Exploiting Hardware Utilization and Adaptive Dataflow for Efficient Sparse Convolution in 3D Point Clouds

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*Equal contribution

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Quick View

- Methodologies:
  - Coded-CSR format **mapping storage**
  - Indicator-assisted FGMS (Fused Gather-MM-Scatter) **fusion**
  - Heuristic **adaptive dataflow selection**
- Compared to SOTA Designs:
  - **1.23x/1.64x end-to-end** speedup on average
  - **1.76x/1.81x sparse convolution** speedup on average

Outline

- Backgrounds and Motivations
- Design Overview
- Solutions
  - Coded-CSR format **mapping storage**
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  - Heuristic **adaptive dataflow selection**
- Experiments
- dgSPARSE: Fast and Efficient Processing with Diverse Sparsity

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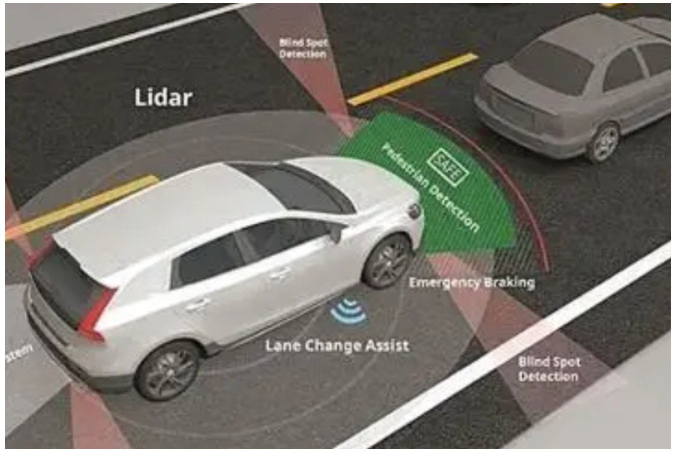
Point Cloud Neural Networks

