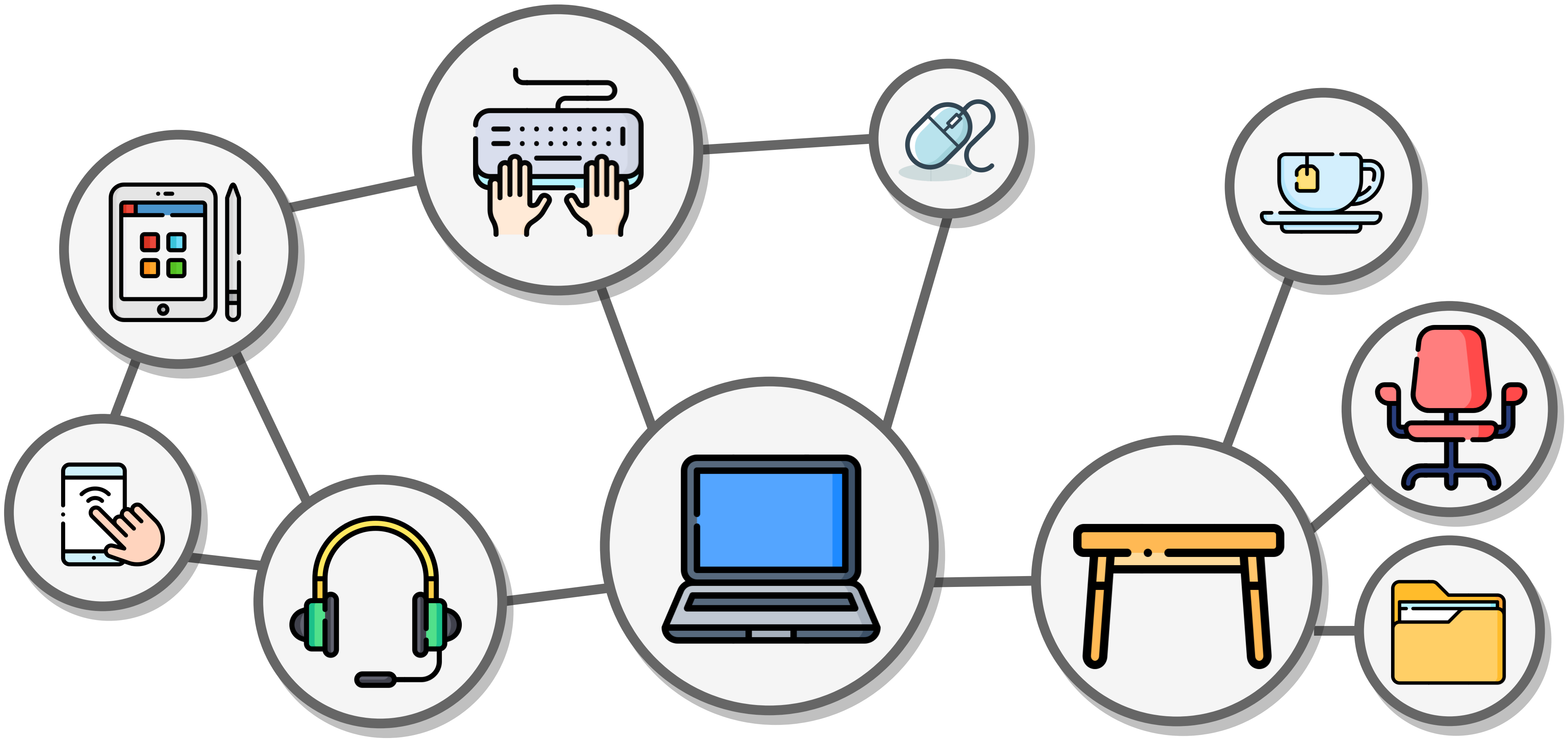



Pro: Scalability of Graph

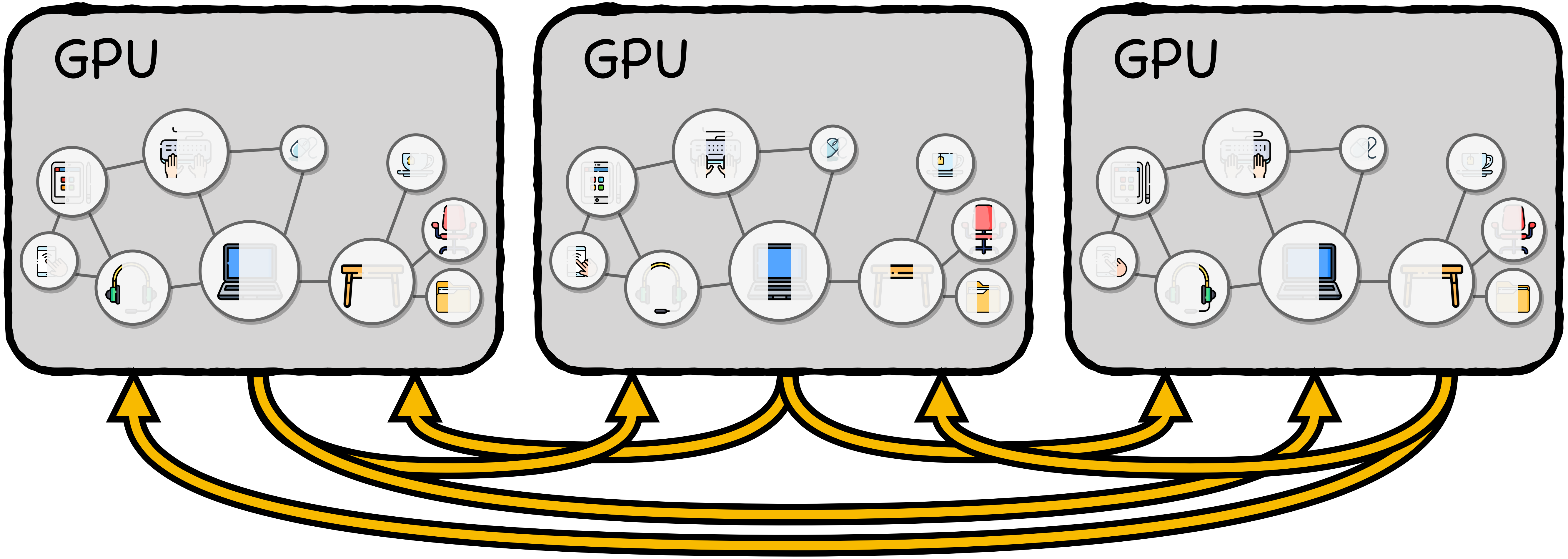
Con: Expensive CPU-GPU Swap

[1] Ma et al. NeuGraph: Parallel Deep Neural Network Computation on Large Graphs. *USENIX ATC'19*
[2] Jia et al. Improving the Accuracy, Scalability, and Performance of Graph Neural Networks with Roc. *MLSys'20*
[3] Fey et al. GNNAutoScale: Scalable and Expressive Graph Neural Networks via Historical Embeddings. *ICML'21*

# Category II

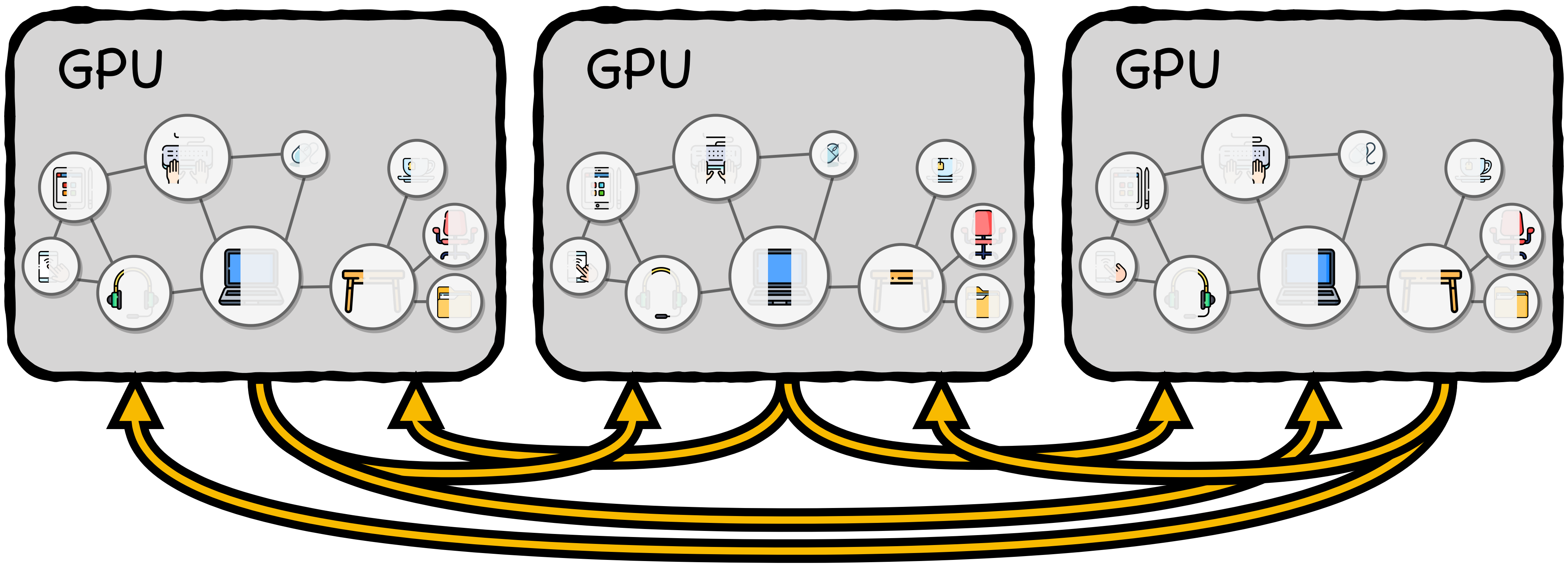


# Slicing features across GPUs




Broadcast

# Category II: Slice-Based Methods

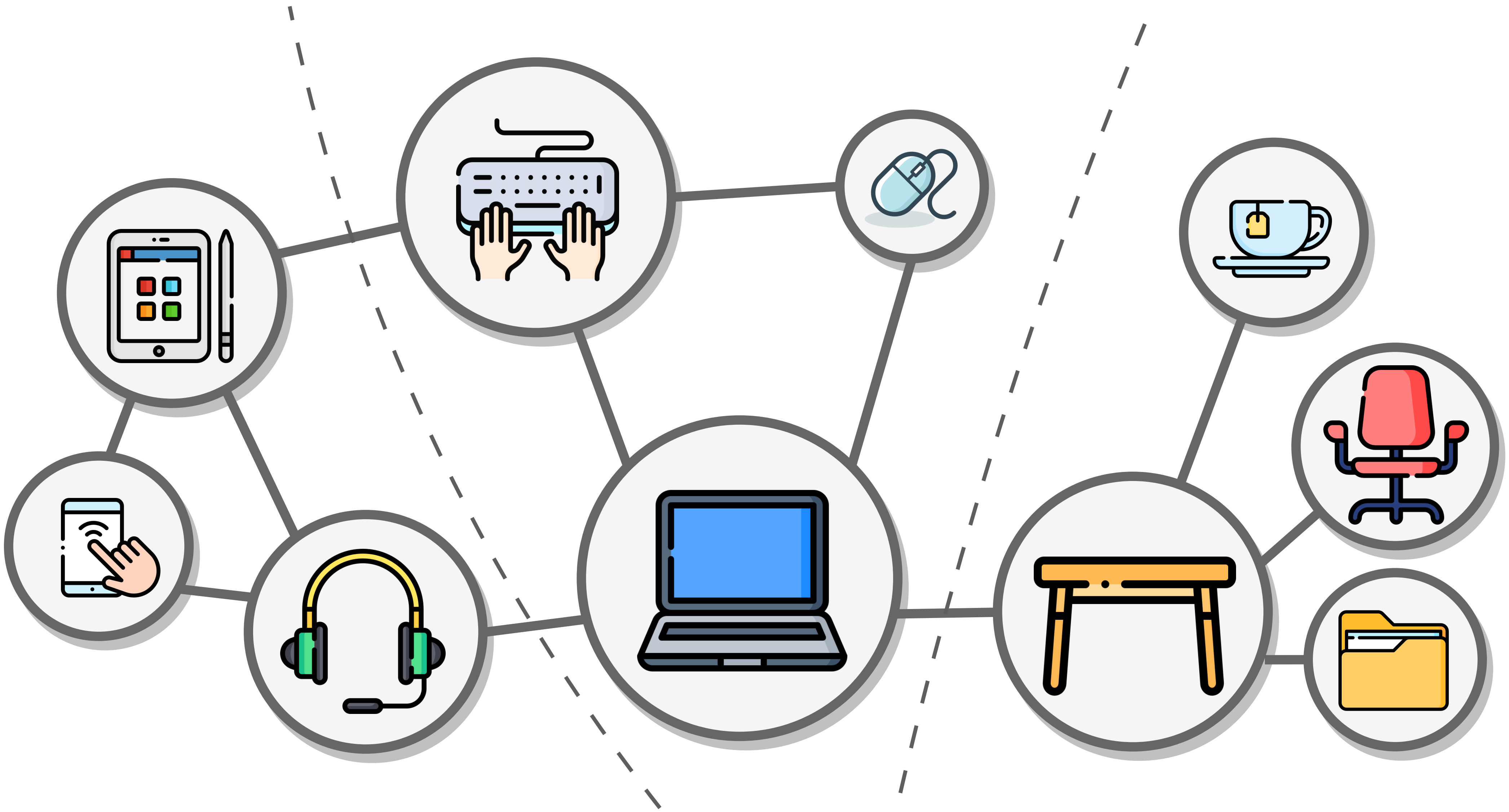



Pro: Balanced Workload

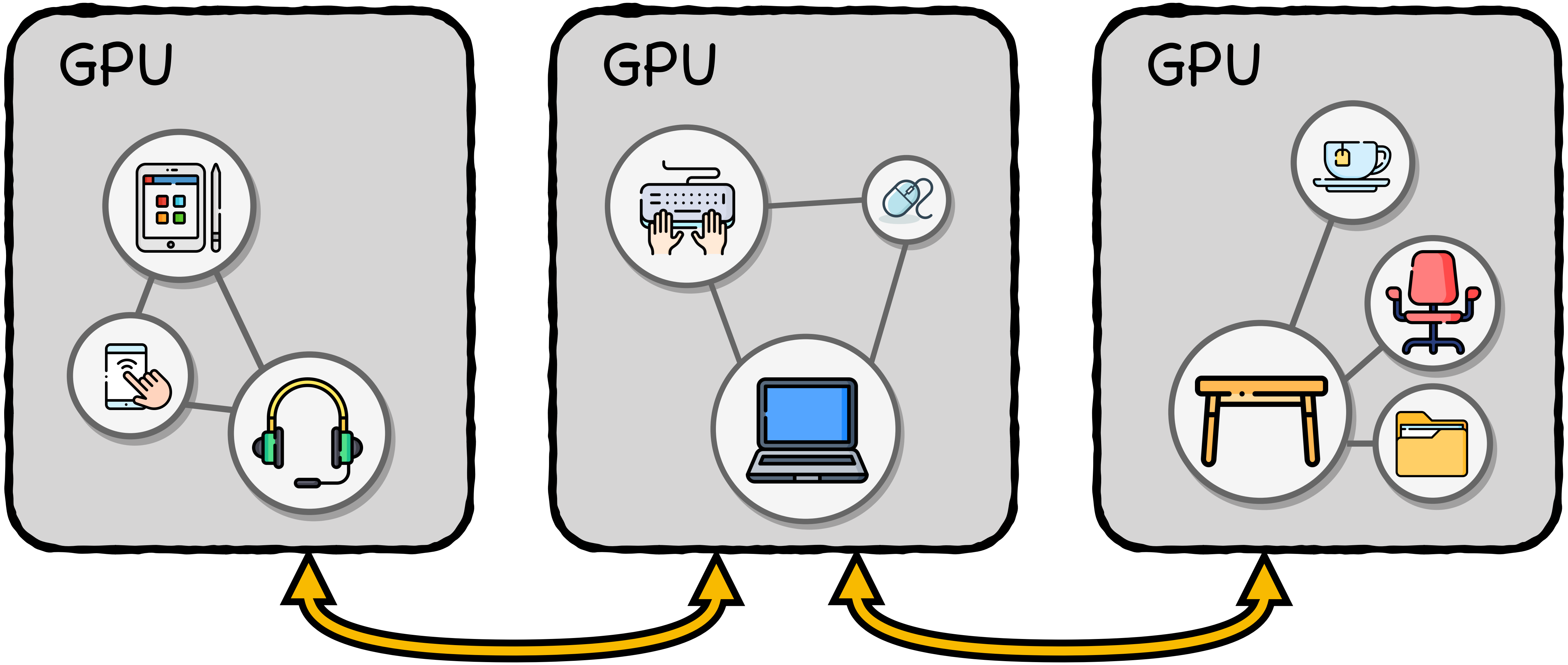
Con: Expensive Broadcast

[1] Tripathy, Yelick and Buluc. Reducing Communication in Graph Neural Network Training. *SC'20*

