NeutronTP: **Load-Balanced** Distributed Full-Graph **GNN Training** with **Tensor Parallelism**

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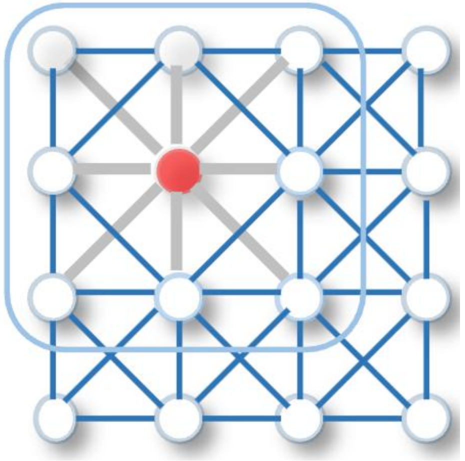
Graph Neural Network (GNN)

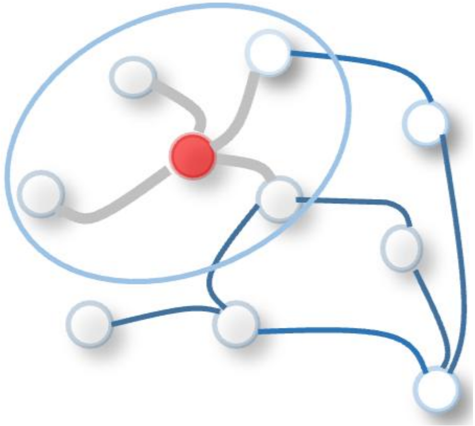
Why is it emerging?

DNN



Regular data
in Euclidean space

GNN



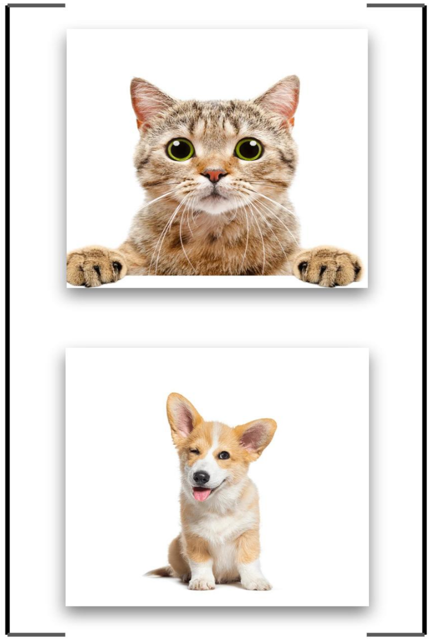
Irregular data
in non-Euclidean space

Image source: A Comprehensive Survey on Graph Neural Networks (TNNLS'20)

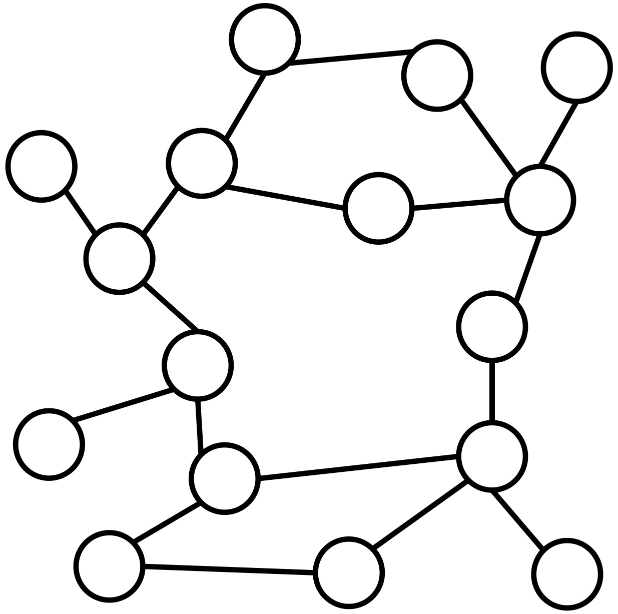
Graph Neural Network (GNN)

Dependency of GNN data samples

DNN inputs



GNN inputs



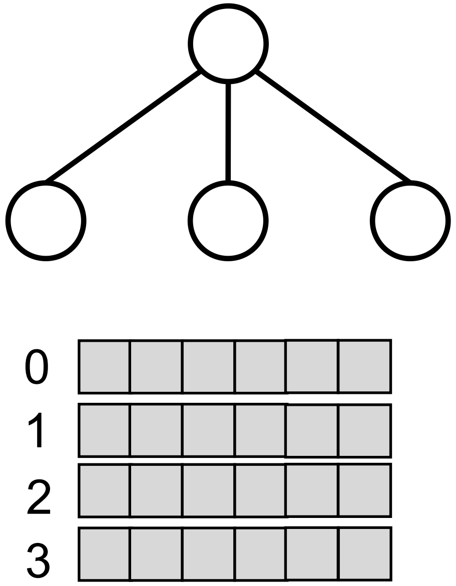
Independence

Dependencies

Graph Neural Network (GNN)

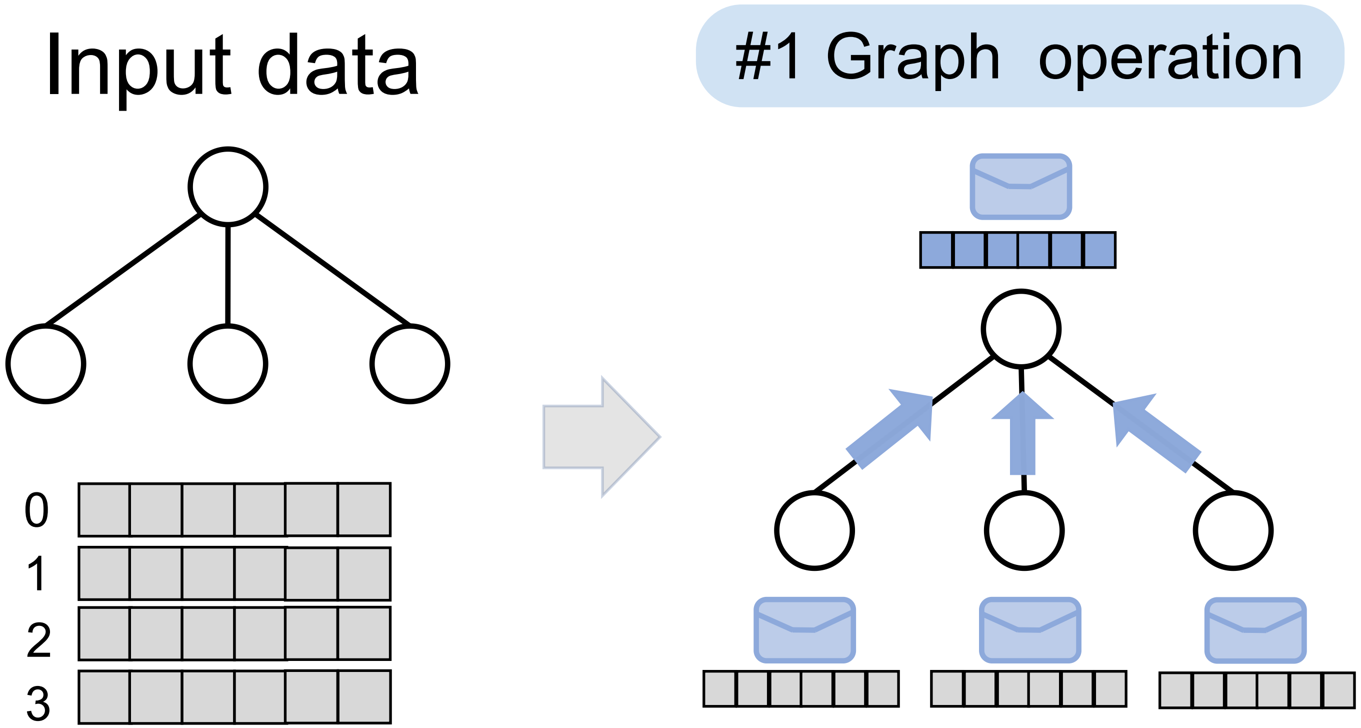
Two key stages of a GNN model

Input data



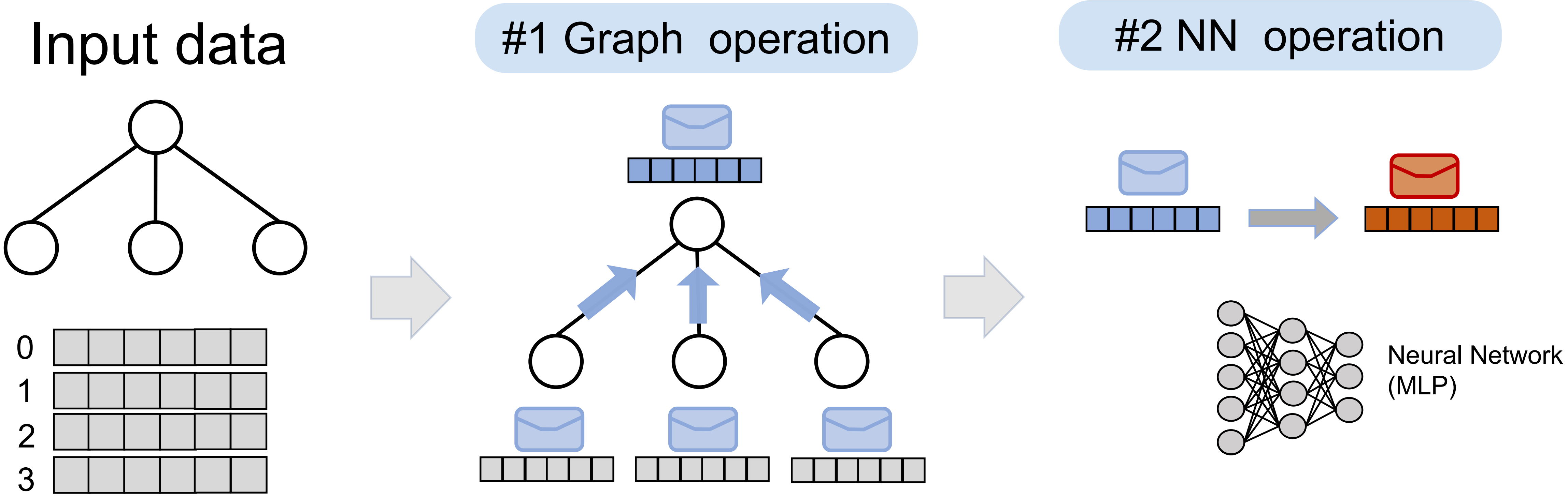
Graph Neural Network (GNN)