Areas

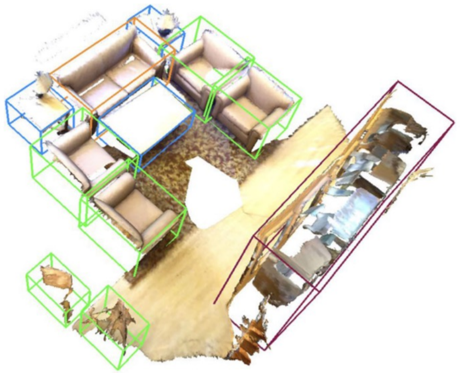


Autonomous Driving

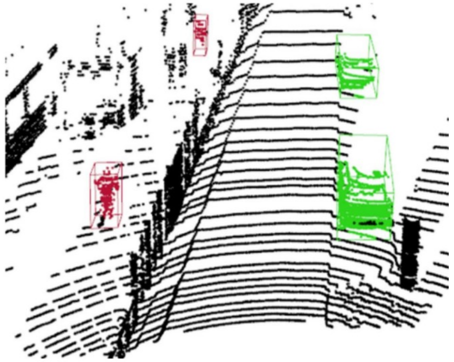
Robotics

Remote Sensing

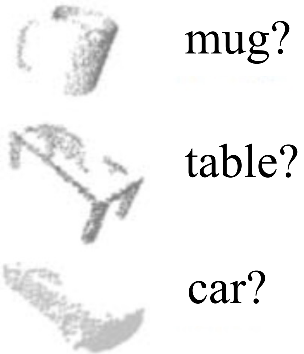
Tasks



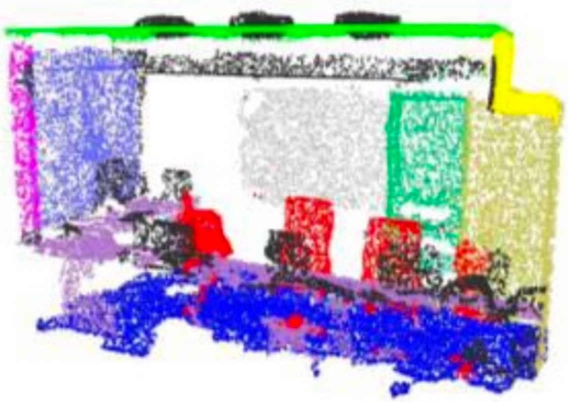
Detection



Tracking



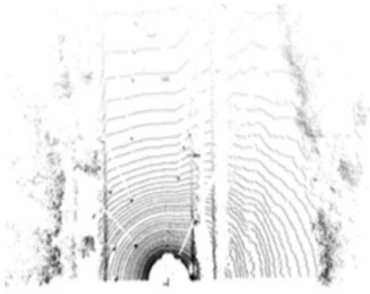
Classification



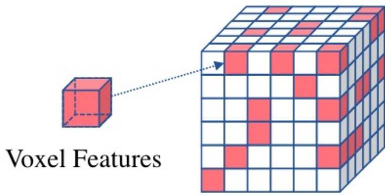
Segmentation

Point Cloud Neural Networks

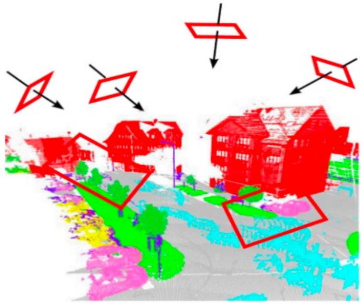
Data



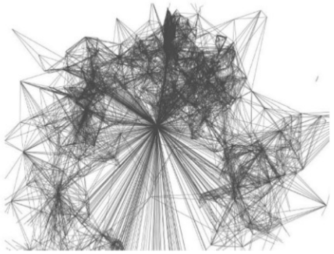
Point



Voxel



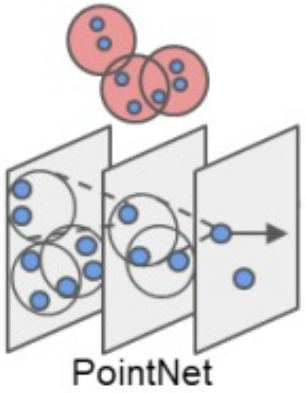
BEV (Bird's Eye View)



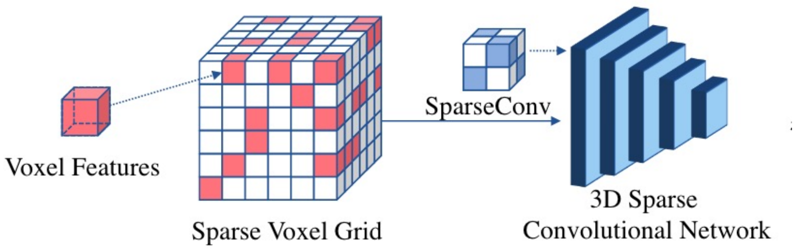
Graph

...

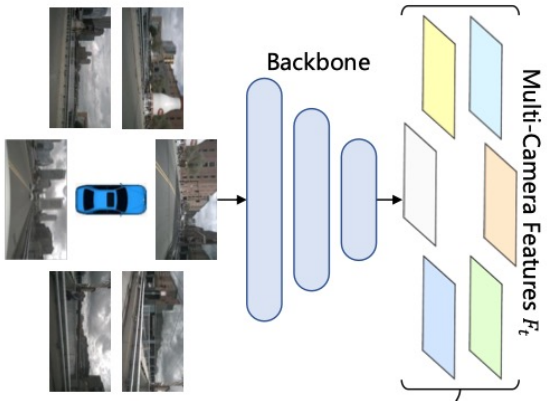
Methods



Point-based



Voxel-based

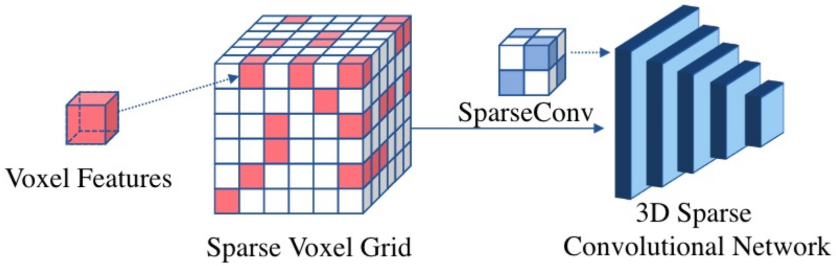


BEV-based

...