# Category III

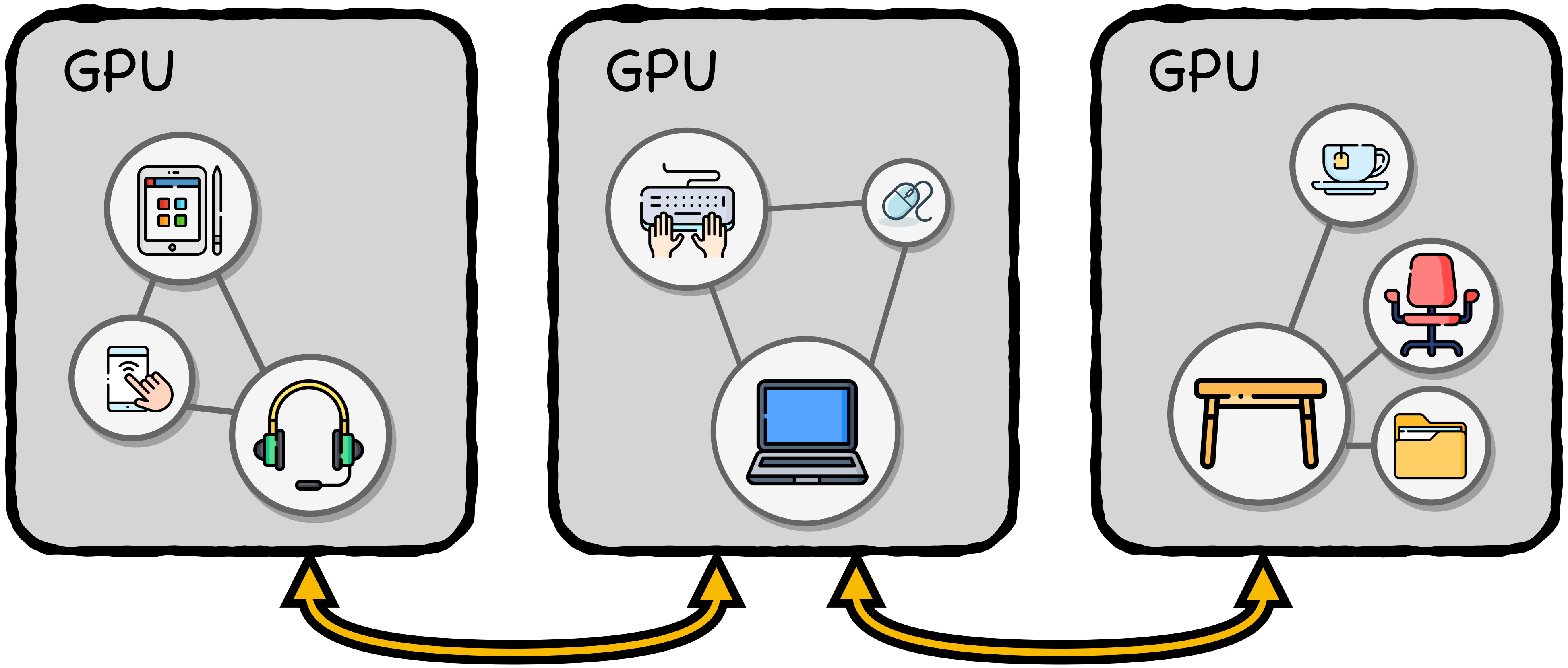


# Assigning one partition to one GPU




Point-to-point

# Category III: Partition-Based Methods




Pro: Reduced Communication

The drawback is **not well studied**

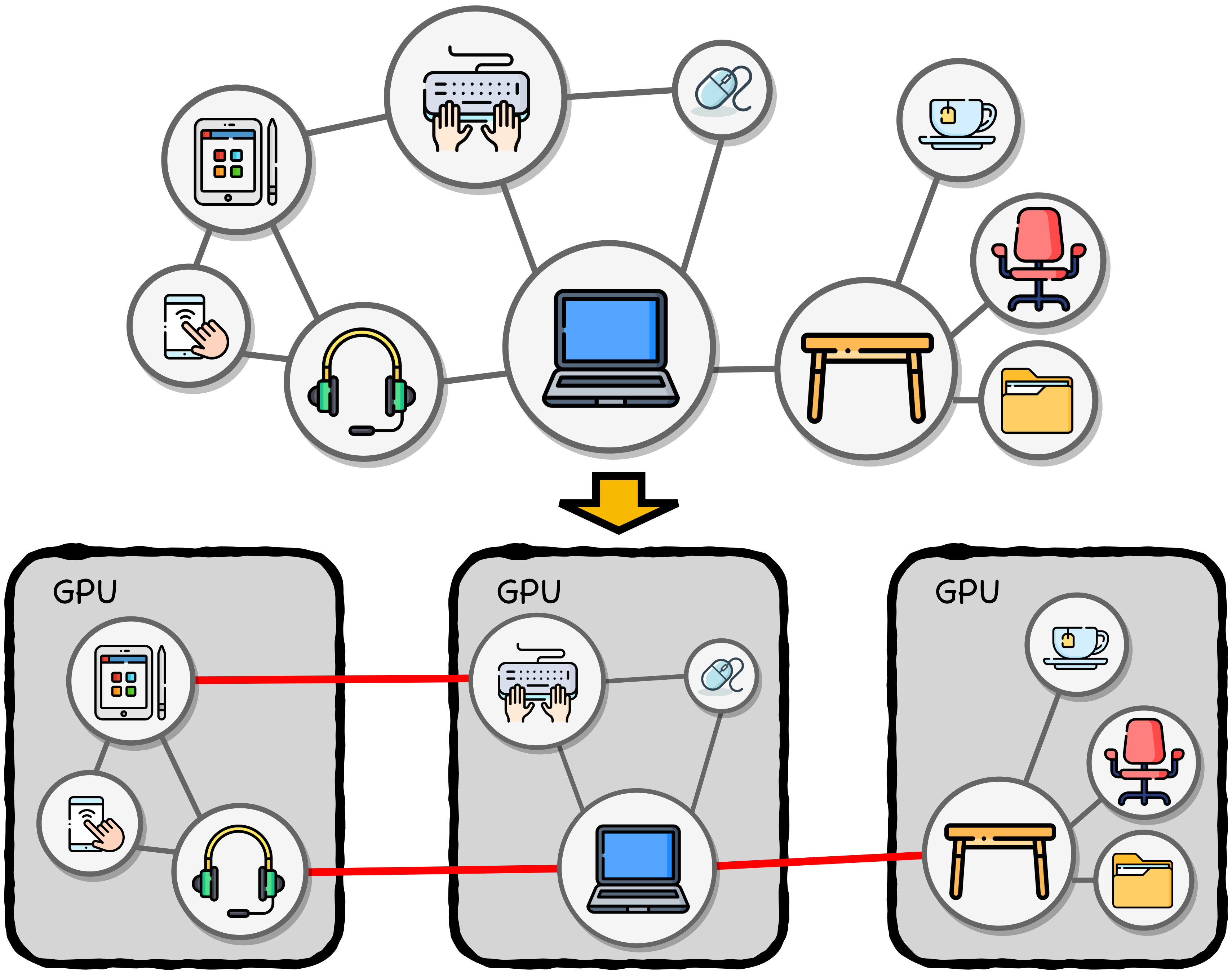
[1] Thorpe et al. Dorylus: Affordable, Scalable, and Accurate GNN Training with Distributed CPU Servers and Serverless Threads. *OSDI'21*
[2] Wan et al. PipeGCN: Efficient Full-Graph Training of Graph Convolutional Networks with Pipelined Feature Communication. *ICLR'22*

# BNS-GCN

# BNS-GCN

- ✦ Identifying **drawbacks** of partition-based training
- ✦ Proposing a simple-yet-effective **solution**
- ✦ Providing theoretical and empirical **validation**