Two key stages of a GNN model



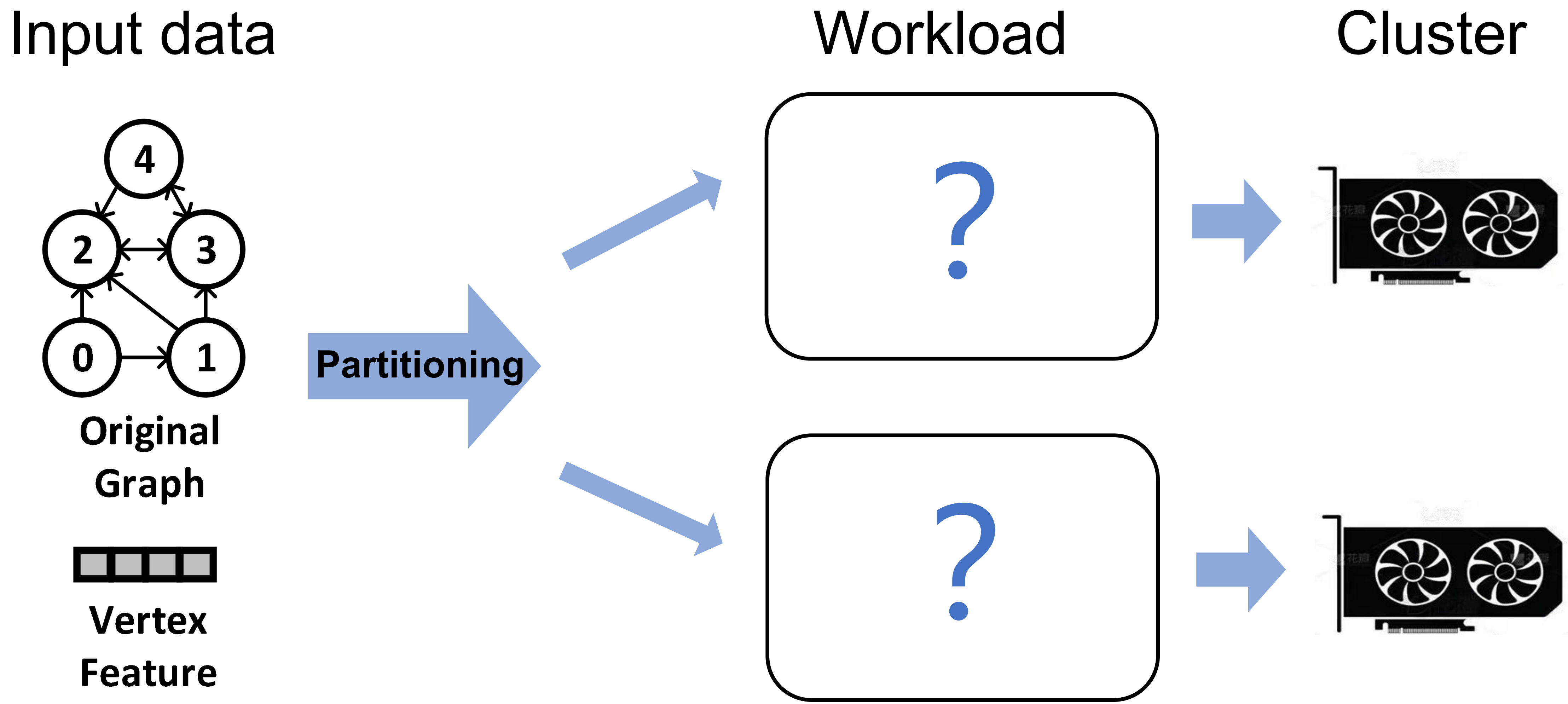
Graph Neural Network (GNN)