Sparse Convolution Neural Networks

Methods



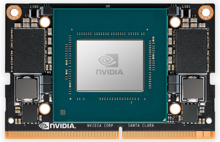
Voxel-based

SOTA Accuracy

nuScenes lidar segmentation task

Leaderboard

			Any	All	All				
>	2022-07-22	LidarMultiNet	Lidar	no	no	0.814	0.909	n/a	
>	2021-11-16	SVQNet	Lidar	no	no	0.813	0.911	n/a	
>	2022-07-18	MSeg3D	Camera, Lidar	no	no	0.811	0.914	n/a	
>	2021-05-27	SPVCNN++	Lidar	no	no	0.811	0.910	n/a	



<5FPS

Nvidia
Xavier GPU

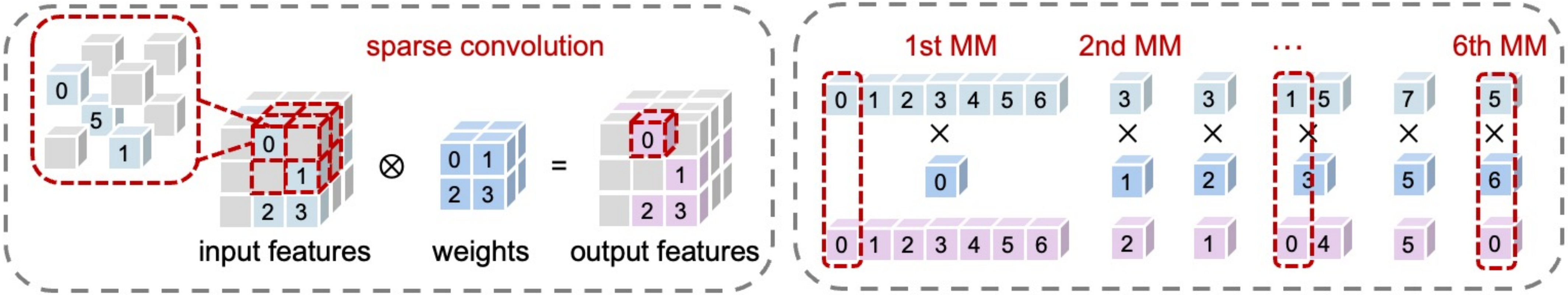
~10FPS

Nvidia
RTX 2080 GPU

Real-time Demand: 25~30FPS

Sparse Convolution Neural Networks

MM: Matrix Multiplication



Sparse Input
Only 0.01%-1% density

Irregular Access
Gather valid features

Dense Computing
MMs between features and weights

Irregular Access
Scatter partial sums

Implementation Dataflows

Device memory

Shared memory /register

GPU kernel

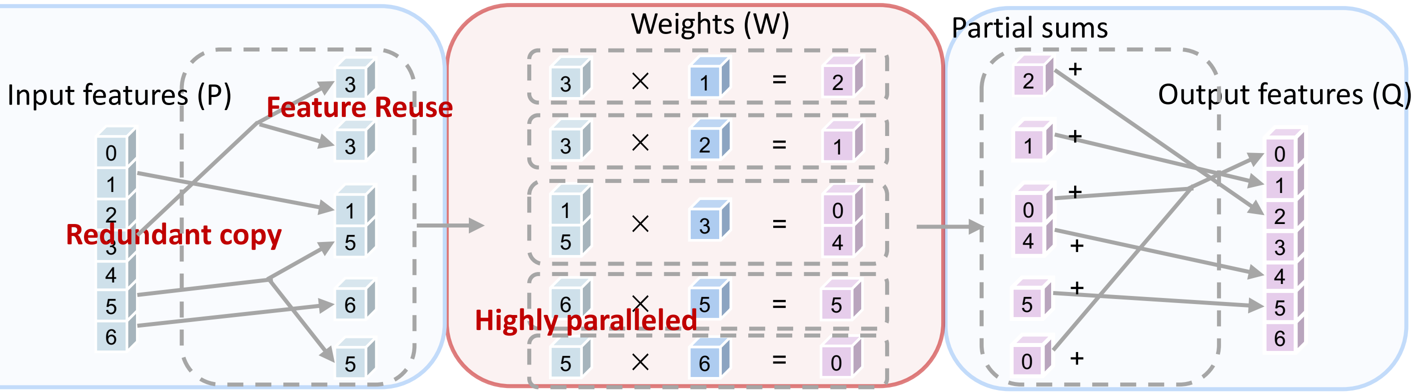
MM: Matrix Multiplication

Sparse Input	**Irregular Access**	**Dense Computing**	**Irregular Access**
Only 0.01%-1% density	**Gather** valid features	**MMs** between features and weights	**Scatter** partial sums