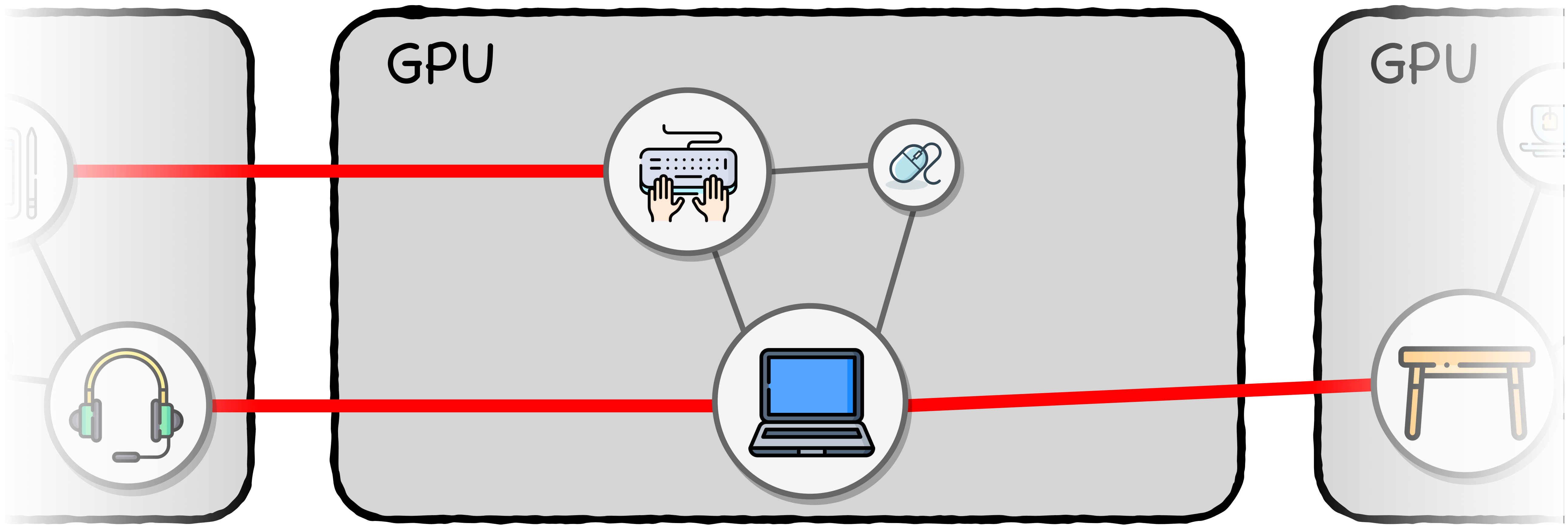
# Understanding Partition-Based Methods



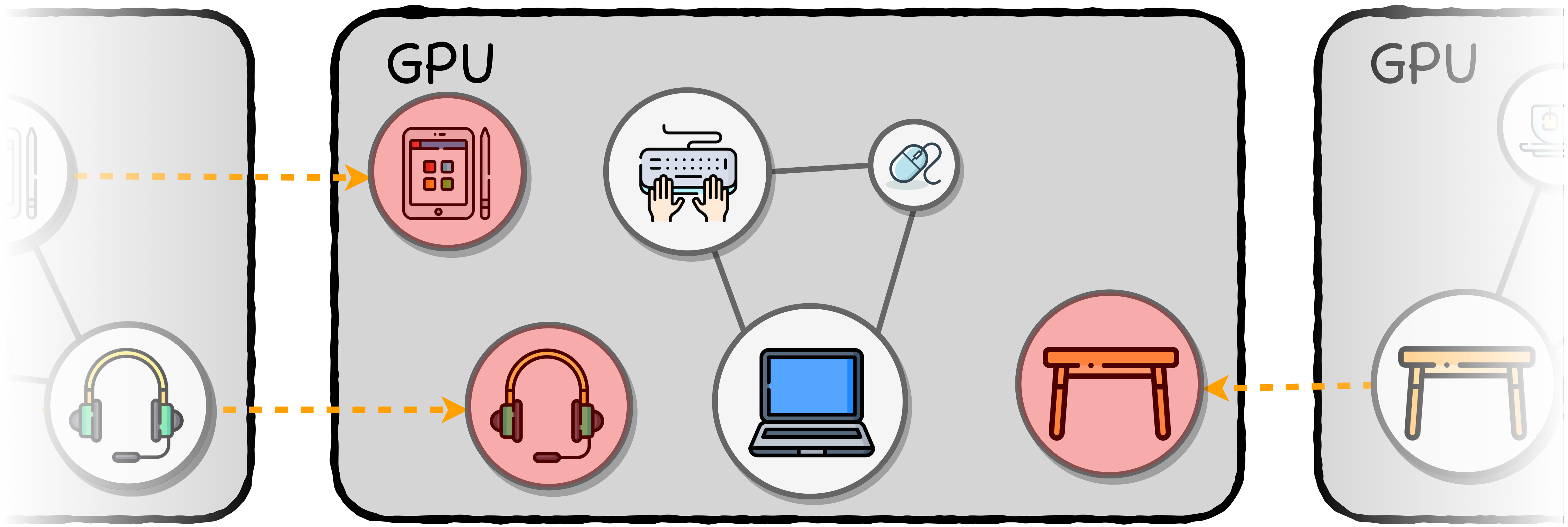

Similar to Data Parallelism

Difference: **Dependency** among Data

# Understanding Partition-Based Methods

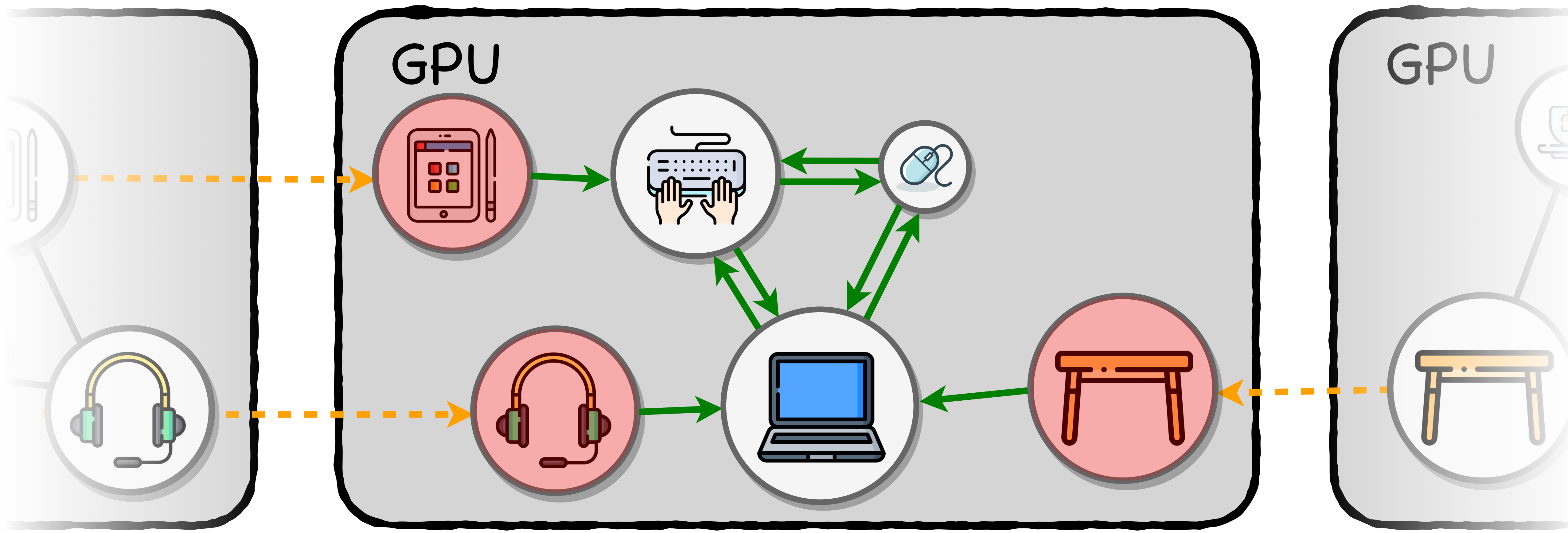


# Understanding Partition-Based Methods



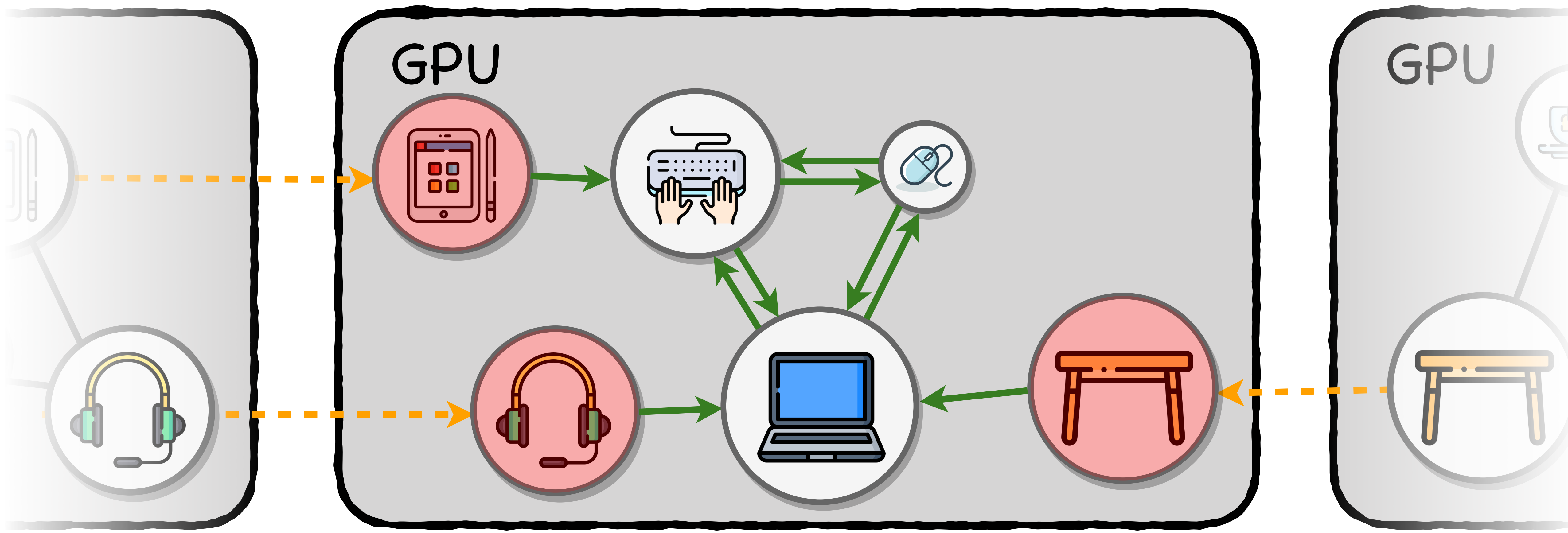

**Communicating remote features**

# Understanding Partition-Based Methods




**Computing** local features

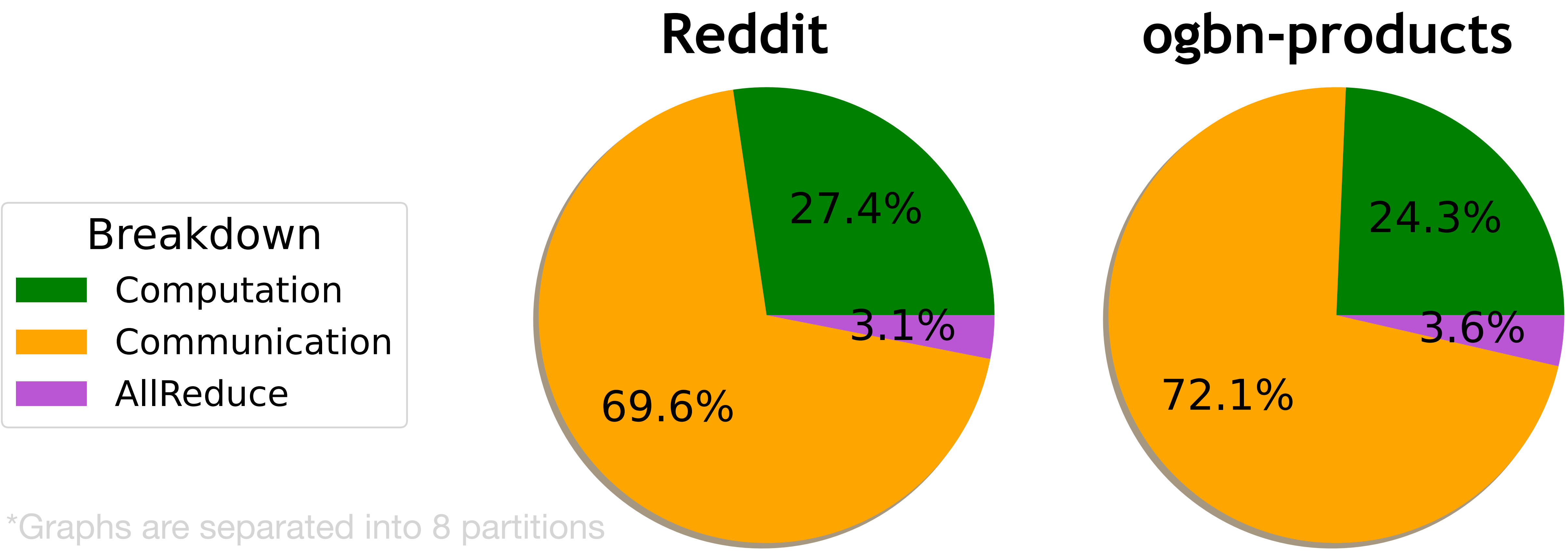
# Understanding Partition-Based Methods




Inner Node    Boundary Node

# Identifying Drawbacks

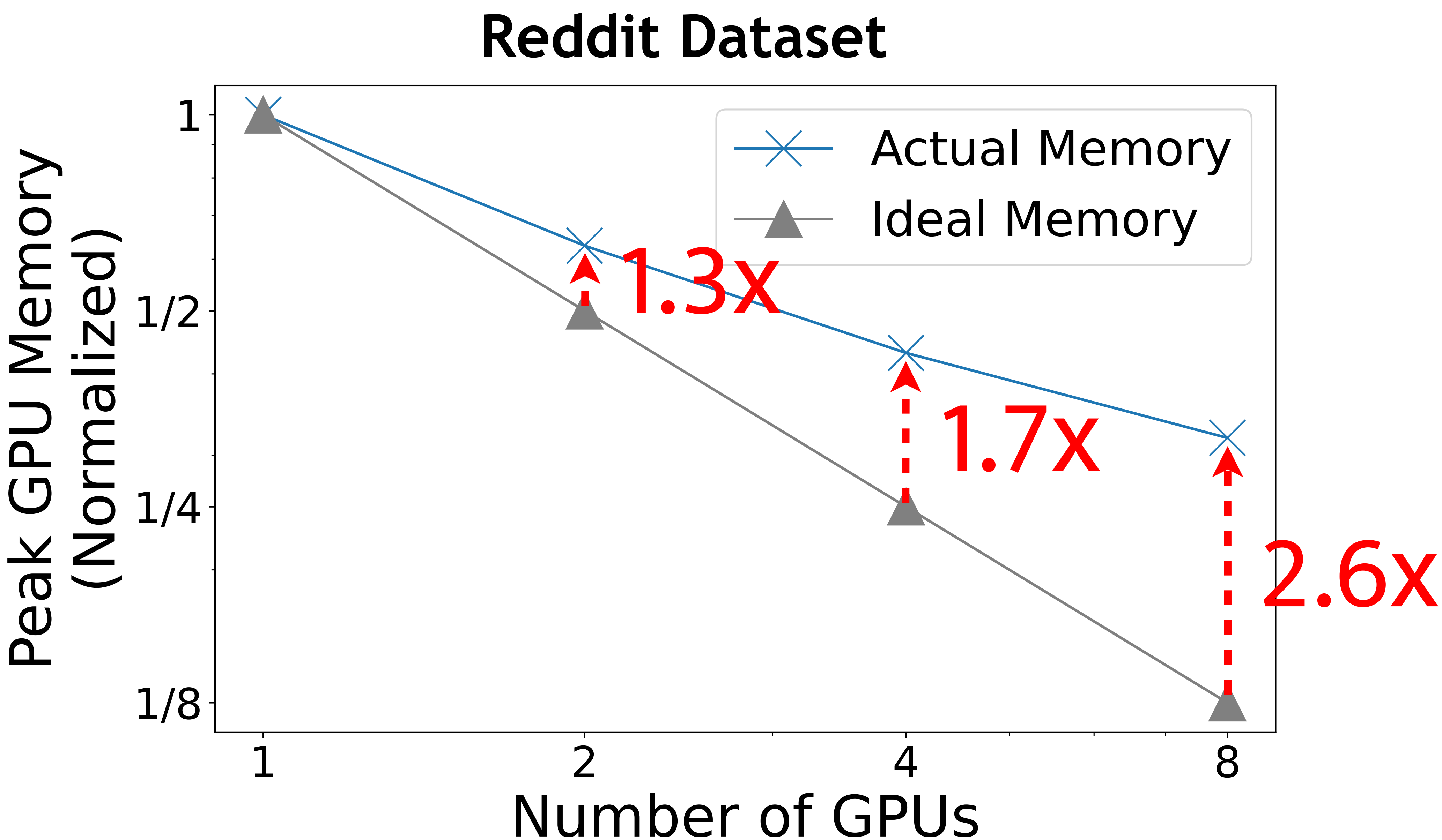
# Training Time Breakdown




*Graphs are separated into 8 partitions

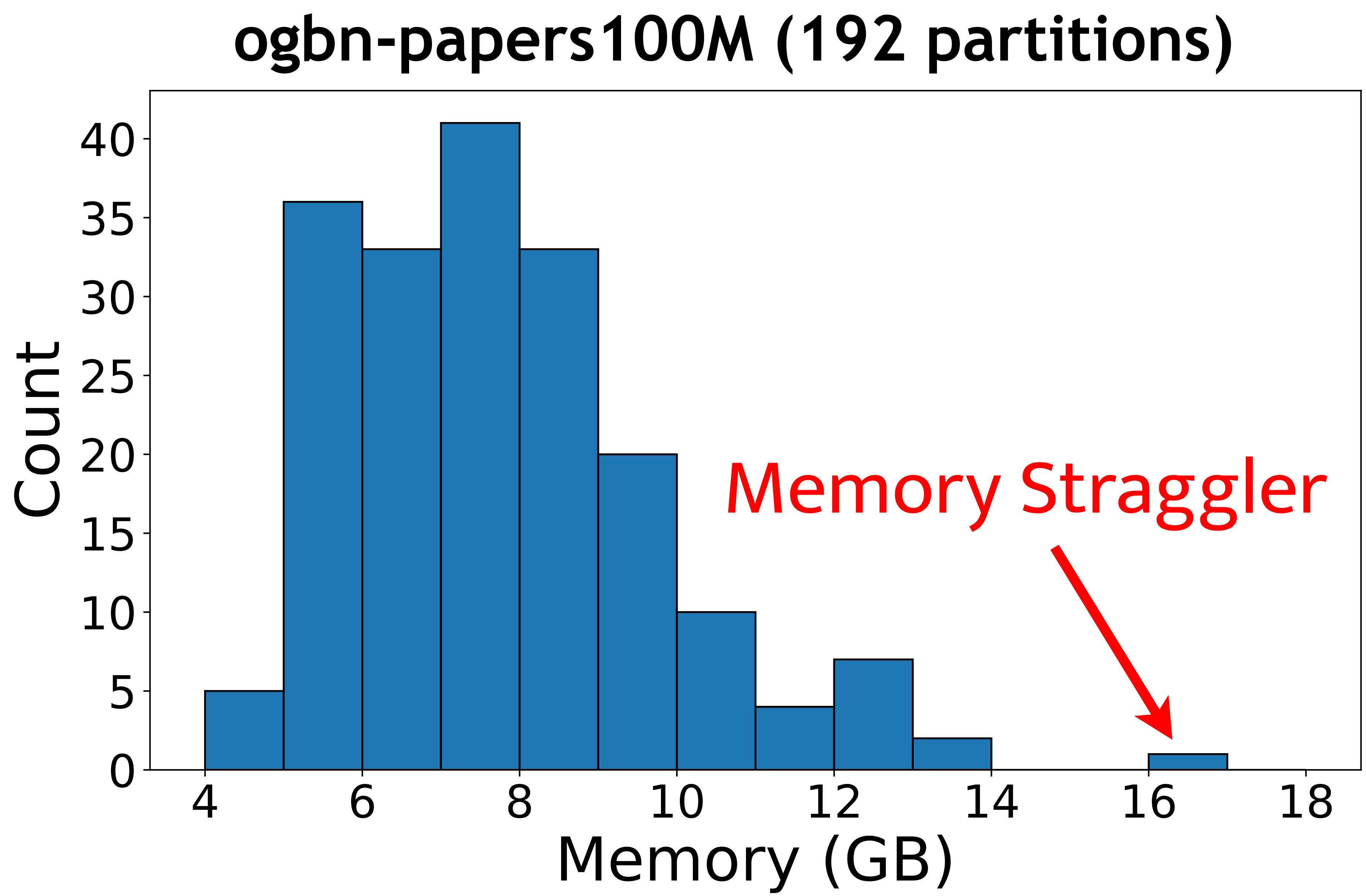
**Drawback I: Significant Communication Overhead**

# Training Memory Requirement




Drawback II: Unscalable Memory Requirement

# Per-GPU Memory Distribution

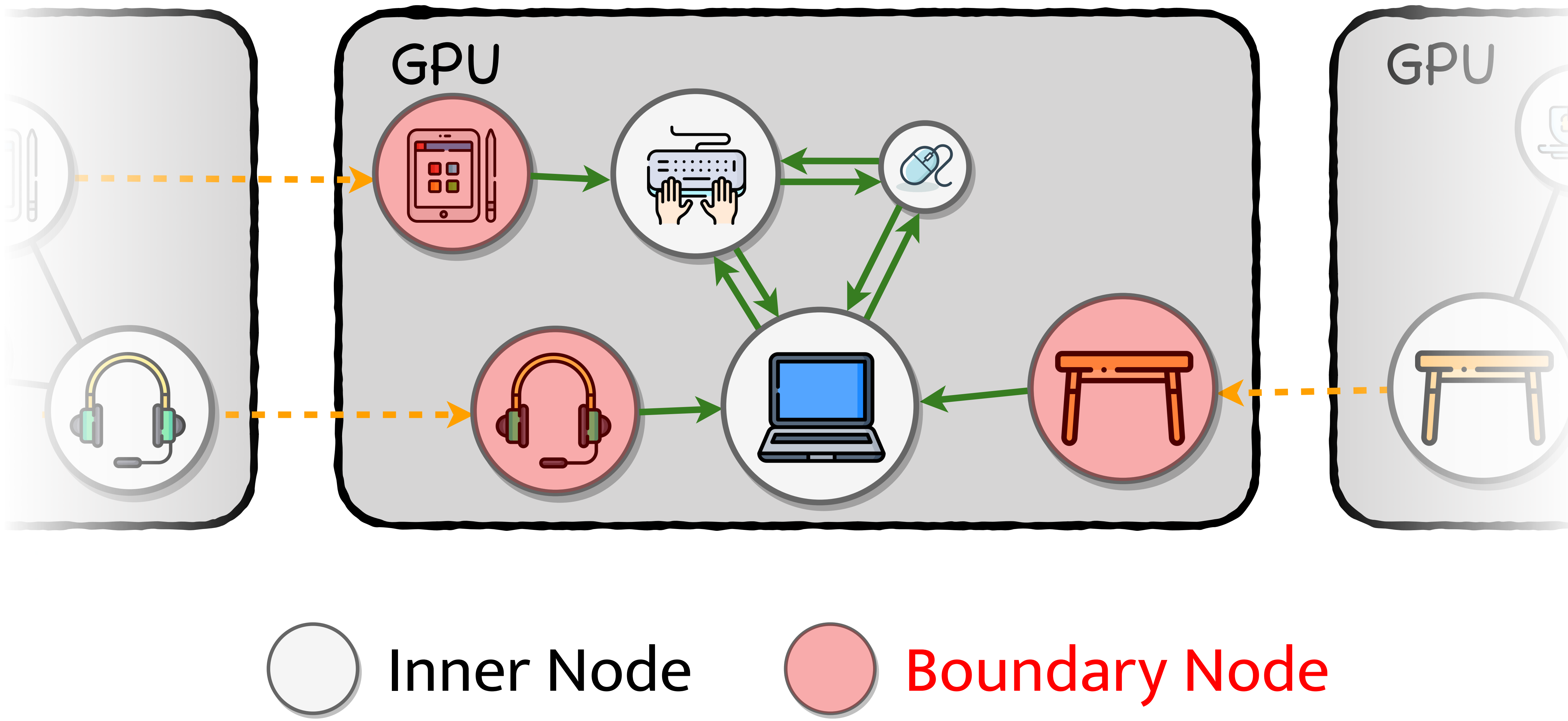



Drawback III: Imbalanced Memory across GPUs

What’s the underlying cause?