Two key stages of a GNN model



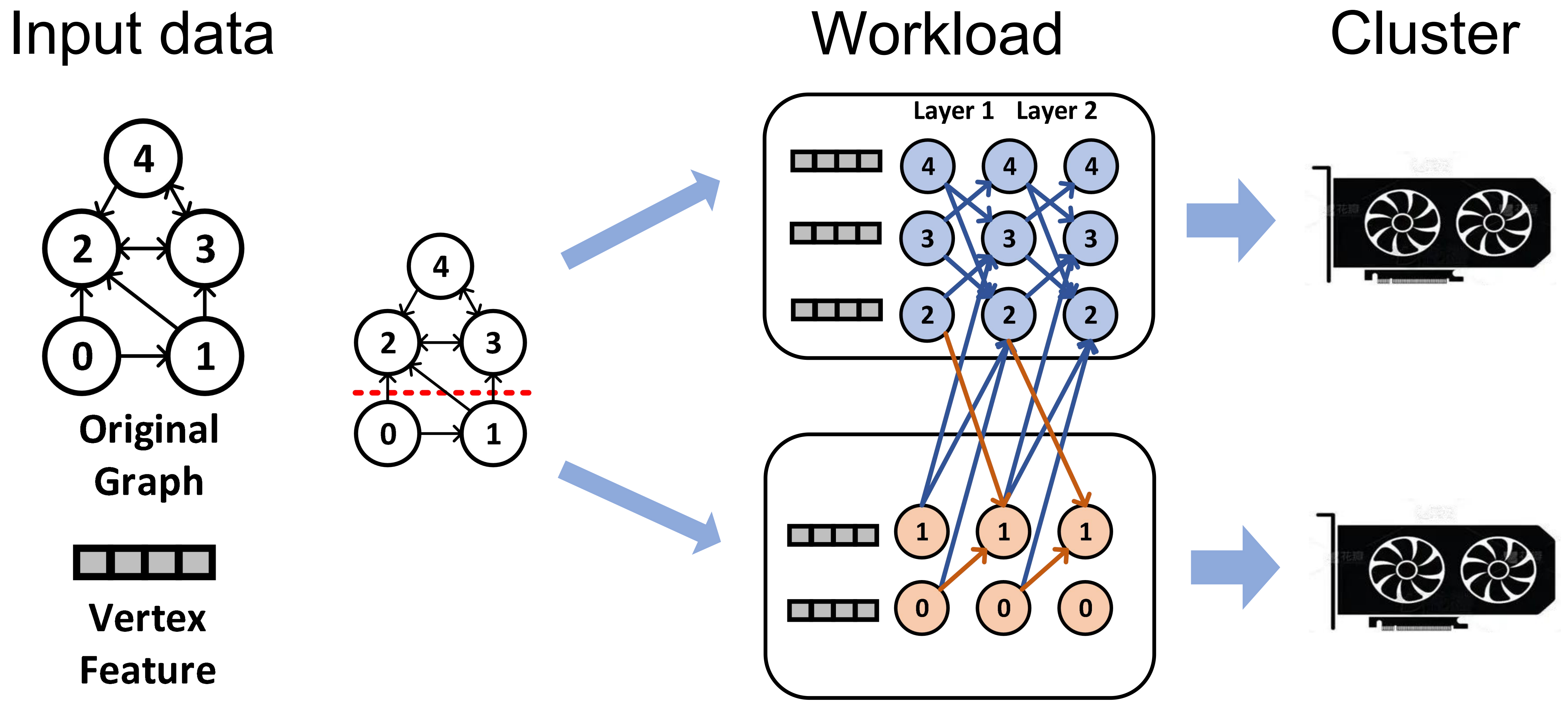
Distributed GNN Training

Workload partitioning is the key problem



Distributed GNN Training with Data Parallelism

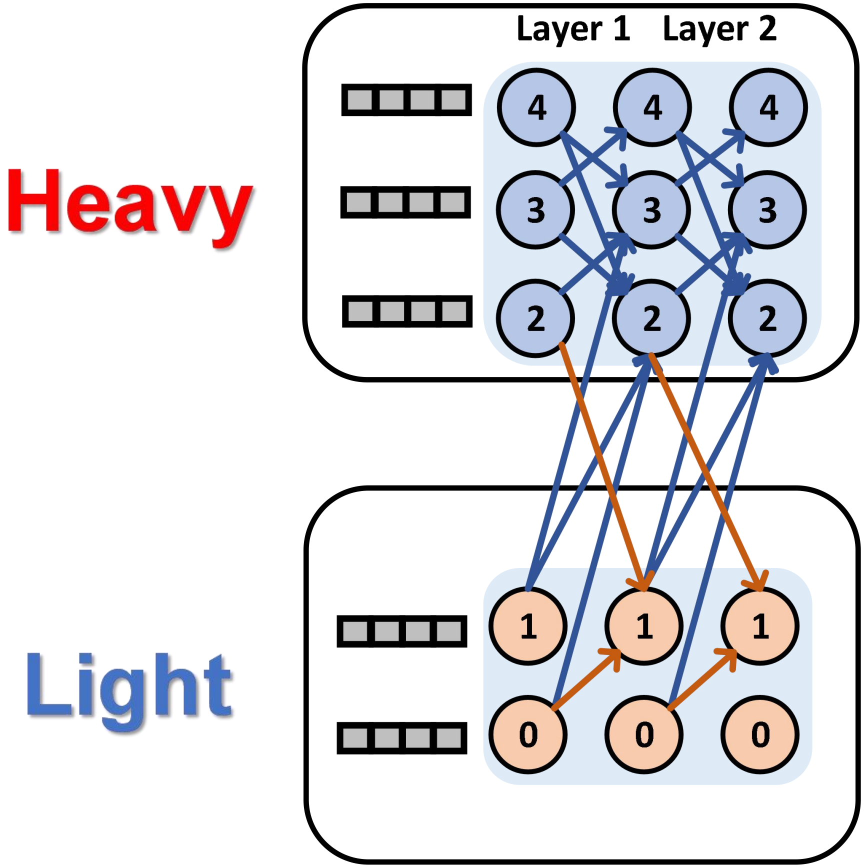
Graph partitioning is a common choice



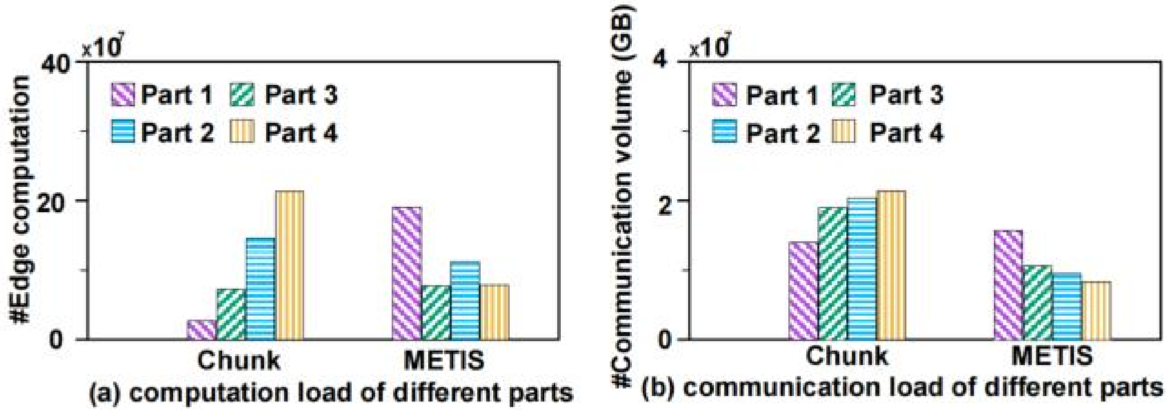
Distributed GNN Training with Data Parallelism

Graphs are difficult to partition uniformly

Workload



☹ **Workload imbalance**

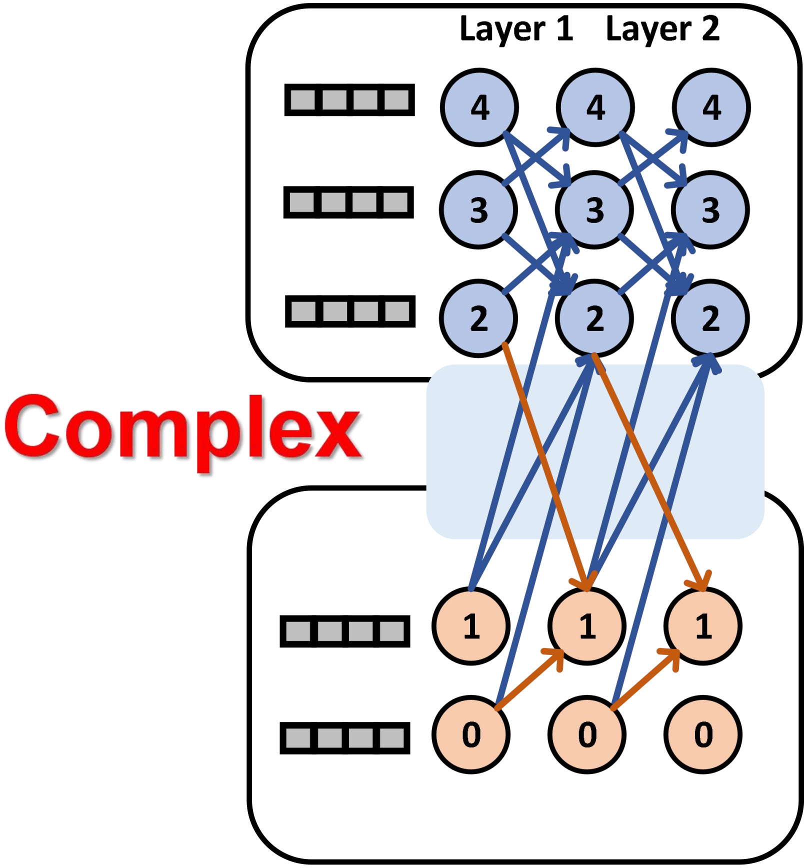


- The workload difference is up to **7.1X**.

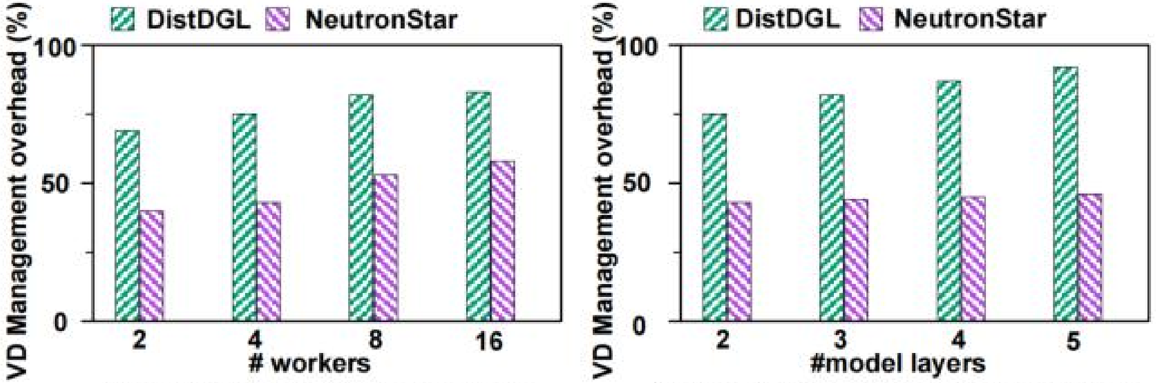
Distributed GNN Training with Data Parallelism

Each node may have many remote neighbors

Workload



☹ **Complex vertex dependencis**

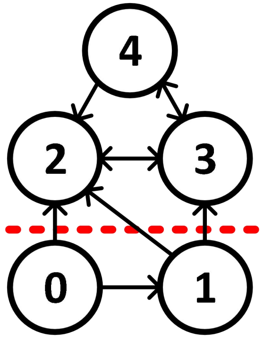


(a) varying the number of workers (b) varying the number of model layers

- VD management overhead dominates the training process, accounting for **40%–90%**.