Dataflow 1
Gather-MM-Scatter

(input, weight)	(output, weight)
P_1, W_3	Q_0, W_3
P_3, W_1	Q_0, W_6
…	
P_5, W_6	Q_4, W_3
P_6, W_5	Q_5, W_5

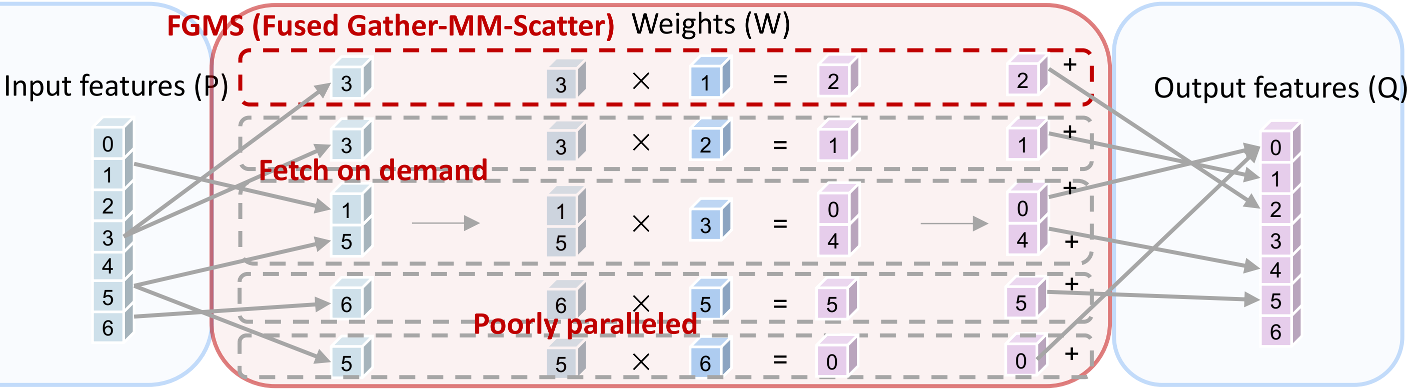
Input/output-major mapping



Dataflow 2
Fetch-on-Demand

(weight, input, output)
W_1, P_3, Q_2
W_2, P_3, Q_1
…
W_5, P_6, Q_5
W_6, P_5, Q_0

Weight-major mapping



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- Solutions
  - Coded-CSR format **mapping storage**
  - Indicator-assisted FGMS (Fused Gather-MM-Scatter) **fusion**
  - Heuristics **adaptive dataflow selection**
- Experiments
- dgSPARSE: Fast and Efficient Processing with Various Sparsity

Design Overview

3. **Heuristic adaptive dataflow selection**

Performance loss against input dynamics:
Dataflow 2 benefits light workload

1. **Coded-CSR format mapping storage**

Redundant mapping loadings:
Up to 79.97% mappings are empty

Dataflow 1
Gather-MM-Scatter

Dataflow 2
Fetch-on-Demand

Irregular Access
Gather valid features

Dense Computing
MMs between features and weights

Irregular Access
Scatter partial sums

Sparse Computing
Sequential FGMS (Fused Gather-MM-Scatter) kernels

Computation under-utilization:
Only 22.84% GPU utilization

2. **Indicator-assisted FGMS fusion**

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Coded-CSR Format Mapping Storage

➢Observation:

- **Redundant loadings** of invalid mappings

	W_0	W_1	W_2	W_3	W_4	W_5	W_6
P_0	0	-1	-1	0	0	-1	0
P_1	-1	0	-1	-1	-1	-1	-1
P_2	-1	-1	0	-1	-1	-1	1
P_3	-1	-1	1	1	-1	-1	2
P_4	-1	1	-1	-1	-1	0	-1