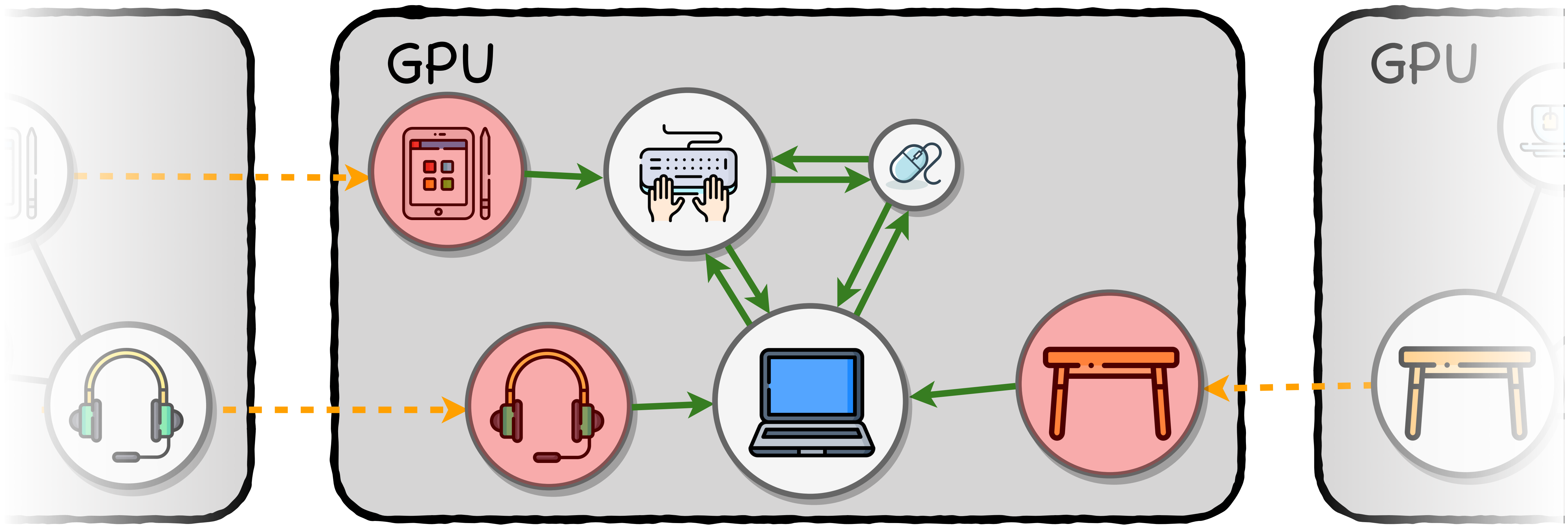
🤔

# Understanding Communication Volume




The $i$-th partition has $n_{in}^{(i)}$ inner nodes and $n_{bd}^{(i)}$ boundary nodes

# Understanding Communication Volume

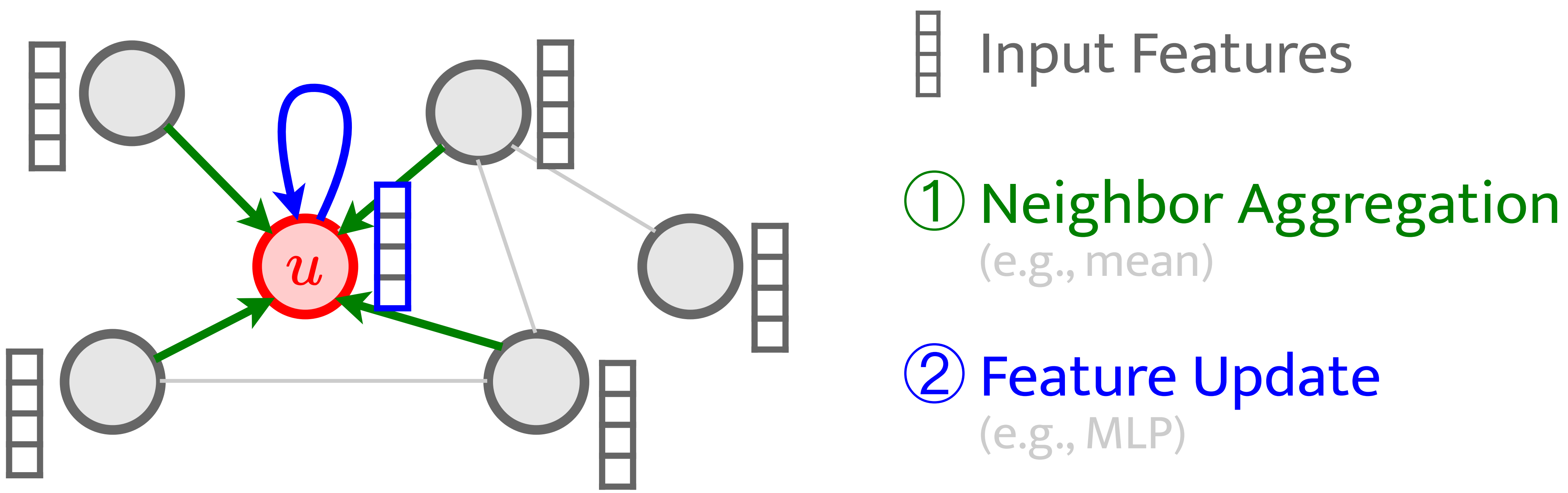



$$\mathrm{Vol}_{\mathrm{total}} = \sum_i \mathrm{Vol}(\mathcal{G}_i) = \sum_i n_{bd}^{(i)}$$

Comm. Volume ∝ # Boundary Nodes

Min-Cut is not Optimal

# Understanding Memory Requirement




$$\mathrm{Mem}(\mathcal{G}_i) \propto \underbrace{3n_{in}^{(i)} + n_{bd}^{(i)}}$$

Aggregation: $n_{in}^{(i)} + n_{bd}^{(i)}$

Linear + Activation: $2n_{in}^{(i)}$

# Contribution I: Identify the Underlying Cause

I Significant Communication Overhead

II Unscalable Memory Requirement

III Imbalanced Memory across GPUs

What's the underlying cause?

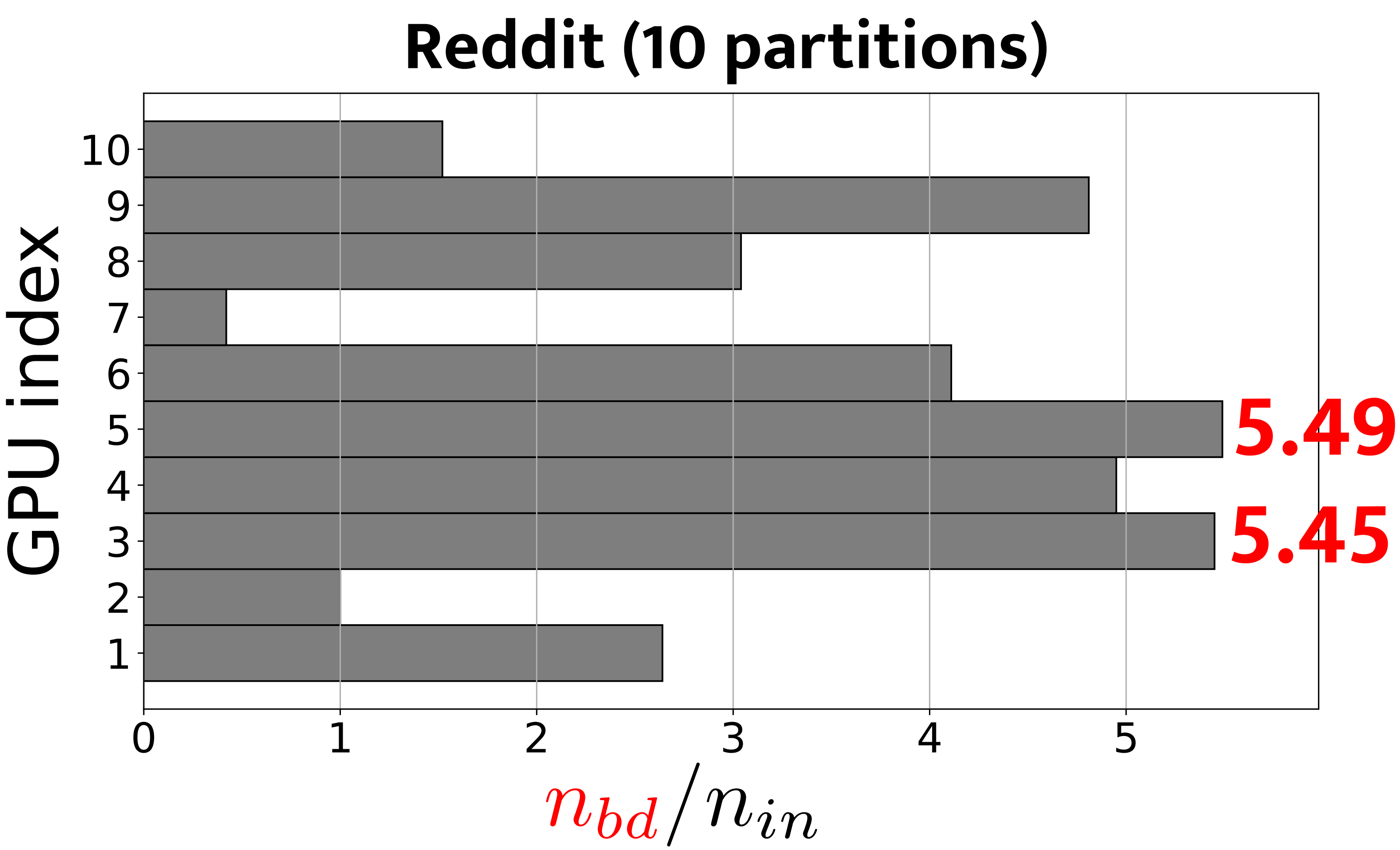
# Contribution I: Identify the Underlying Cause

I Significant Communication Overhead — $\mathrm{Vol}_{\mathrm{total}} = \sum_i \mathrm{Vol}(\mathcal{G}_i) = \sum_i n_{bd}^{(i)}$

II Unscalable Memory Requirement

III Imbalanced Memory across GPUs

$\mathrm{Mem}(\mathcal{G}_i) \propto 3n_{in}^{(i)} + n_{bd}^{(i)}$

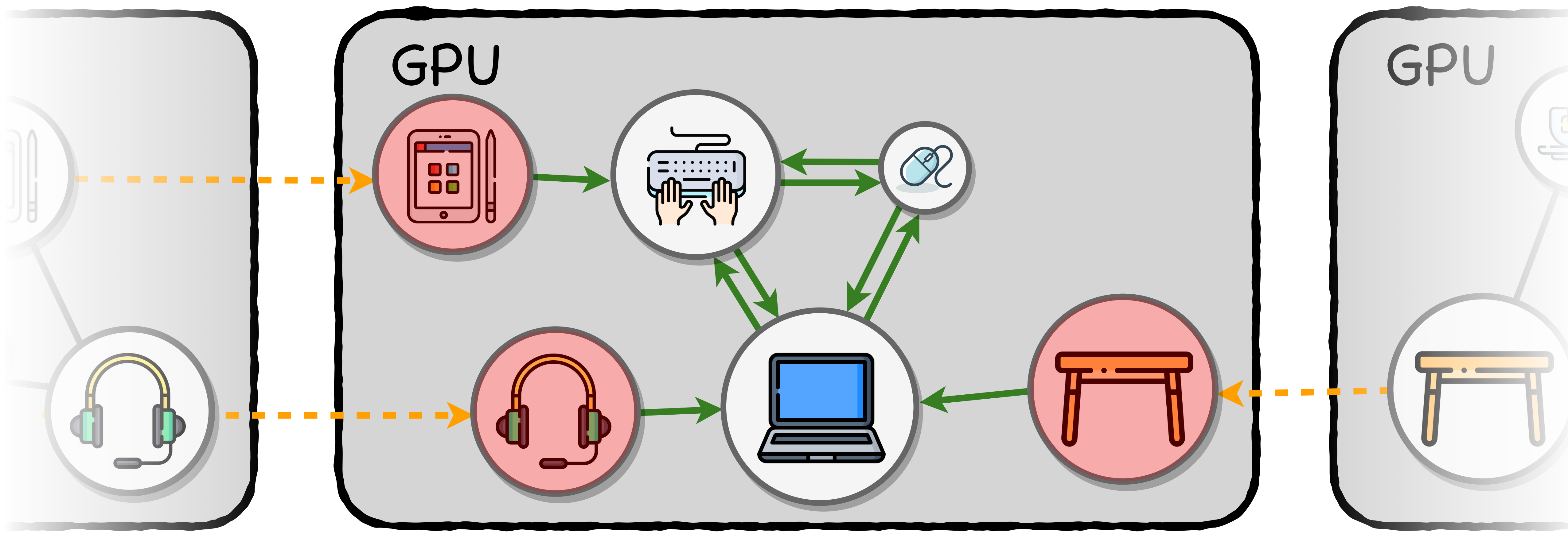



**Boundary nodes** are the cause 😣

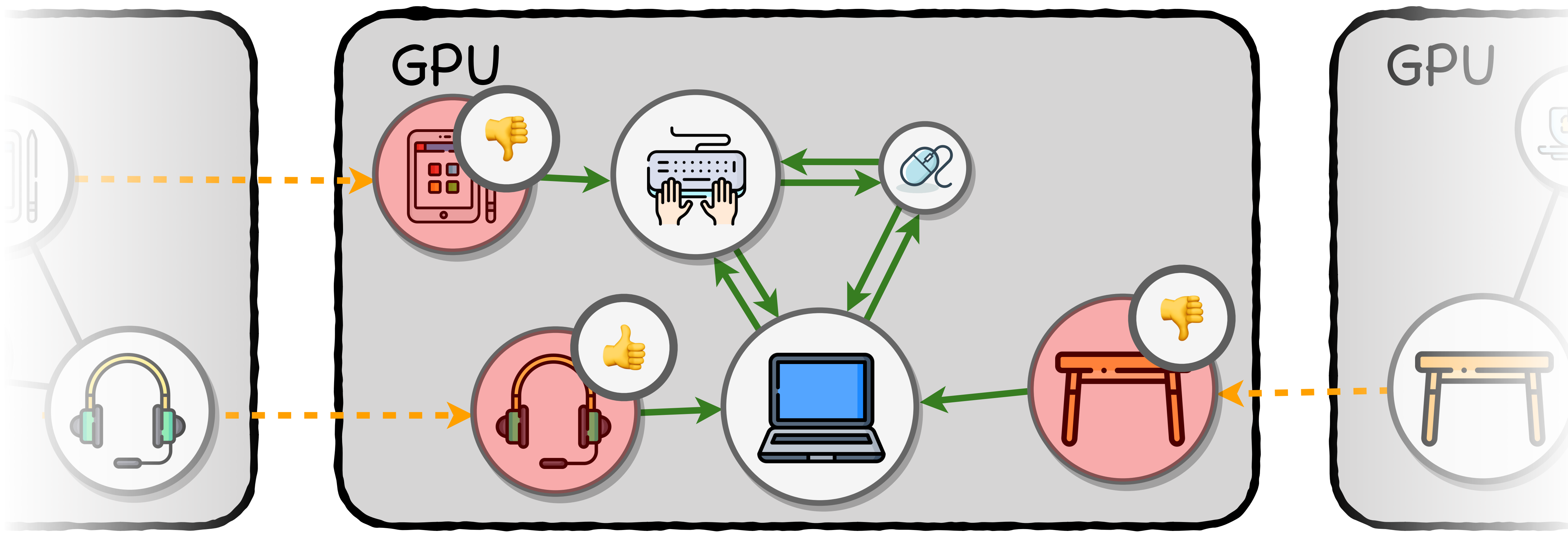
How to solve them? One stone three birds?