Distributed GNN Training with Data Parallelism

Graph partitioning is the root of both problems



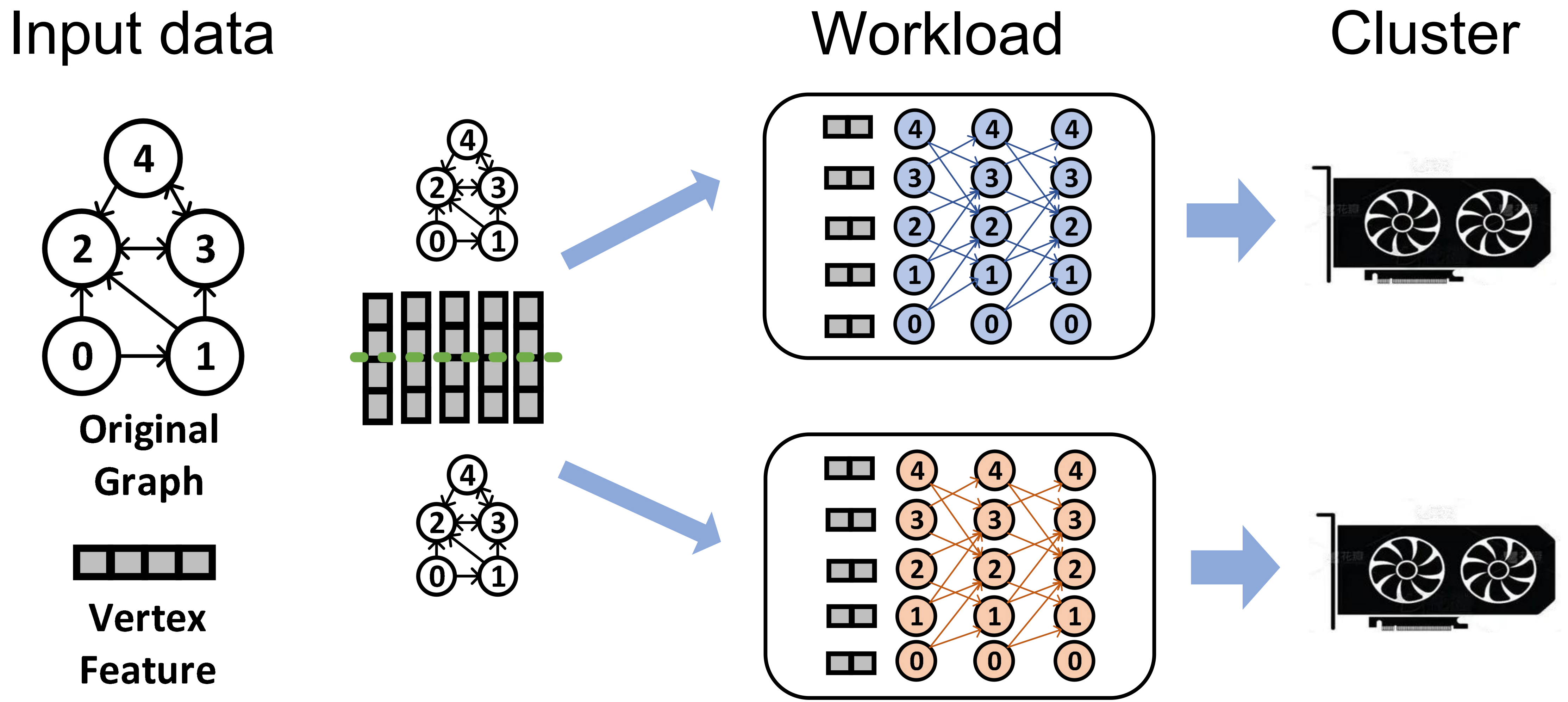
☹ **Workload imbalace**

☹ **Complex vertex dependencis**

Do we really need to **partition the graph?**

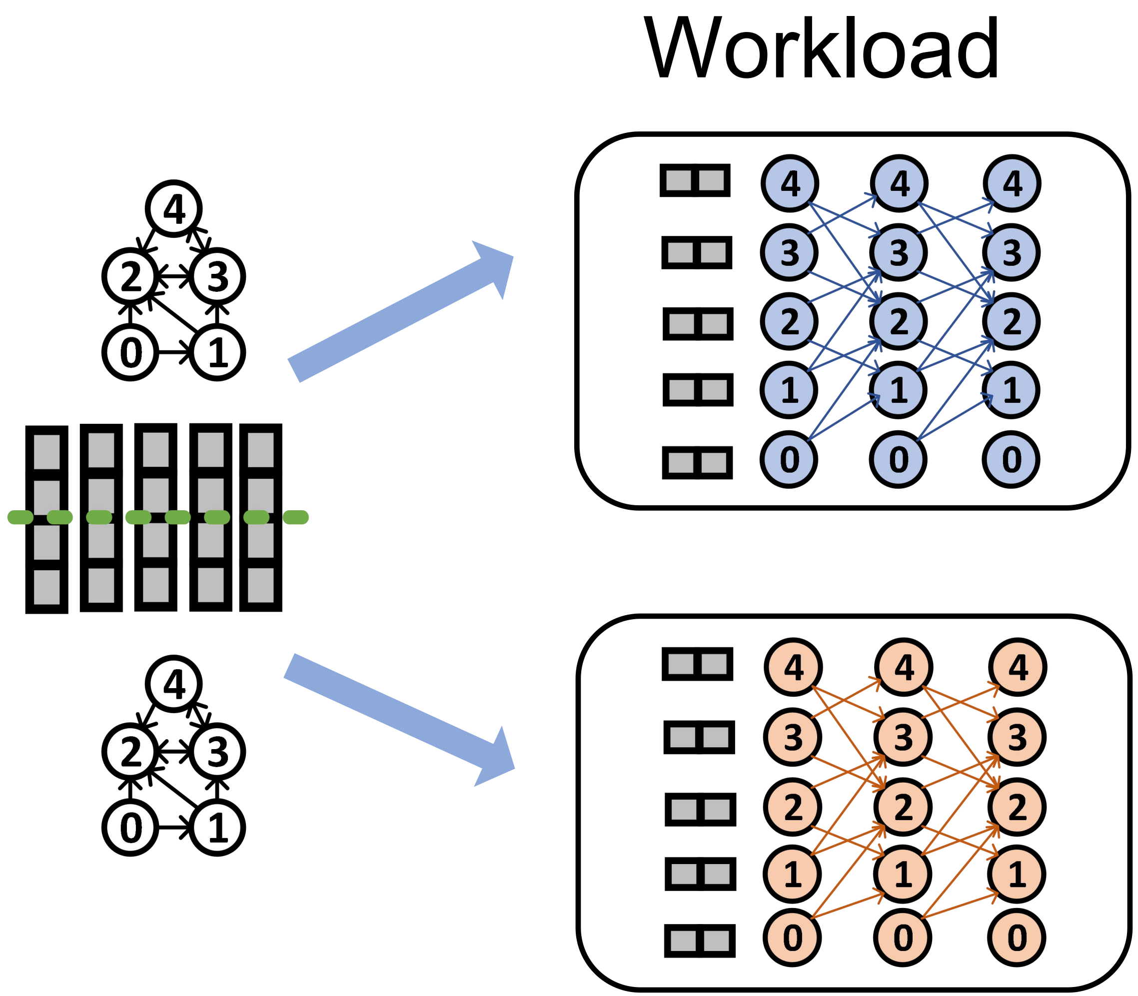
Our Solution: Tensor Parallelism

Partitioning features instead of graph structures



Our Solution: Tensor Parallelism

Partitioning features achieves balanced workload

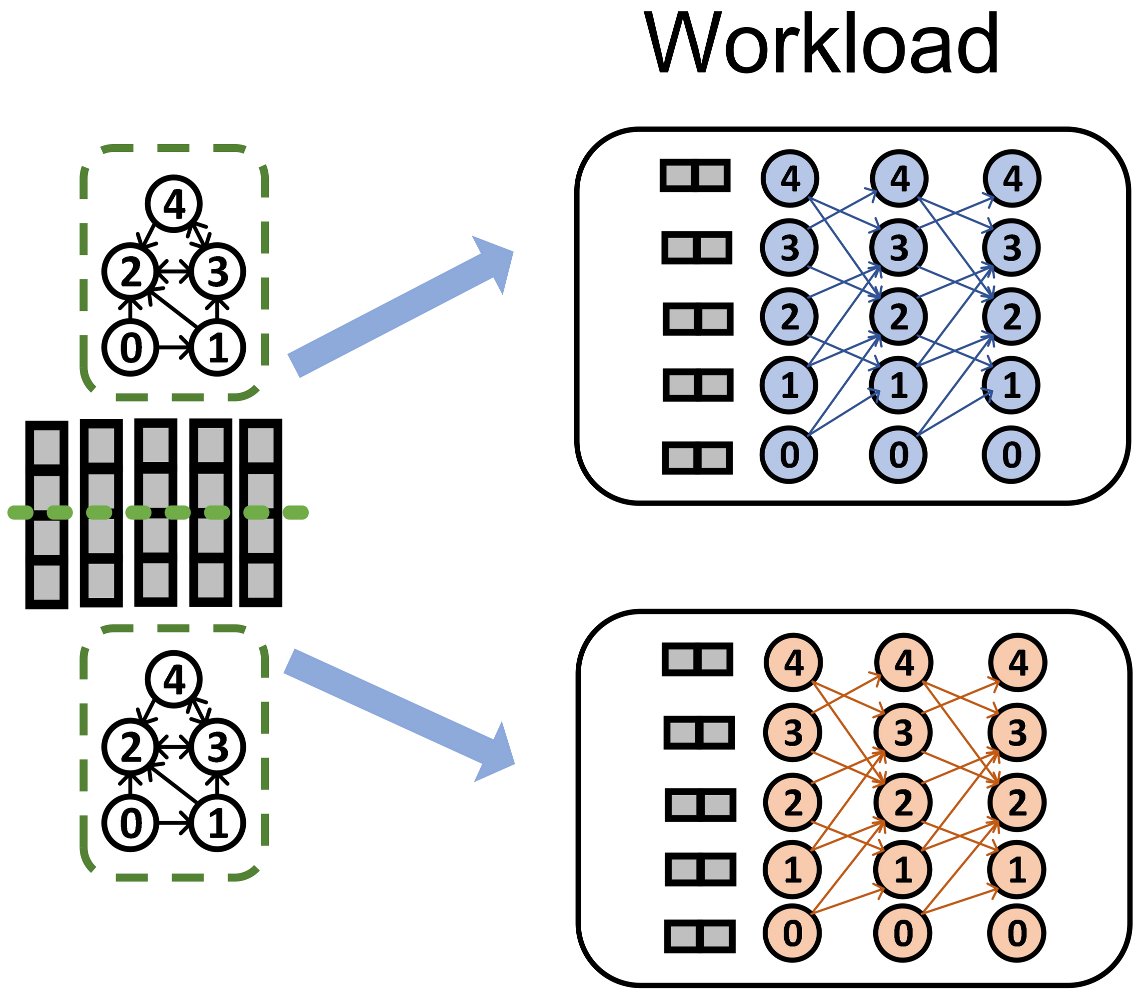


Workload balance

- Evenly partitioning feature
- The graph is replicated
- Completely balanced workload