🤔

# Contribution II: Propose Boundary Node Sampling

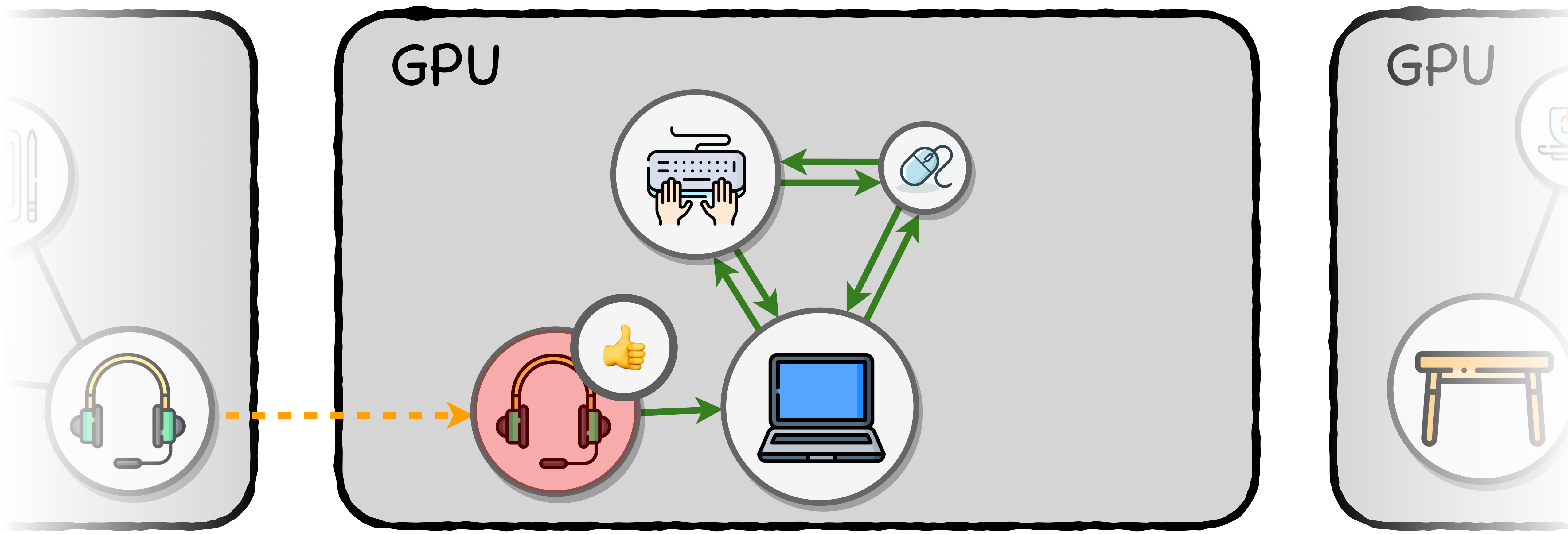


# Contribution II: Propose Boundary Node Sampling




Step 1: Sampling each boundary node with probability $p$

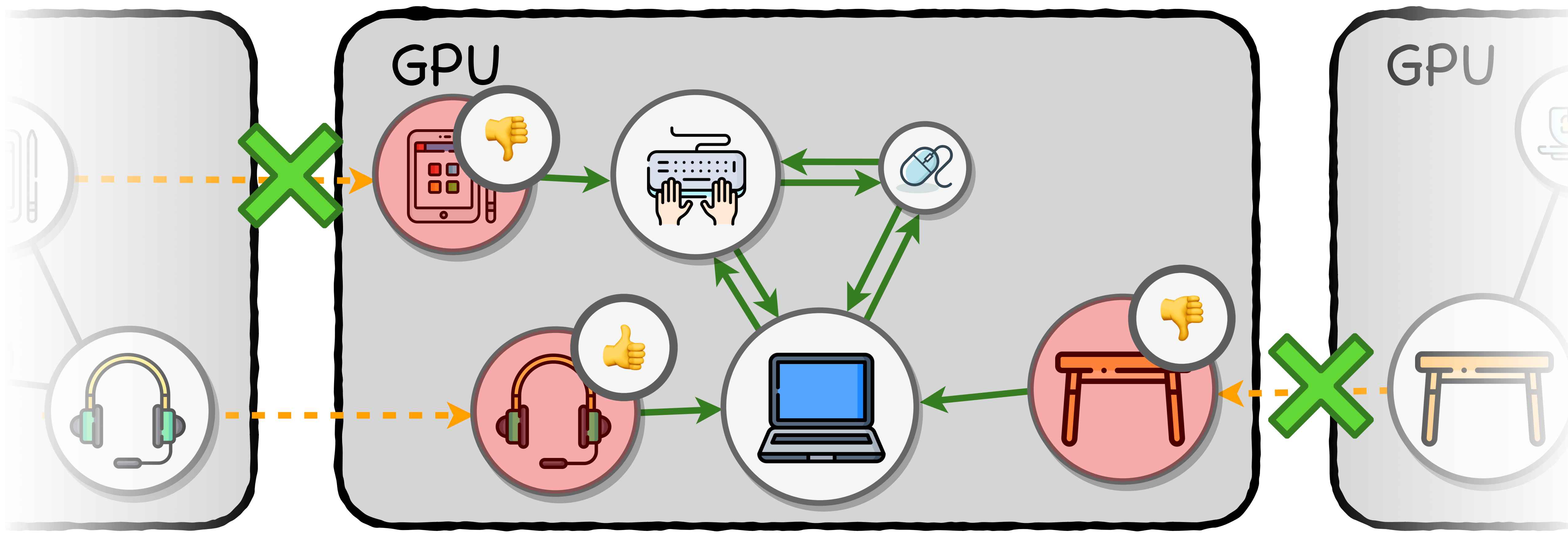
# Contribution II: Propose Boundary Node Sampling




Step 1: Sampling each boundary node with probability $p$

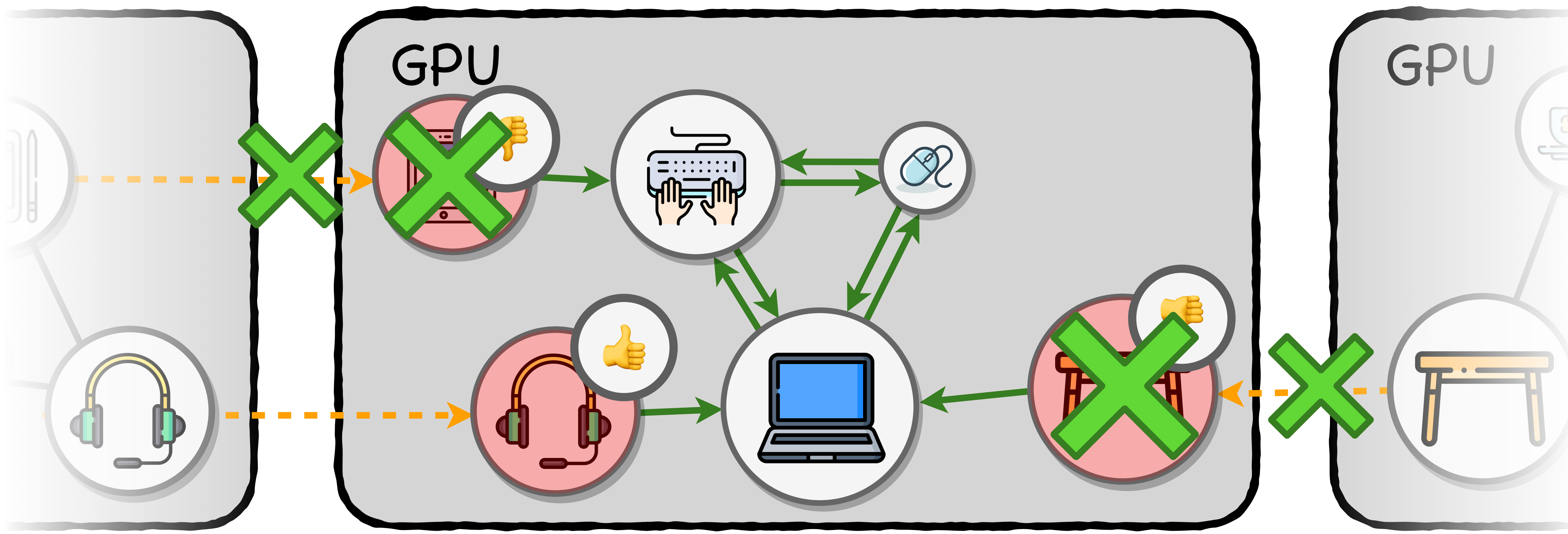
Step 2: Removing unsampled nodes

# Contribution II: Propose Boundary Node Sampling




Reducing communication volume

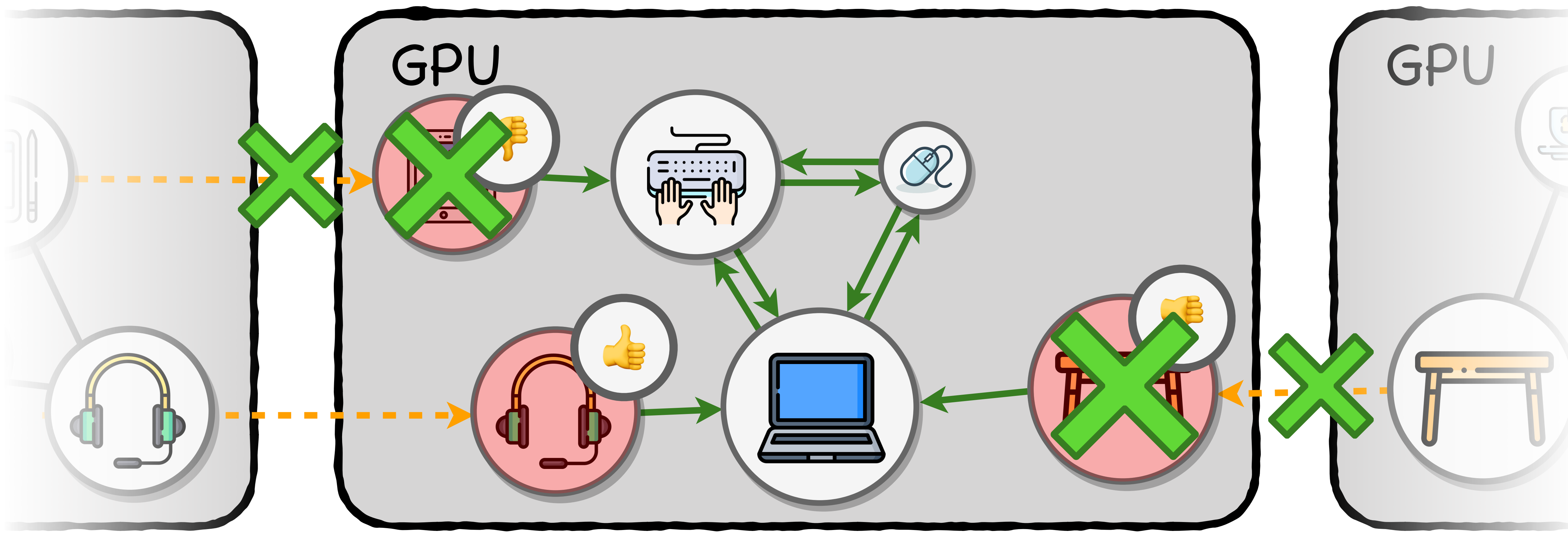
# Contribution II: Propose Boundary Node Sampling




Reducing communication volume

Reducing memory requirement

# Contribution II: Propose Boundary Node Sampling




Reducing communication volume

Reducing memory requirement

Balancing memory across GPUs

($n_{bd}^{(i)}$ becomes negligible)

# Contribution III: Validate BNS-GCN in **Theory**

| **Method** | **Variance** |
|---|---|

We compare the **variance** of feature approximation

(lower is better)

# Contribution III: Validate BNS-GCN in **Theory**

| **Method** | **Variance** | |
|---|---|---|
| BNS-GCN | $\mathcal{O}(\lvert\mathcal{B}\rvert)$ | boundary neighbor set |
| LADIES [NeurIPS'19] | $\mathcal{O}(\lvert\mathcal{N}\rvert)$ | neighbor set |
| FastGCN [ICLR'18] | $\mathcal{O}(\lvert\mathcal{V}\rvert)$ | global node set |

*We fix output nodes and sampling size

$\mathcal{B} \subseteq \mathcal{N} \subseteq \mathcal{V}$ ➡ BNS-GCN has the best feature approximation

# Contribution III: Validate BNS-GCN in **Theory**

| **Method** | **Variance** |
|---|---|
| BNS-GCN | $\mathcal{O}(\lvert\mathcal{B}\rvert\,\gamma^2)$ |
| LADIES [NeurIPS'19] | $\mathcal{O}(\lvert\mathcal{N}\rvert\,\gamma^2)$ |
| FastGCN [ICLR'18] | $\mathcal{O}(\lvert\mathcal{V}\rvert\,\gamma^2)$ |
| VR-GCN [ICML'18] | $\mathcal{O}(D\Delta\gamma^2)$ |
| GraphSAGE [NIPS'17] | $\mathcal{O}(D\gamma^2)$ |

*We fix output nodes and sampling size

More analysis is in our paper

# Experiments

# Experiment Setup

## Considered Datasets

Reddit, ogbn-products, Yelp and ogbn-papers100M

**Dataset Description**

| Name | # Nodes | # Edges | Environment |
|---|---|---|---|
| Reddit | 233K | 114M | 10 RTX-2080Ti (11GB) |
| ogbn-products | 2.4M | 62M | |
| Yelp | 716K | 7.0M | |
| ogbn-papers100M | 111M | 1.6B | 32 x (6 Tesla V100 (16GB)) |