Our Solution: Tensor Parallelism

Each worker holds a full replica of the graph



☺ **Workload balance**

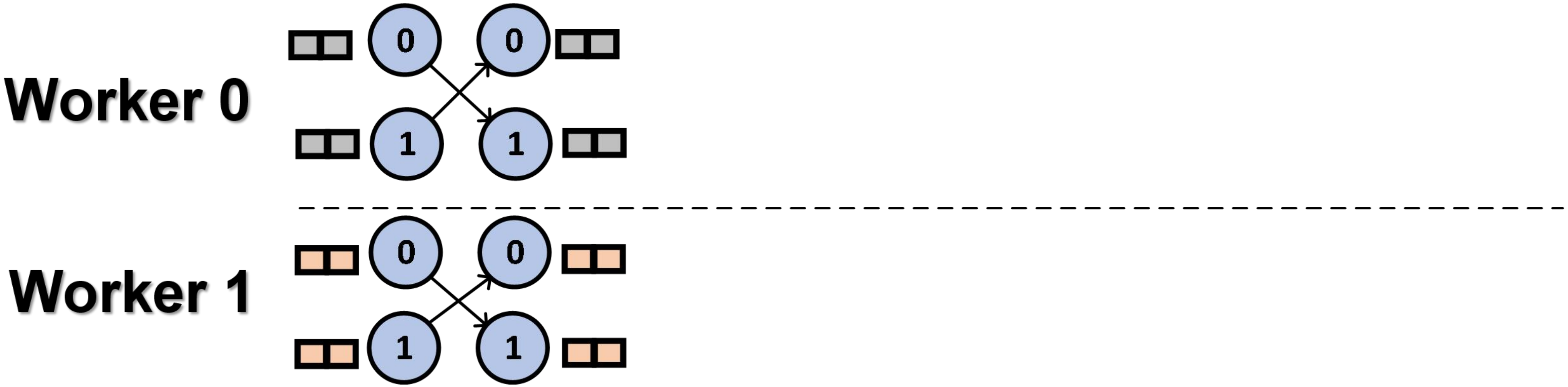
- **Evenly partitioning feature**
- **The graph is replicated**
- **Completely balanced workload**