# Experiment Setup

**Considered Datasets**

Reddit, ogbn-products, Yelp and ogbn-papers100M

**Benchmarked Baselines**

ROC [MLSys'20] (swap-based) and CAGNET [SC'20] (slice-based)

# Experiment Setup

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Reddit, ogbn-products, Yelp and ogbn-papers100M

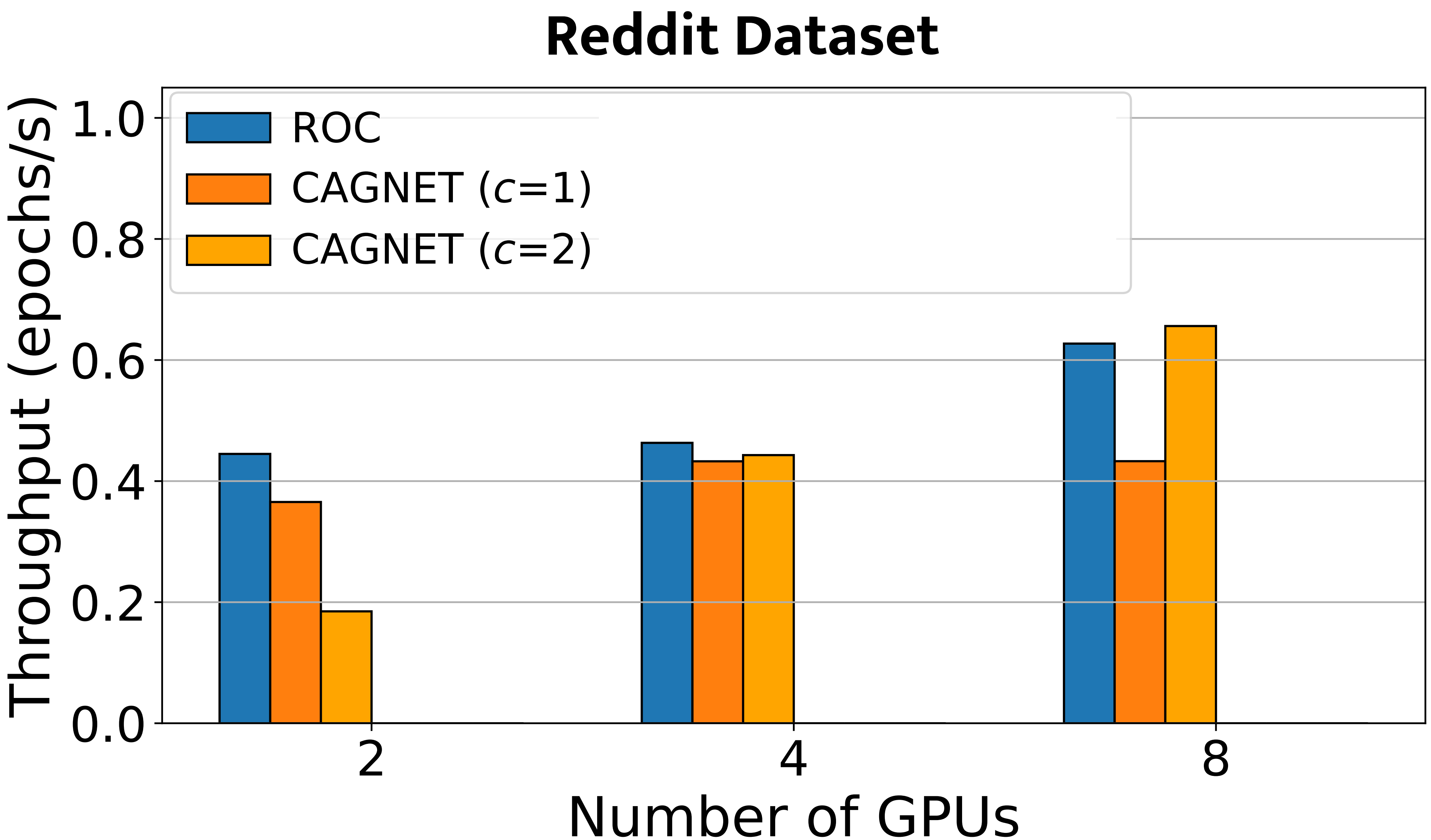
**Benchmarked Baselines**

ROC [MLSys'20] (swap-based) and CAGNET [SC'20] (slice-based)