☺ **No vertex dependencies**

Workflow of Tensor Parallelism

Workflow for a single layer

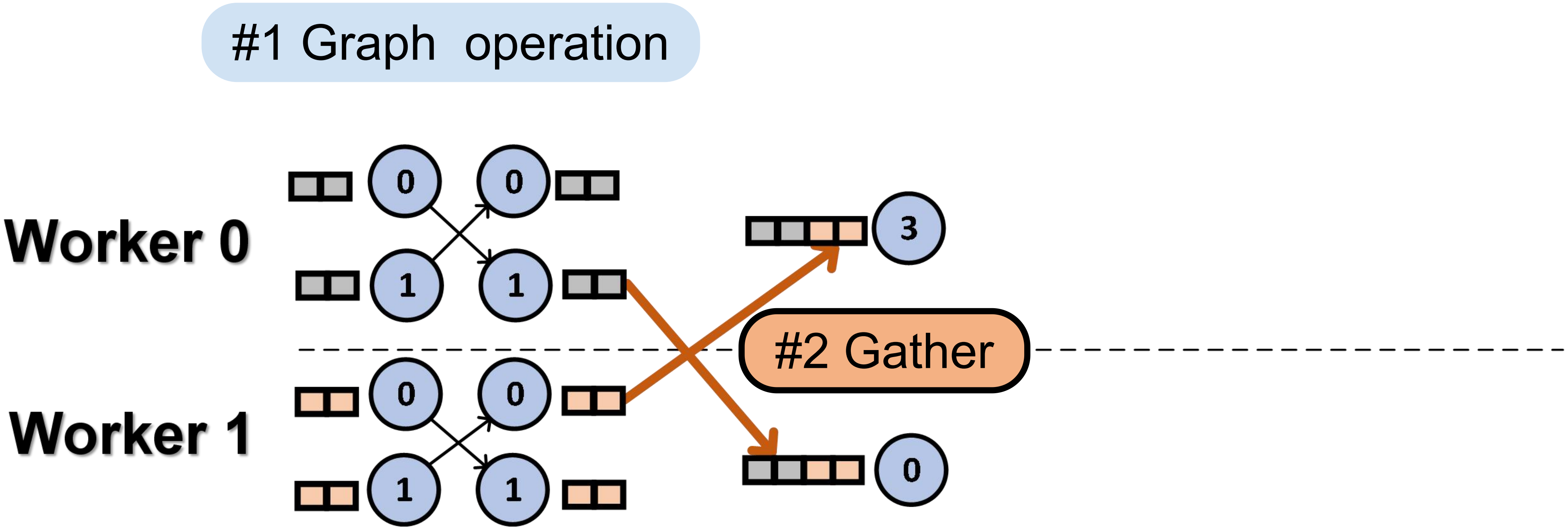
#1 Graph operation



Graph aggregation with feature slicing

Workflow of Tensor Parallelism

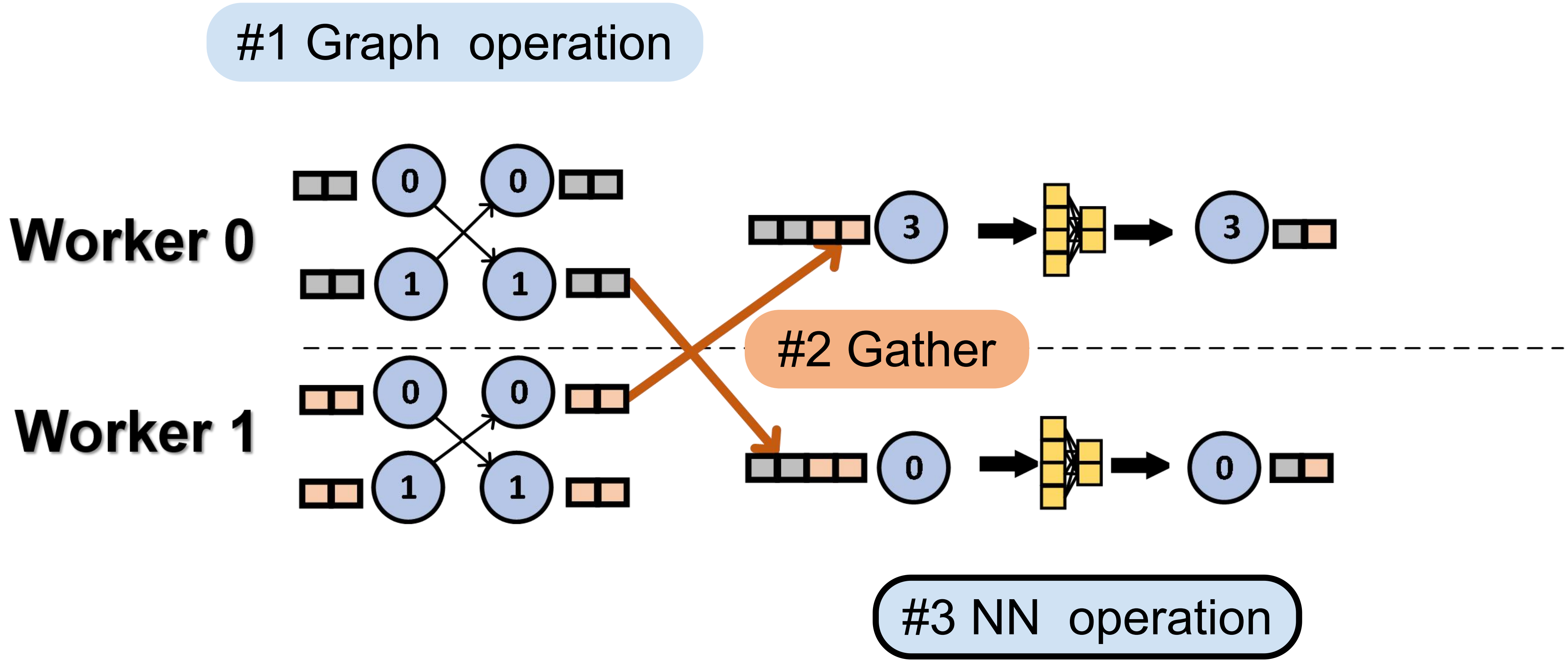
Workflow for a single layer



Gathering full features

Workflow of Tensor Parallelism

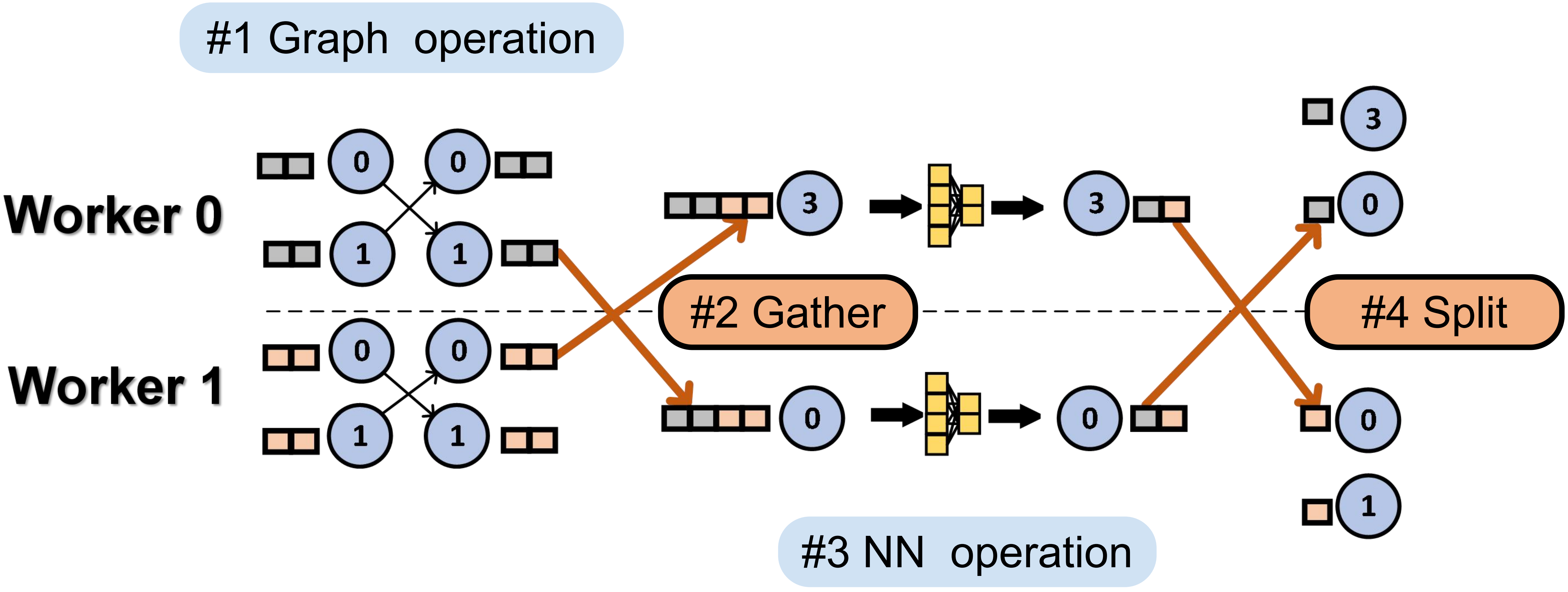
Workflow for a single layer



NN operation with full feature

Workflow of Tensor Parallelism

Workflow for a single layer



Splitting feature slicing

Challenges in Tensor Parallelism

Tensor parallelism has two major challenges

Challeges #1: Frequent collective communication

- Gather and Split in every layer
- Substantial layer-wise sync

Challeges #2: Processing the entire graph on a single worker

- Entire graph and corresponding embedding slices
- Limited GPU memory in each worker

NeutronTP

A distributed GNN system based on tensor parallelism

Generalized decoupled training method

- Decouple two opertions in GNN training
- Keep comparable model accuracy

Challeges #1

Memory-efficient task scheduling method

- Chunk-based task scheduling
- Inter-chunk pipelining

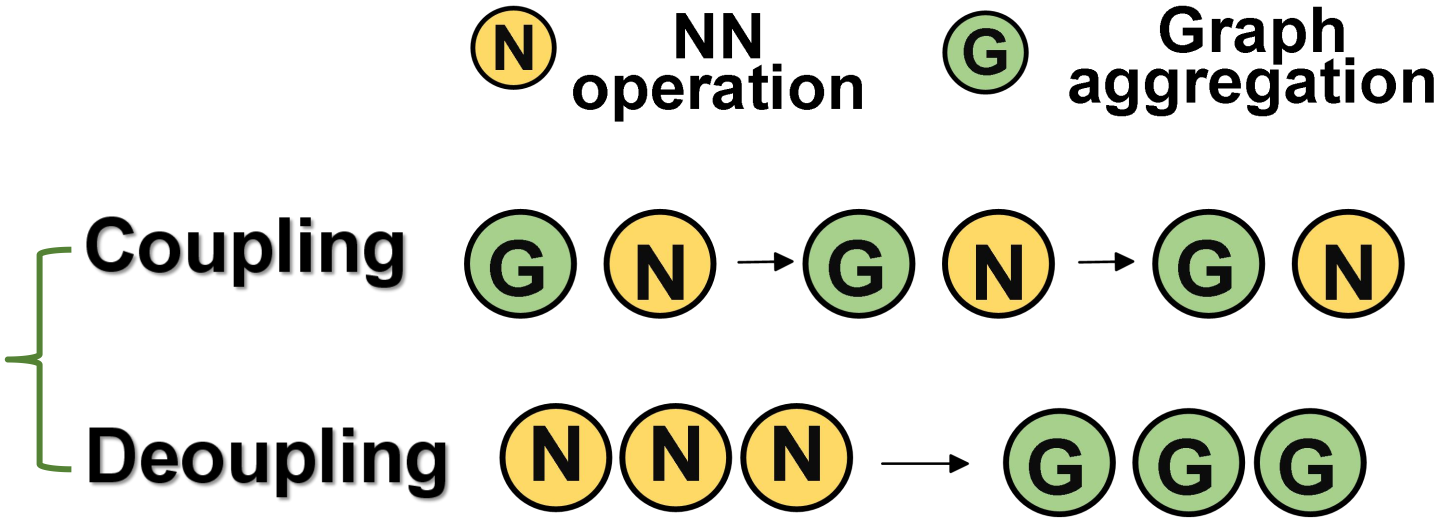
Challeges #2

Generalized Decoupled Training Method

Decoupling two opertions in GNN training

Observation: The power of GNNs stems from NN and graph operations, not their coupling execution

Comparable expressive power
Accuracy gap ≤ 1%



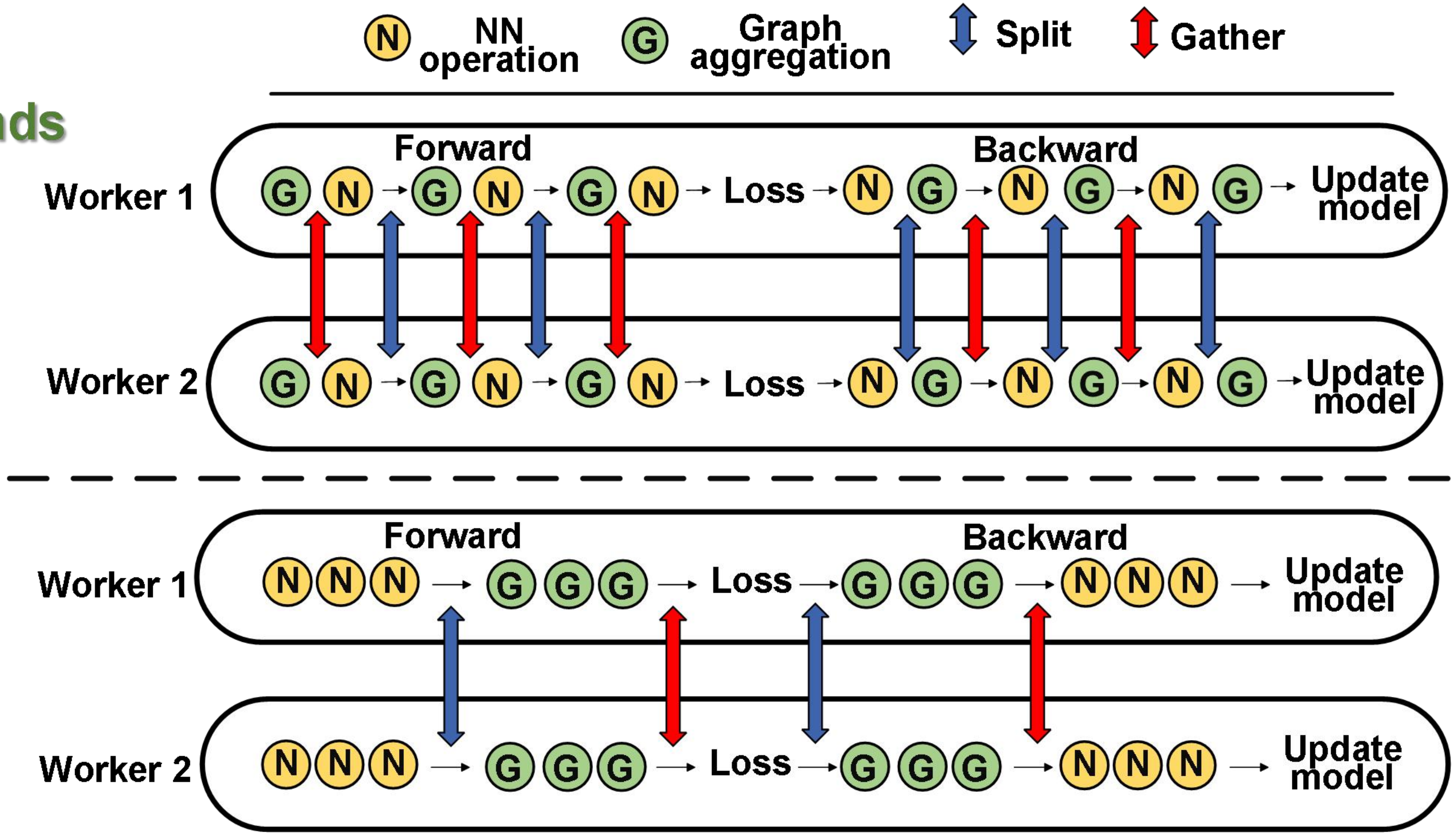
Generalized Decoupled Training Method

Reduce collective communication frequency

Reduce communication rounds

4× model depth - 2

Just 4 times



Generalized Decoupled Training Method

Provide Convergence analysis

Convergence Analysis

- **Decoupled training converges under infinite iterations**
- **Experiments demonstrate comparable accuracy**

Support decoupled training for edge-based NN operation (e.g., GAT)