**Adopted Toolkits**

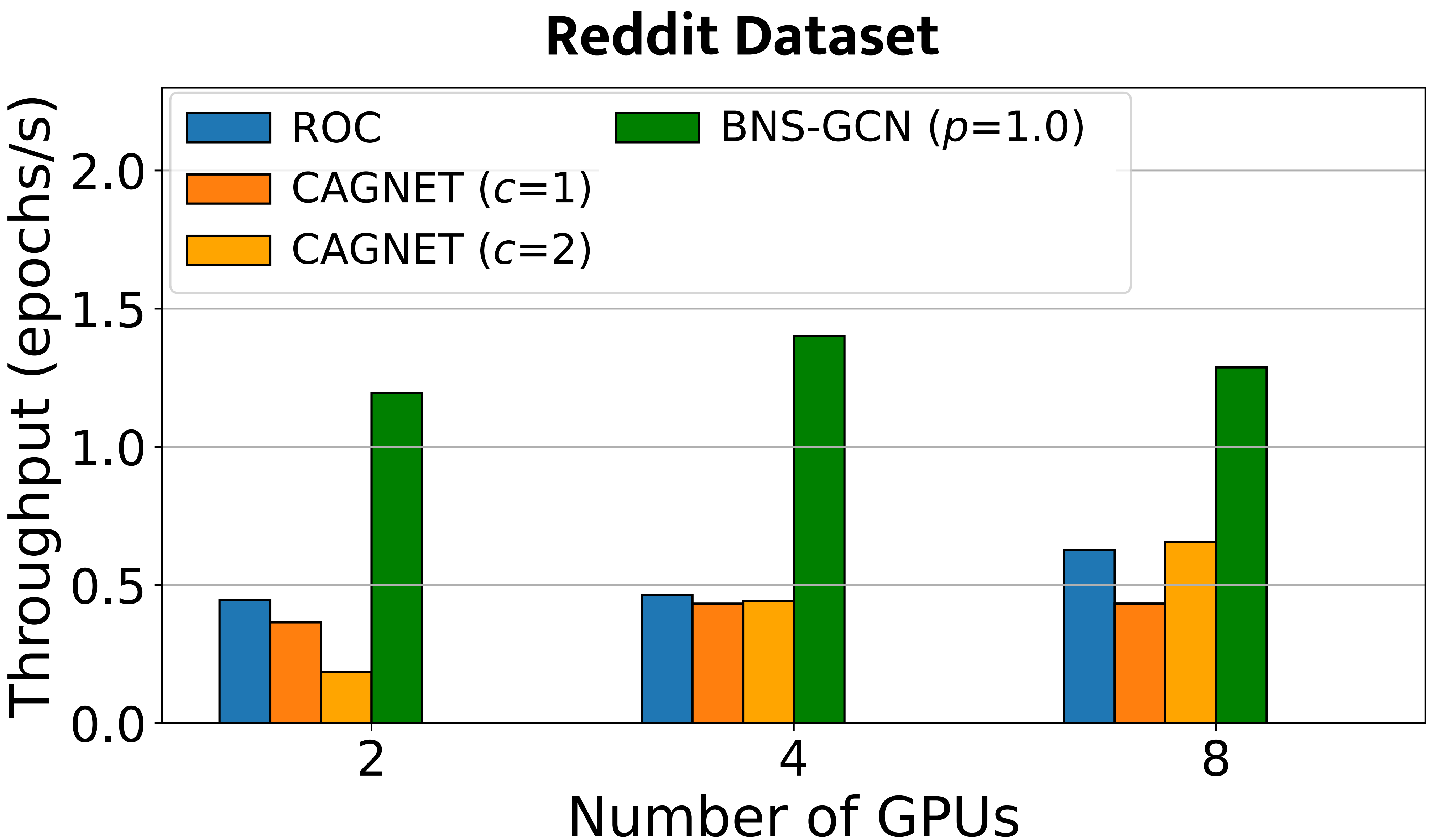
DGL 0.7.0 and PyTorch 1.9.1

# Training Throughput Comparison



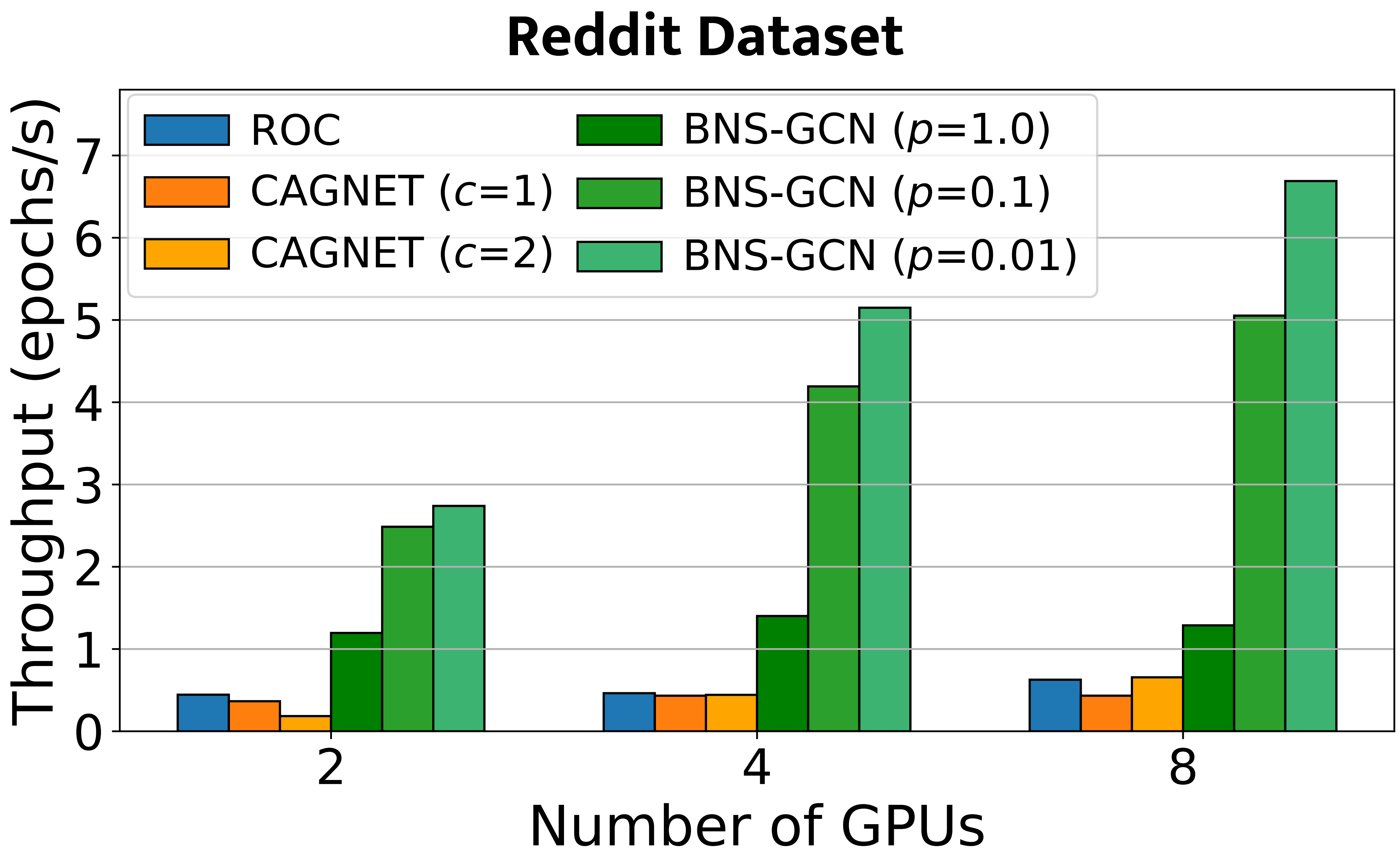

Baselines: throughput <0.7 epochs/s

# Training Throughput Comparison



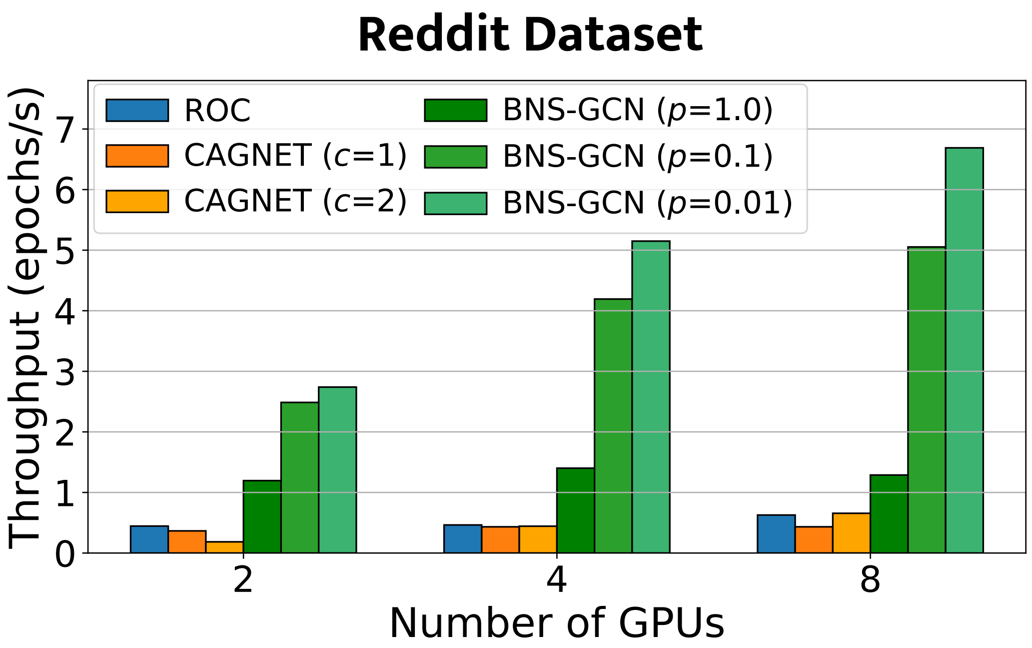

Partition-based training: throughput >1.2 epochs/s

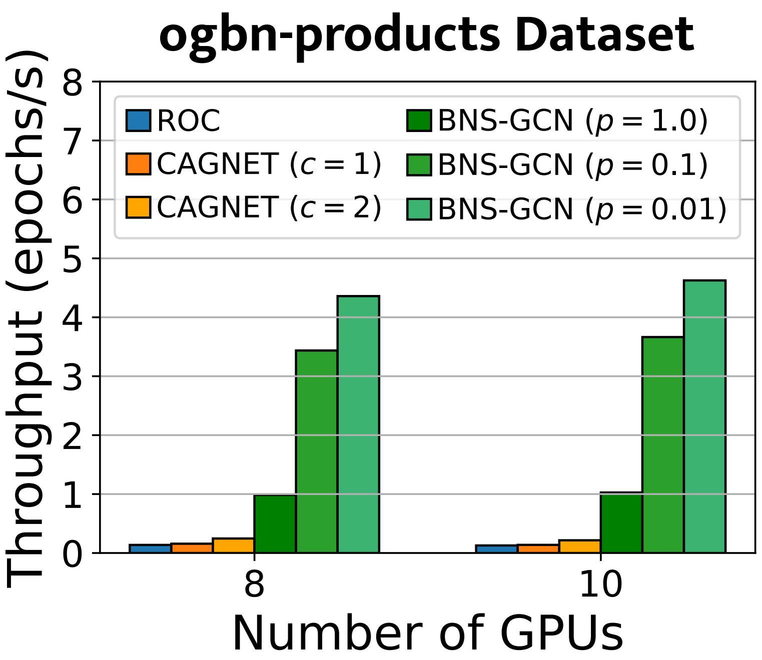
# Training Throughput Comparison

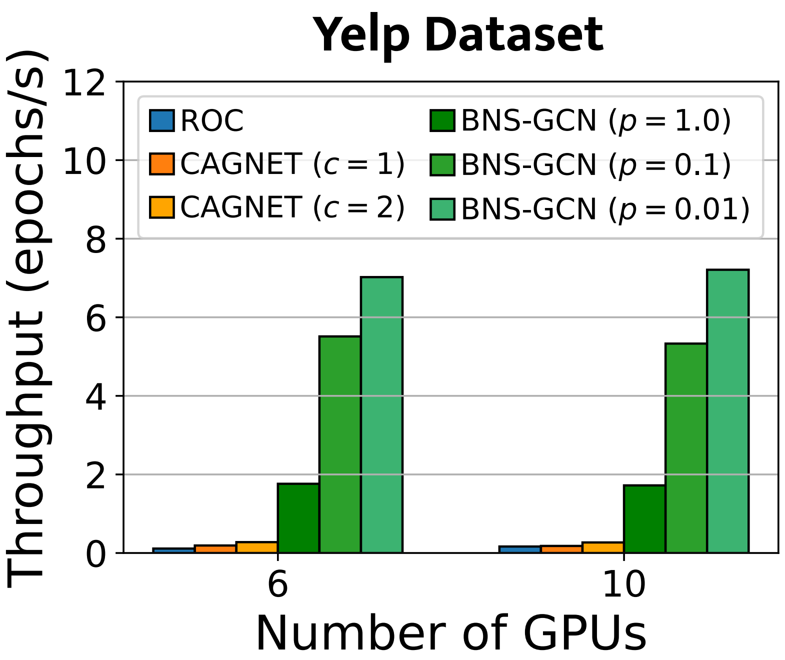



BNS-GCN: 8.9x~16.2x throughput improvement

# Training Throughput Comparison

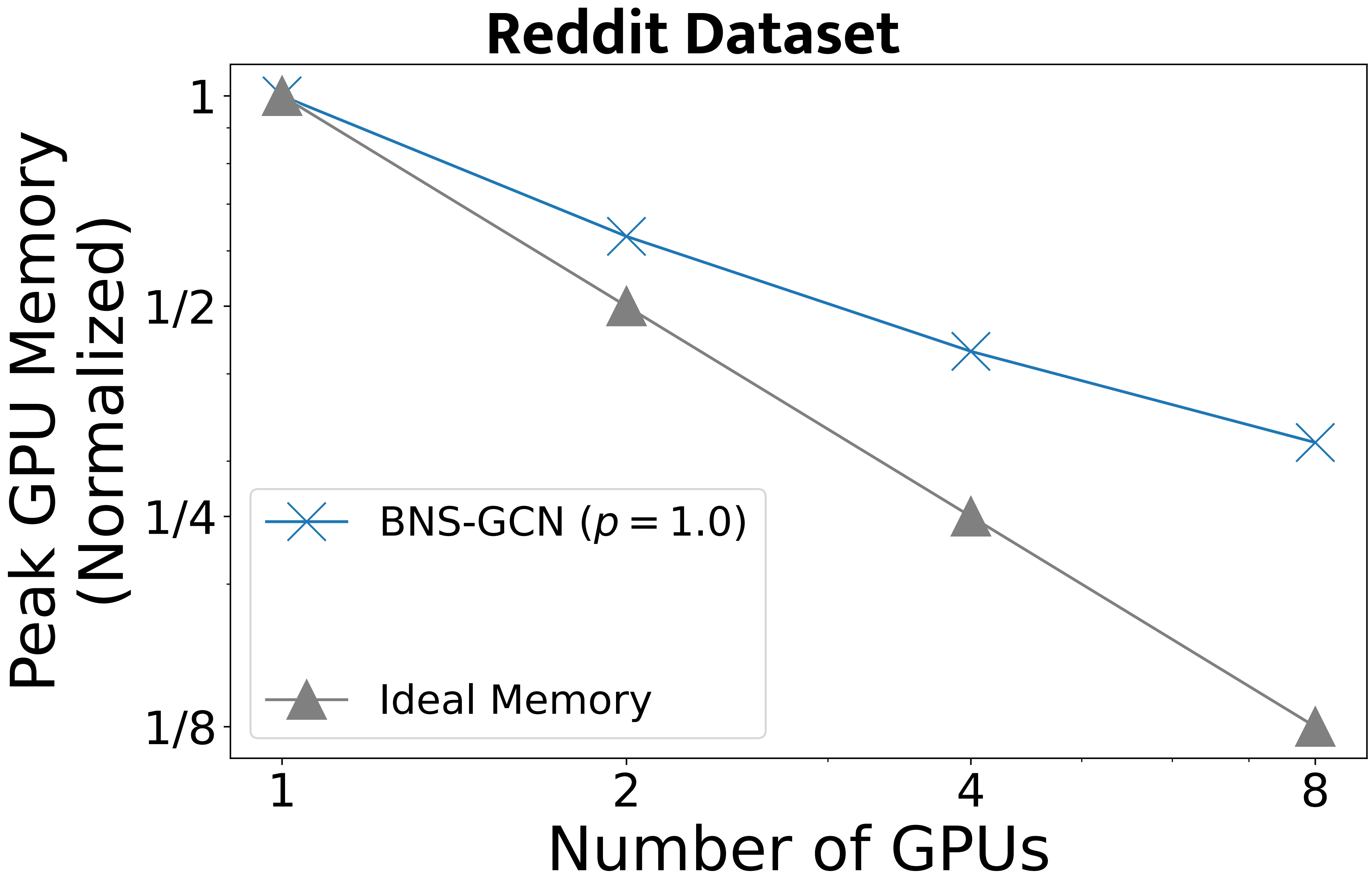


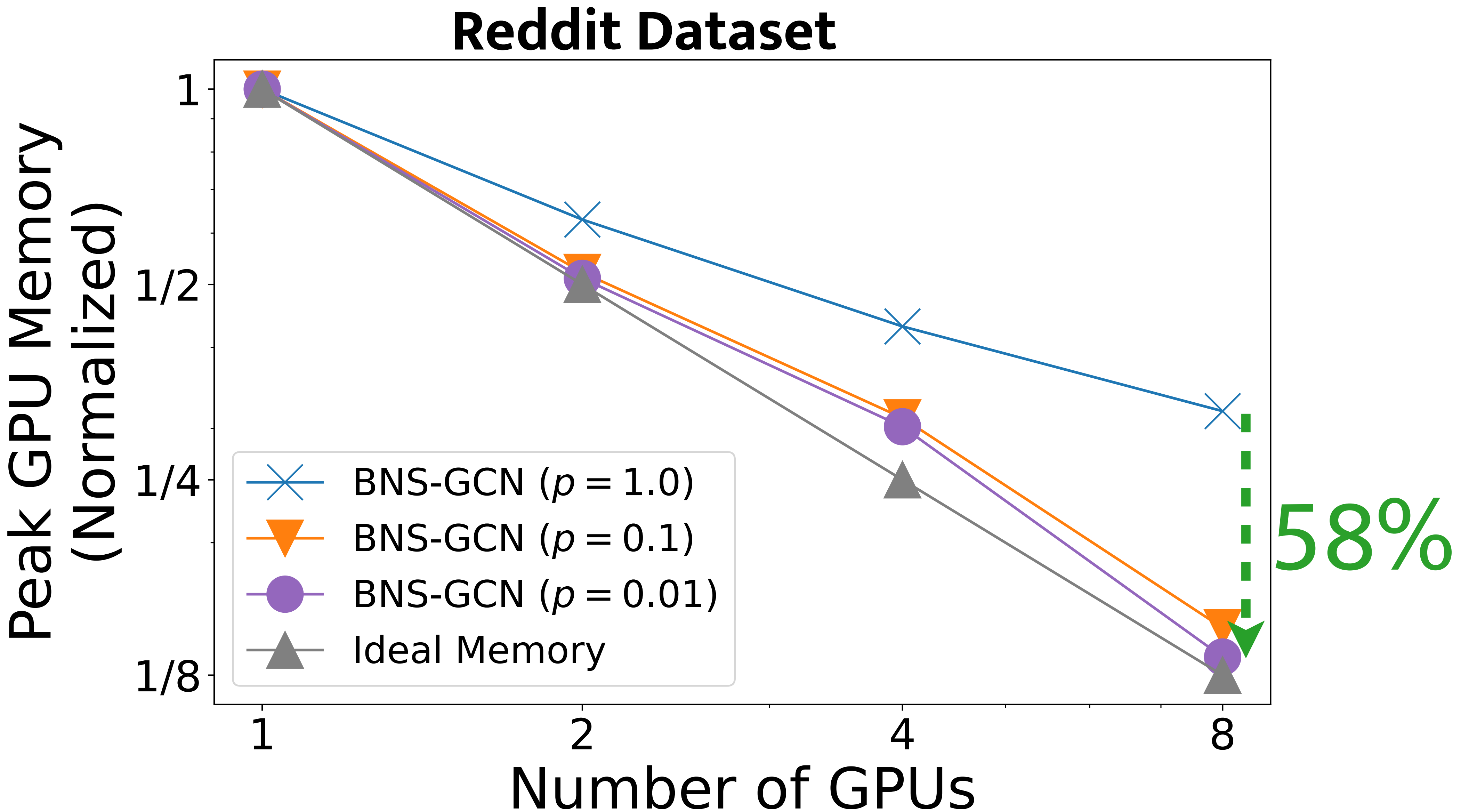




BNS-GCN is consistently faster

# Memory Saving

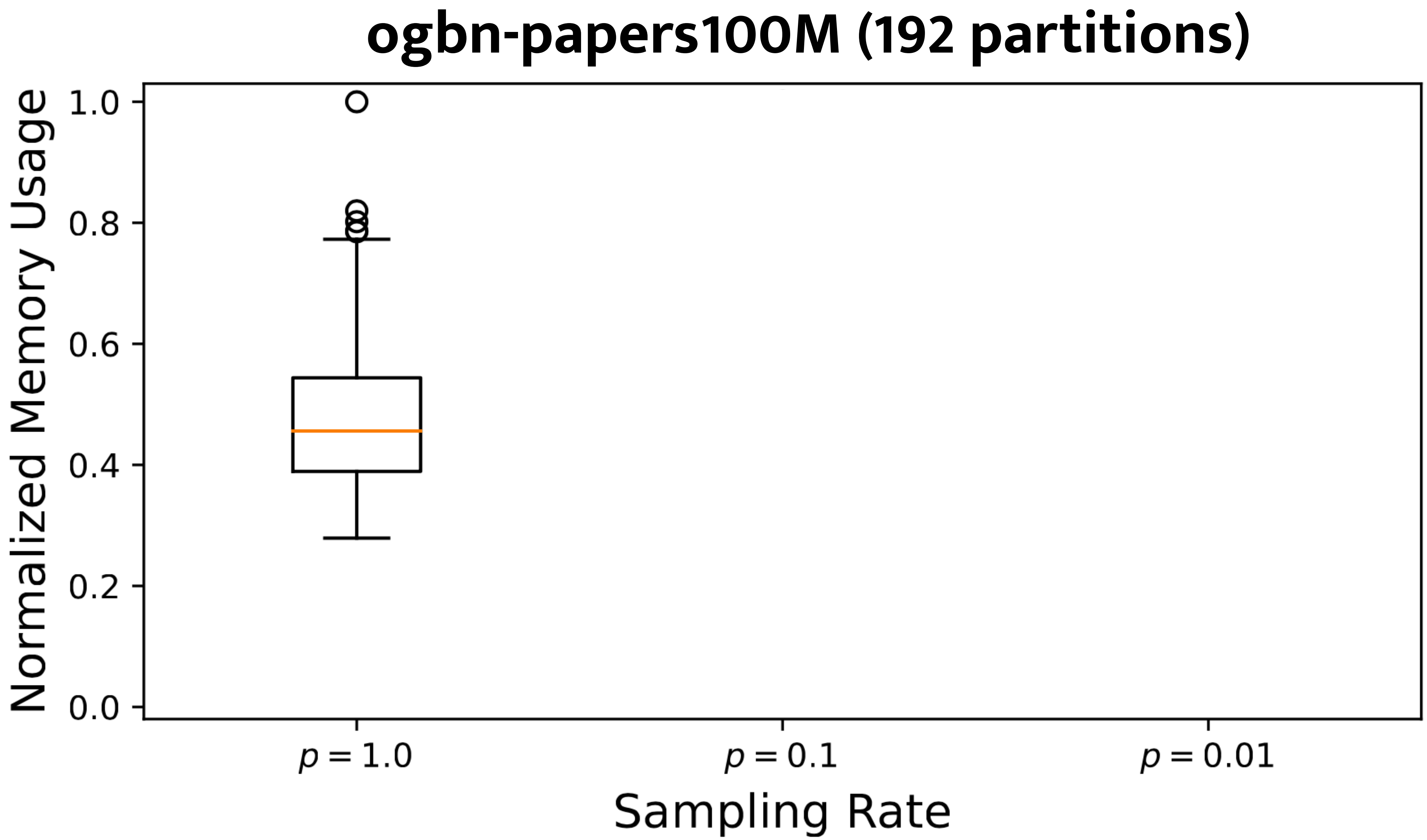


# Memory Saving



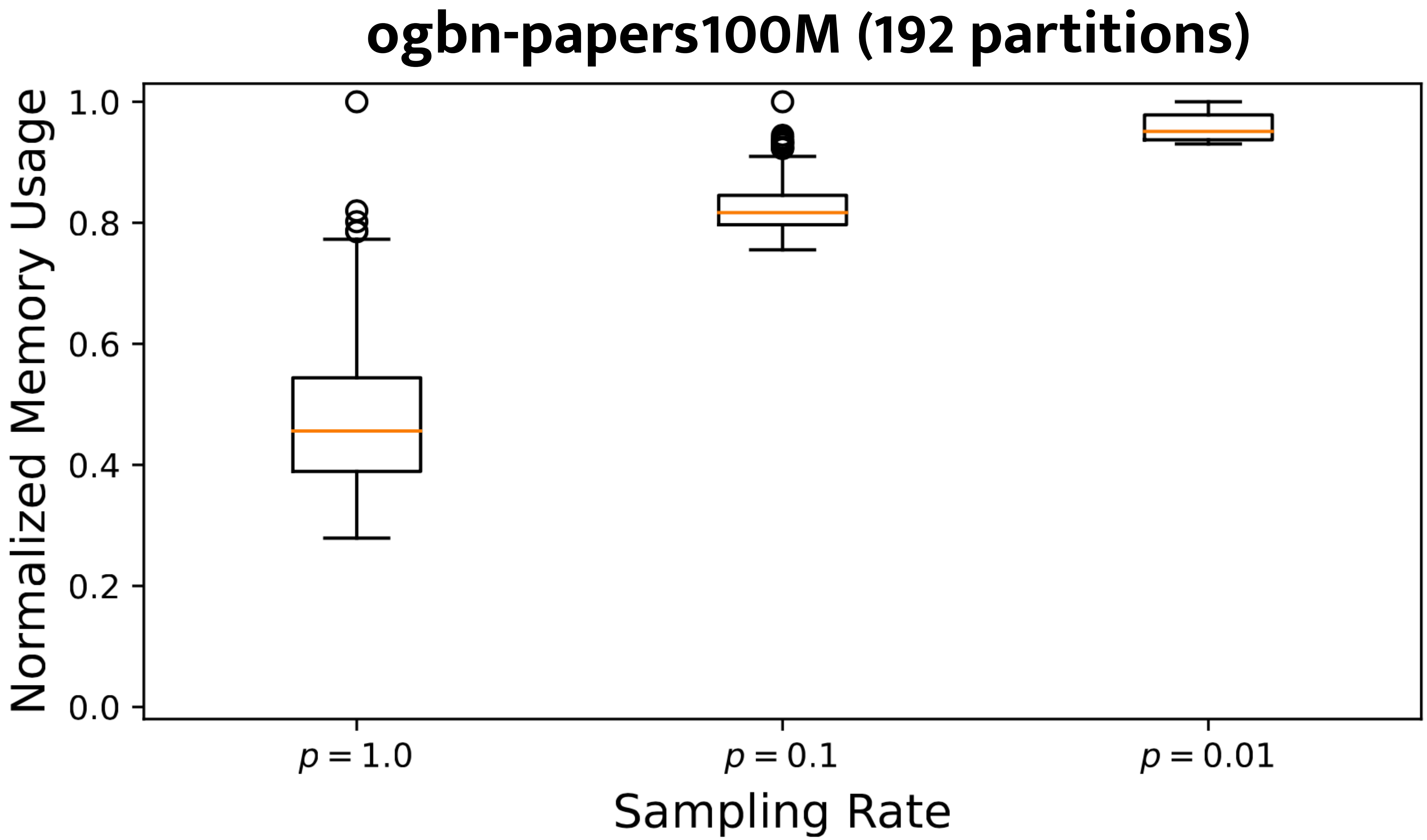

BNS-GCN saves the memory by up to 58%

# Balancing Memory Requirement




Without BNS: >75% partitions utilize <60% memory

# Balancing Memory Requirement




Without BNS: >75% partitions utilize <60% memory

With BNS: nearly all partitions utilize >80% memory

# Training Accuracy Comparison

| **Dataset** | **Reddit** | | | **ogbn-products** | | | **Yelp** | | |
|---|---|---|---|---|---|---|---|---|---|
| # Partitions | 2 | 4 | 8 | 5 | 8 | 10 | 3 | 6 | 10 |
| | | | | | | | | | |
| | | | | | | | | | |
| | | | | | | | | | |
| | | | | | | | | | |