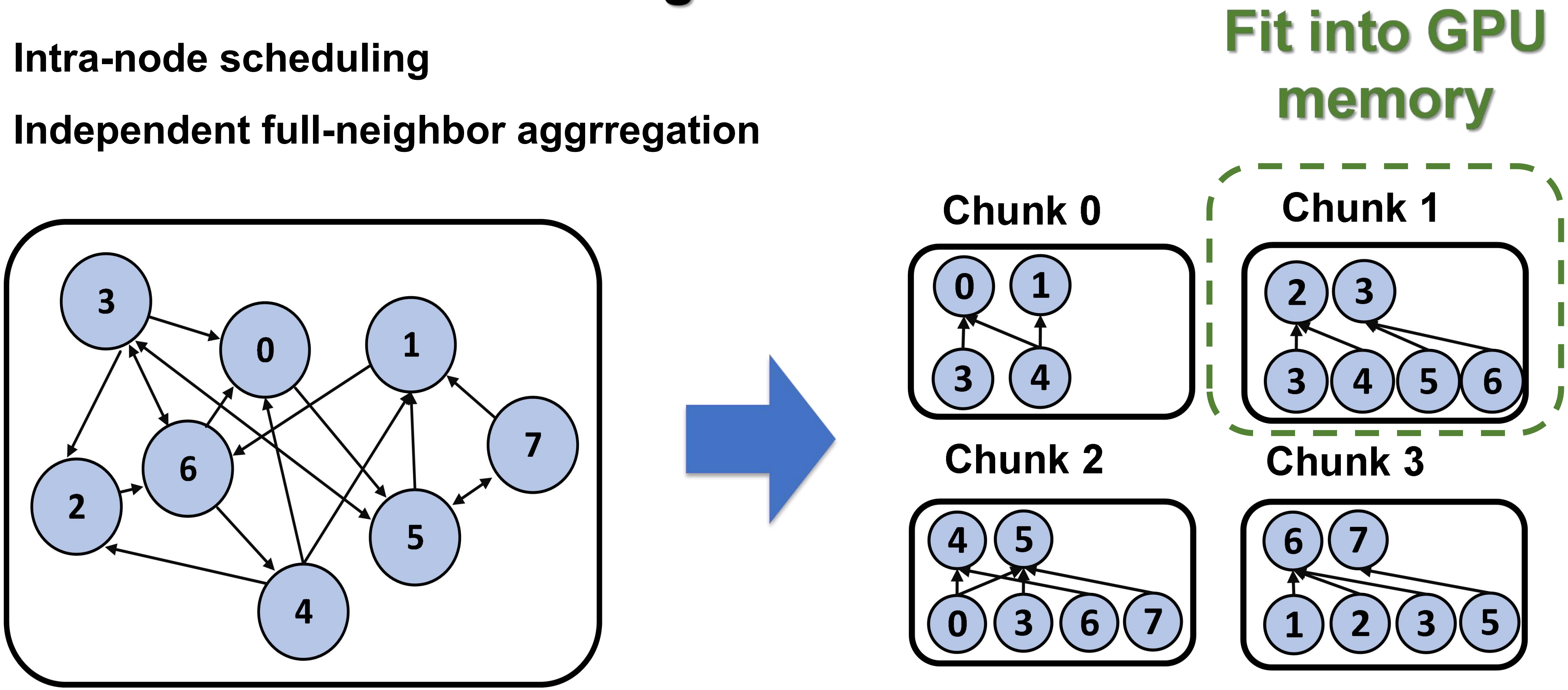
- **Edge weight precomputing**
- **Tensor-data hybrid parallelism**

Memory-efficient task scheduling method

Partition graph into chunks that can fit into GPU memory

Chunk-based task Scheduling

- Intra-node scheduling
- Independent full-neighbor aggrregation

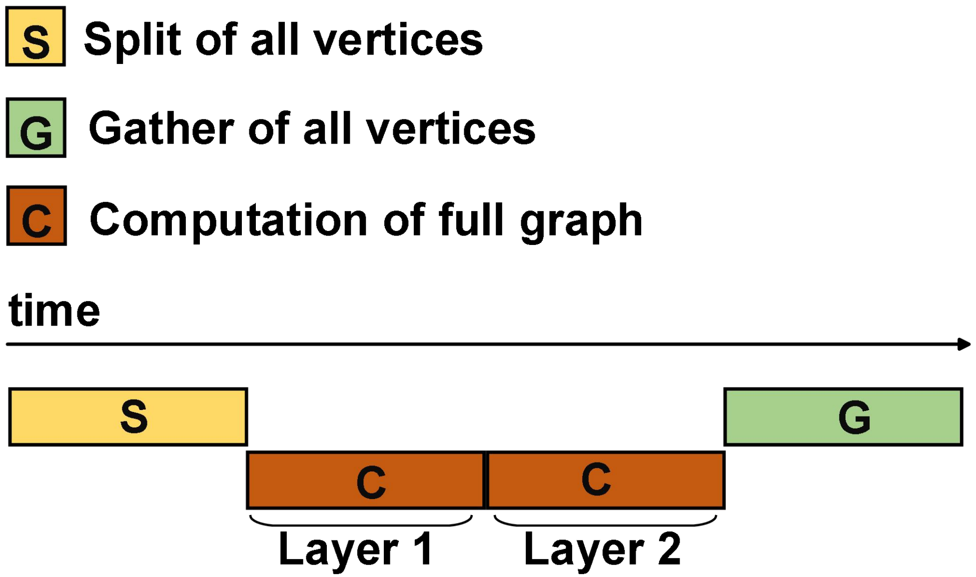


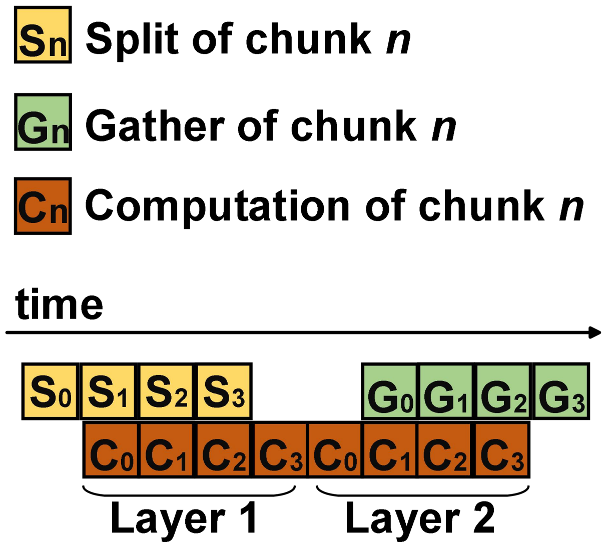
Memory-efficient task scheduling method

Hidden communication latency

Inter-chunk pipelining

- Chunk-level gather and split
- Computation-communication overlap





Experimental Setting

Competitors: **DistDGL** [Arxiv'20], **Sancus** [VLDB'22], **NeutronStar** [Sigmod'22].

Test Platforms:

A 16-node Aliyun ECS cluster[1] (Each: 16 vCPUs, 62GB RAM, 1 NVIDIA-T4 GPU)

Algorithms and Datasets:

- 2 Graph Neural Networks
  GCN, GAT
- 6 real world graphs

Softeware Environment:

- Ubuntu 18.04 LTS
- CUDA 10.1 (418.67 driver)

Table 1: Dataset description

Dataset	|V|	|E|	ftr. dim	#$\mathbb{L}$	hid. dim
Reddit (RDT)	0.23M	114M	602	41	256
Ogbn-products (OPT)	2.45M	61.68M	100	47	64
Ogbn-paper (OPR)	111.1M	1.616B	128	172	128
Friendster (FS)	65.6M	2.5B	256	64	128
Ogbn-mag (MAG)	1.9M	21M	128	349	64
Mag-lsc (LSC)	244.2M	1.7B	768	153	256

[1] Clusters are connected via 6GigE

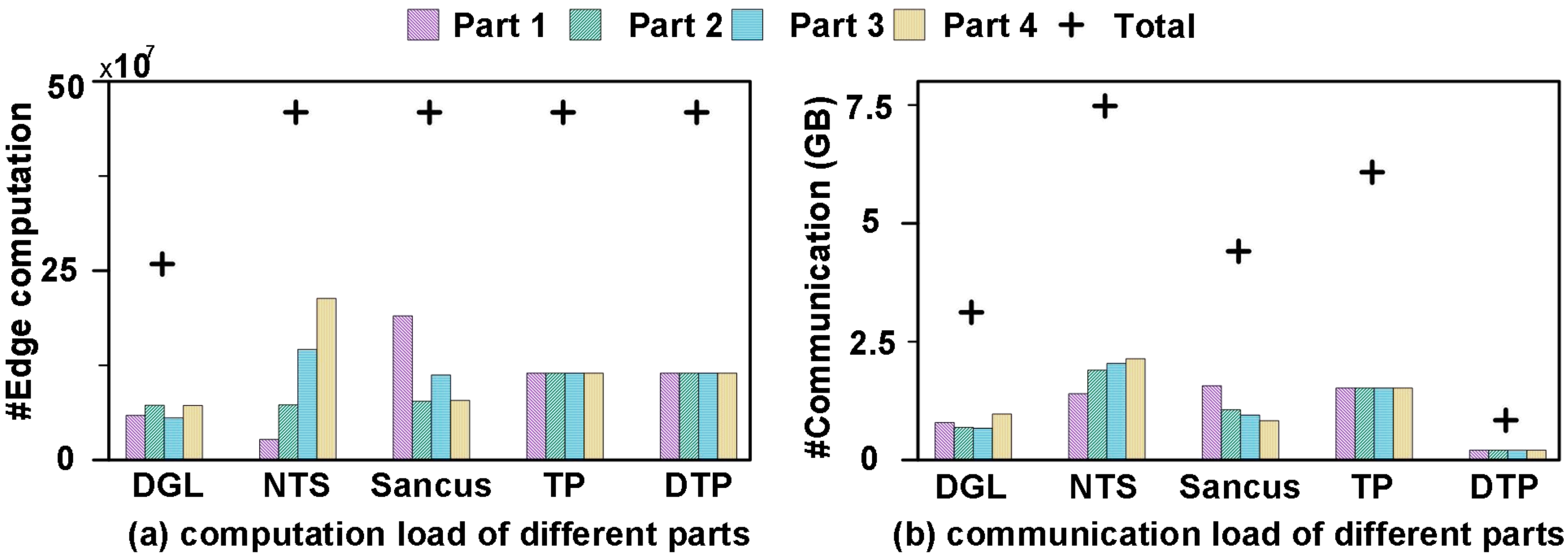
Overall Results

NeutronTP shows better performance than the competitors

- 1.29X-6.36X faster than **DistDGL**
- 4.68X-8.72X faster than **NeutronStar**
- 3.41X-4.81X faster than **Sancus**