# Training Accuracy Comparison

| Dataset | Reddit | | | ogbn-products | | | Yelp | | |
|---|---|---|---|---|---|---|---|---|---|
| # Partitions | 2 | 4 | 8 | 5 | 8 | 10 | 3 | 6 | 10 |
| BNS-GCN (p=1.0) | 97.11 | 97.11 | 97.11 | 79.14 | 79.14 | 79.14 | 65.26 | 65.26 | 65.26 |

BNS-GCN (p=1.0) is equivalent to vanilla training

# Training Accuracy Comparison

| Dataset | Reddit | | | ogbn-products | | | Yelp | | |
|---|---|---|---|---|---|---|---|---|---|
| # Partitions | 2 | 4 | 8 | 5 | 8 | 10 | 3 | 6 | 10 |
| BNS-GCN (p=1.0) | 97.11 | 97.11 | 97.11 | 79.14 | 79.14 | 79.14 | 65.26 | 65.26 | 65.26 |
| BNS-GCN (p=0.1) | **97.15** | **97.14** | **97.18** | 79.36 | **79.48** | **79.30** | **65.32** | 65.26 | **65.34** |
| BNS-GCN (p=0.01) | 97.09 | 97.03 | 96.91 | **79.43** | 79.28 | 79.21 | 65.27 | **65.31** | 65.29 |

BNS-GCN (p=1.0) is equivalent to vanilla training

Sampling boundary nodes maintains the accuracy

# Training Accuracy Comparison

| Dataset | Reddit | | | ogbn-products | | | Yelp | | |
|---|---|---|---|---|---|---|---|---|---|
| # Partitions | 2 | 4 | 8 | 5 | 8 | 10 | 3 | 6 | 10 |
| BNS-GCN (p=1.0) | 97.11 | 97.11 | 97.11 | 79.14 | 79.14 | 79.14 | 65.26 | 65.26 | 65.26 |
| BNS-GCN (p=0.1) | **97.15** | **97.14** | **97.18** | 79.36 | **79.48** | **79.30** | **65.32** | 65.26 | **65.34** |
| BNS-GCN (p=0.01) | 97.09 | 97.03 | 96.91 | **79.43** | 79.28 | 79.21 | 65.27 | **65.31** | 65.29 |
| BNS-GCN (p=0.0) | 97.03 | 96.87 | 96.81 | 78.65 | 78.83 | 78.79 | 65.28 | 65.27 | 65.23 |

BNS-GCN (p=1.0) is equivalent to vanilla training

Sampling boundary nodes maintains the accuracy

Dropping boundary nodes decreases the accuracy

# Training Accuracy Comparison

| Dataset | Reddit | | | ogbn-products | | | Yelp | | |
|---|---|---|---|---|---|---|---|---|---|
| # Partitions | 2 | 4 | 8 | 5 | 8 | 10 | 3 | 6 | 10 |
| BNS-GCN (p=1.0) | 97.11 | 97.11 | 97.11 | 79.14 | 79.14 | 79.14 | 65.26 | 65.26 | 65.26 |
| BNS-GCN (p=0.1) | **97.15** | **97.14** | **97.18** | 79.36 | **79.48** | **79.30** | **65.32** | 65.26 | **65.34** |
| BNS-GCN (p=0.01) | 97.09 | 97.03 | 96.91 | **79.43** | 79.28 | 79.21 | 65.27 | **65.31** | 65.29 |
| BNS-GCN (p=0.0) | 97.03 | 96.87 | 96.81 | 78.65 | 78.83 | 78.79 | 65.28 | 65.27 | 65.23 |
| FastGCN [ICLR'18] | | 93.7 | | | 60.42 | | | 26.5 | |
| GraphSAGE [NIPS'17] | | 95.4 | | | 78.70 | | | 63.4 | |
| AS-GCN [NIPS'18] | | 96.3 | | | OOM | | | OOM | |
| LADIES [NeurIPS'19] | | 94.3 | | | 77.46 | | | 60.2 | |
| VR-GCN [ICML'18] | | 96.3 | | | OOM | | | 64.0 | |
| ClusterGCN [KDD'19] | | 96.6 | | | 78.97 | | | 60.9 | |
| GraphSAINT [ICLR'20] | | 96.6 | | | 79.08 | | | 65.3 | |

Full-graph training reaches higher accuracy than sampling-based methods

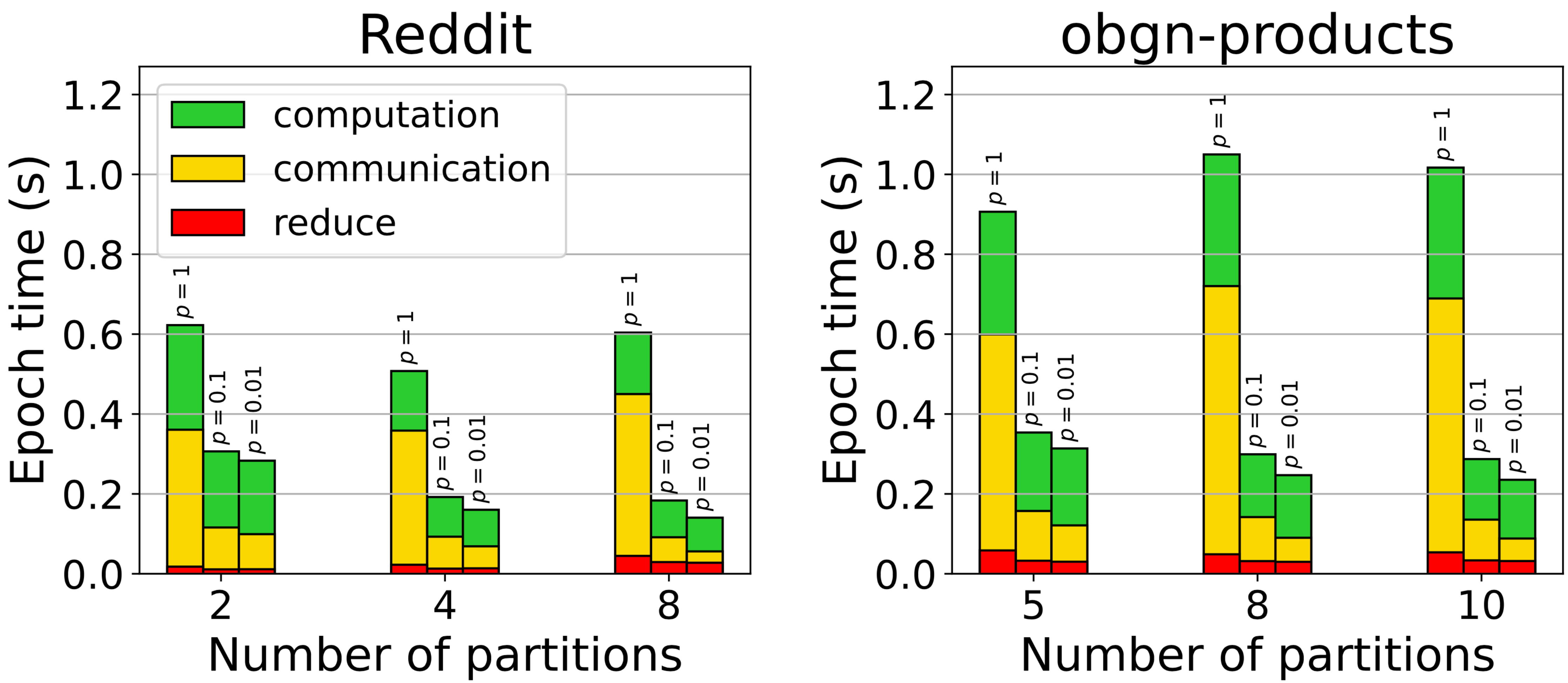
# Conclusion

- Identified three key drawbacks in partition-based GCN training
  - Underlying cause: boundary nodes
- Proposed Boundary Node Sampling (BNS-GCN) to tackle the three drawbacks
- Validated BNS-GCN in both theory and experiments

https://github.com/RICE-EIC/BNS-GCN

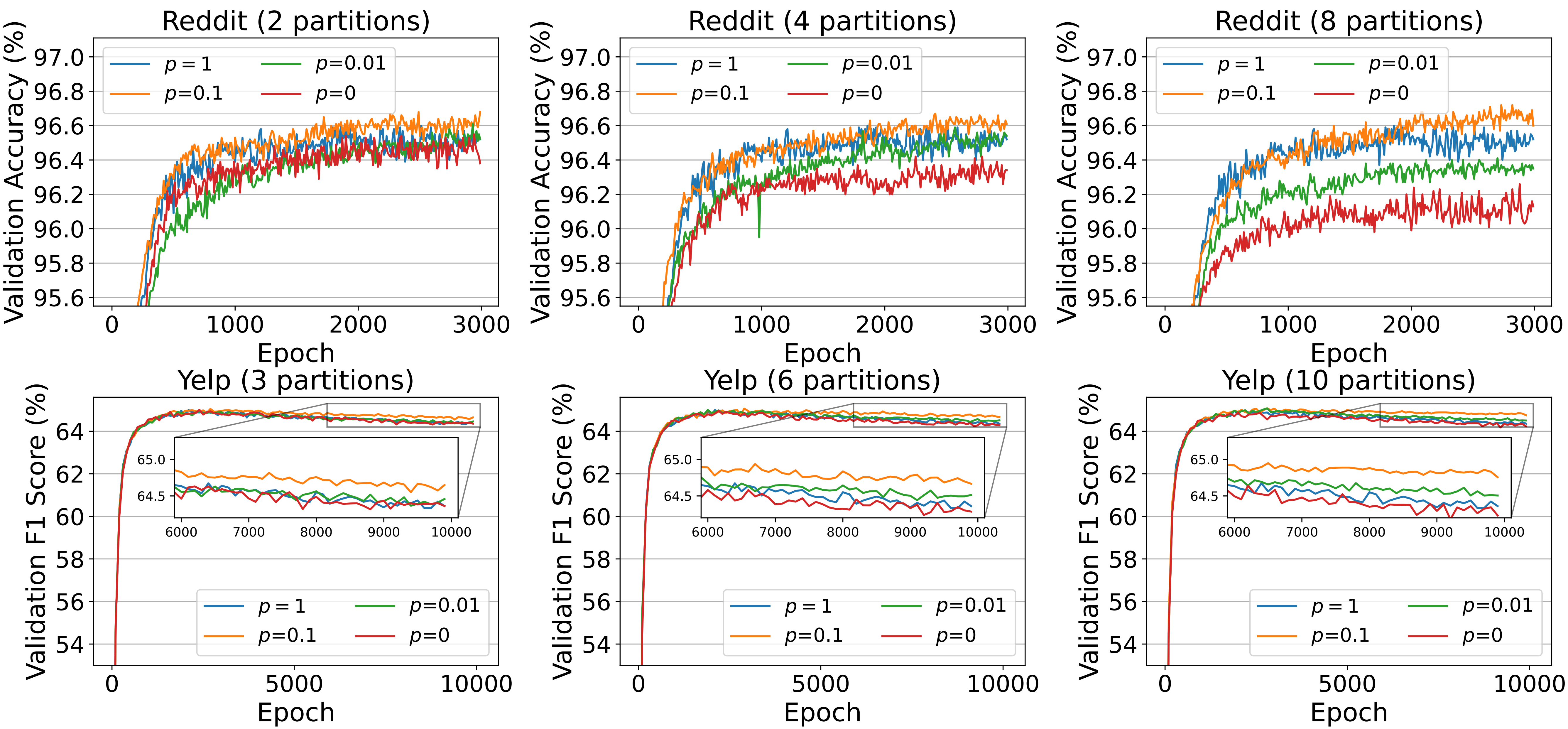
# Backup Slides

# Time Breakdown




Communication overhead is reduced by 74%~93%

# Training Convergence




On Reddit: p=0 has the worst convergence

On Yelp: p=0/1 suffers from overfitting

# BNS-GCN with Random Partition

Table 7: Test score (%) of BNS-GCN on top of random partition, where +/- shows the accuracy difference from BNS-GCN on top of METIS in Table 4.

| Method | Reddit (8 partitions) | | ogbn-products (10 partitions) | | Yelp (10 partitions) | |
|---|---|---|---|---|---|---|
| **Random**+BNS ($p = 1.0$) | 97.11 | +0.00 | 79.14 | +0.00 | 65.26 | +0.00 |
| **Random**+BNS ($p = 0.1$) | 96.95 | -0.20 | 79.57 | +0.27 | 65.18 | -0.16 |
| **Random**+BNS ($p = 0.0$) | 93.37 | -3.47 | 75.39 | -3.40 | 64.92 | -0.31 |

Table 8: Training efficiency improvement of BNS-GCN ($p = 0.1$) on top of different partition methods.

| Dataset | Throughput | | Memory | | # Boundary Nodes | |
|---|---|---|---|---|---|---|
| | METIS | Random | METIS | Random | METIS | Random |
| Reddit (8 partitions) | 3.1× | 5.0× | 0.47× | 0.36× | 460k | 1,016k |
| ogbn-products (10 partitions) | 3.4× | 7.3× | 0.75× | 0.31× | 1,848k | 16,797k |
| Yelp (10 partitions) | 3.1× | 5.1× | 0.83× | 0.49× | 649k | 2,026k |

# BNS-GCN vs DropEdge vs BES

Table 9: Comparison between BNS-GCN and edge sampling methods, DropEdge and Boundary Edge Sampling (BES).

| Dataset | Method | Epoch Comm (MB) | Epoch Time (sec) | Test Score (%) |
|---|---|---|---|---|
| Reddit (2 partitions) | DropEdge | 301.3 | 0.613 | 97.12 |
| | BES | 207.9 | 0.484 | 97.16 |
| | **BNS-GCN** | **30.4** | **0.319** | **97.17** |
| ogbn-products (5 partitions) | DropEdge | 1364.0 | 0.938 | **79.38** |
| | BES | 521.1 | 0.551 | 79.31 |
| | **BNS-GCN** | **138.7** | **0.388** | 79.36 |
| Yelp (3 partitions) | DropEdge | 718.7 | 0.606 | 65.30 |
| | BES | 195.3 | 0.328 | 65.30 |
| | **BNS-GCN** | **75.7** | **0.270** | **65.32** |