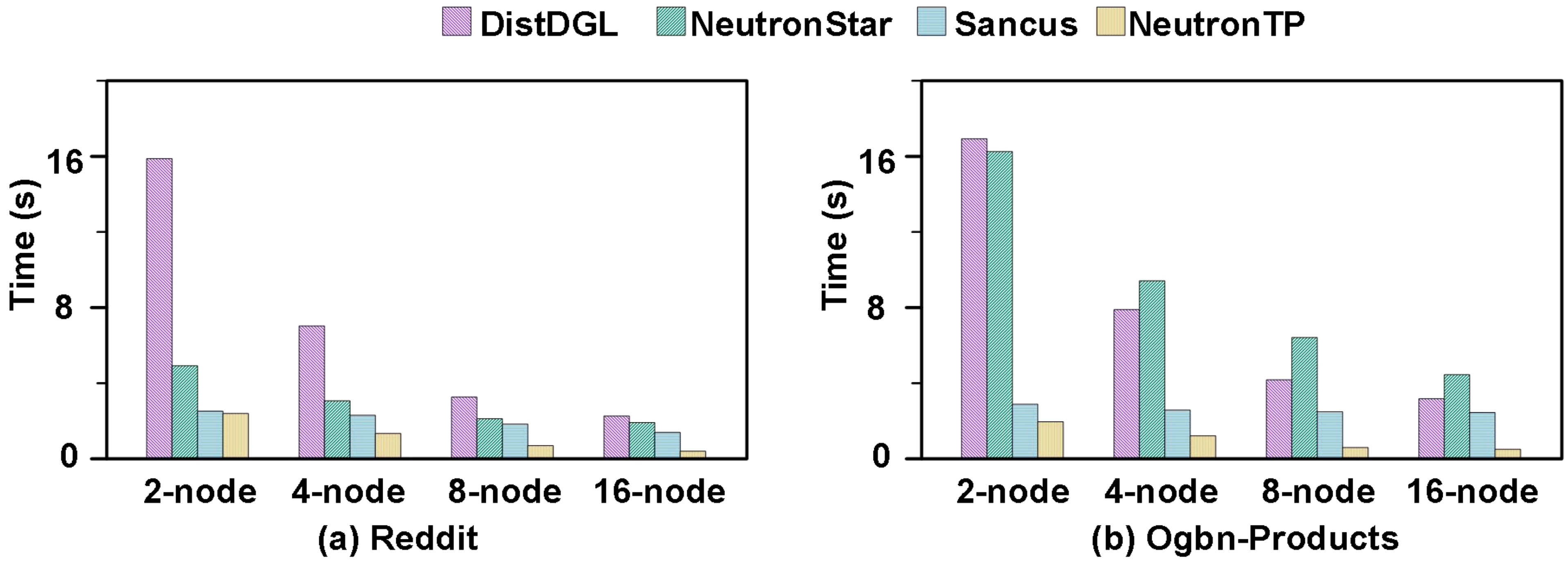
Model	Dataset	System	Runtime (s)				
			Computation		Communication		total
			max	**min**	**max**	**min**	
GCN	RDT	DistDGL	0.15	0.11	2.12	1.38	2.27
		NeutronStar	0.86	0.77	1.17	0.87	1.92
		Sancus	0.35	0.31	0.82	0.71	1.17
		NeutronTP	0.39	0.38	0.19	0.18	**0.40**
	OPT	DistDGL	0.26	0.16	2.82	1.28	3.18
		NeutronStar	2.71	1.42	2.89	1.78	4.45
		Sancus	0.86	0.36	1.59	1.22	2.45
		NeutronTP	0.46	0.44	0.24	0.22	**0.50**
	OPR	DistDGL	5.35	4.19	20.1	11.21	**25.4**
		NeutronStar	-	-	-	-	OOM
		Sancus	-	-	-	-	OOM
		NeutronTP	95.8	95.2	53.6	49.4	134.4
	FS	DistDGL	136.4	118.9	323.4	197.5	459.5
		NeutronStar	-	-	-	-	OOM
		Sancus	-	-	-	-	OOM
		NeutronTP	74.3	73.5	32.9	29.4	**90.5**
GAT	RDT	DistDGL	0.75	0.52	2.17	1.49	2.92
		NeutronStar	-	-	-	-	OOM
		Sancus	-	-	-	-	OOM
		NeutronTP	0.92	0.88	0.48	0.42	**1.29**
	OPT	DistDGL	1.17	0.94	2.76	1.29	3.93
		NeutronStar	8.72	5.98	15.9	8.29	22.4
		Sancus	-	-	-	-	OOM
		NeutronTP	2.17	1.94	1.06	0.95	**3.03**
	OPR	DistDGL	8.40	6.48	21.1	11.7	**29.5**
		NeutronStar	-	-	-	-	OOM
		Sancus	-	-	-	-	OOM
		NeutronTP	154.3	136.4	98.9	84.7	235.4
	FS	DistDGL	157.8	110.4	419.8	283.7	577.6
		NeutronStar	-	-	-	-	OOM
		Sancus	-	-	-	-	OOM
		NeutronTP	115.2	92.5	72.1	61.4	**167.9**

Workload Analysis



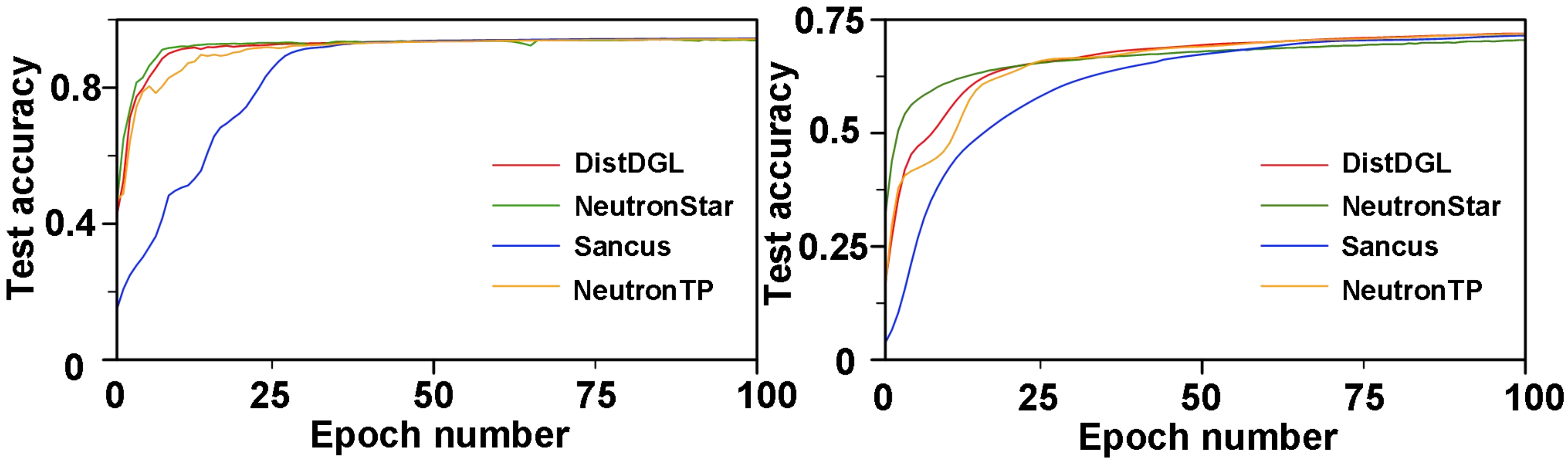
- Tensor Parallelism (TP) achieved a more balanced workload.
- Decouple training significantly reducing communication volume by up to 7.2 X.

Scalability Analysis



- **Across different cluster sizes, NeutronTP acheves an average speedup of 6.33X, 5.97X, and 2.69X compared to DistDGL, NeutronStar, and Sancus, respectively.**

Accuracy Comparison



(a) GCN on Reddit

(b) GCN on Product

- Decoupled training maintains comparable accuracy and convergence speed.

Summary

NeutronTP: Load-Balanced Distributed Full-Graph GNN Training with Tensor Parallelism.

- **GNN tensor parallelism**

  We propose a distributed GNN training method based on tensor parallelism, which eliminates cross-worker vertex dependencies and achieves complete load balancing.

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  We propose a distributed GNN training method based on tensor parallelism, which eliminates cross-worker vertex dependencies and achieves complete load balancing.
- **Generalized decoupling training method**
  We propose a generalized decoupling training method to separate NN operations from graph aggregation, significantly reducing communication frequency in GNN tensor parallelism.

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  We propose a memory-efficient task scheduling strategy to support large-scale graph processing and overlap the communication and computation.

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- **Delivering a fast distributed GNN system**
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- **The codes are publicly available on github**
  https://github.com/iDC-NEU/NeutronTP

Thanks for your listening