35 integers

(a) Matrix

1) Load input feature (P)

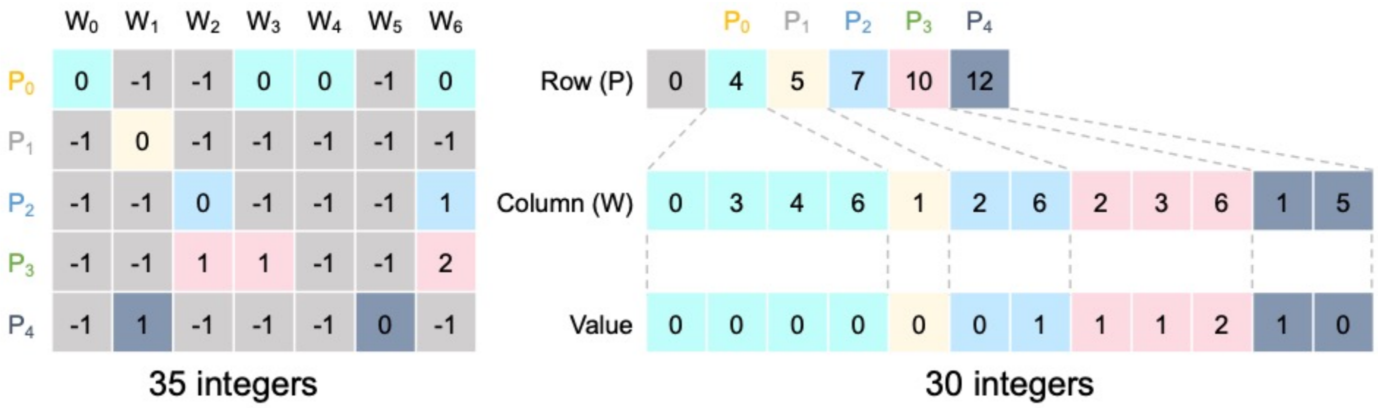
2) Traverse mappings of all weights (W)

3) If mapping is valid, write feature to the buffer

Redundant mapping loadings:
Up to 79.97% mappings are empty

Coded-CSR Format Mapping Storage

- **Observation:**
  - **Redundant loadings** of invalid mappings
  - Column array and value array can be **further compressed**
    - Column element < K (kernel size), value element < N (number of input non-zeros)

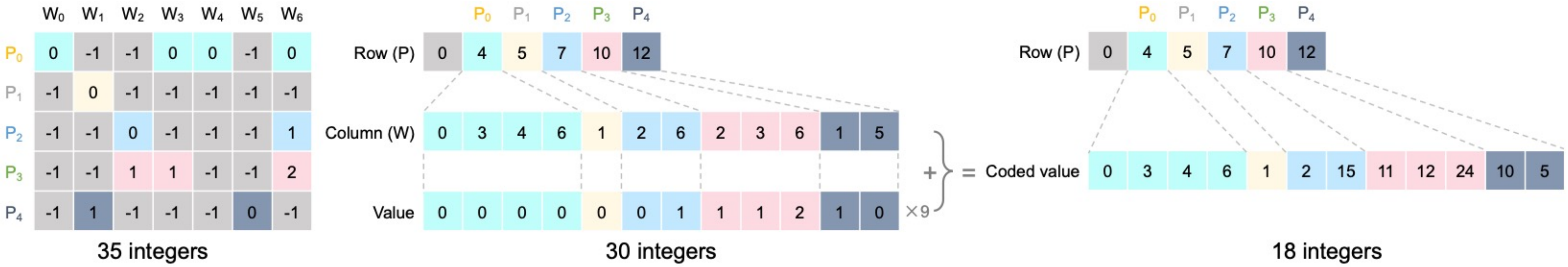


(a) Matrix (b) CSR (Compress Sparse Row)

Only valid mappings are stored

Coded-CSR Format Mapping Storage

- Solution:
  - **Sparse format** for mapping storage
  - Column array and value array are further **coded into one array**
    - Encoder function: c = a + *M*b, *M* ≥ *K.*



(a) Matrix

(b) CSR (Compress Sparse Row)

(c) Coded-CSR

about 1 (int32) loading for a valid mapping

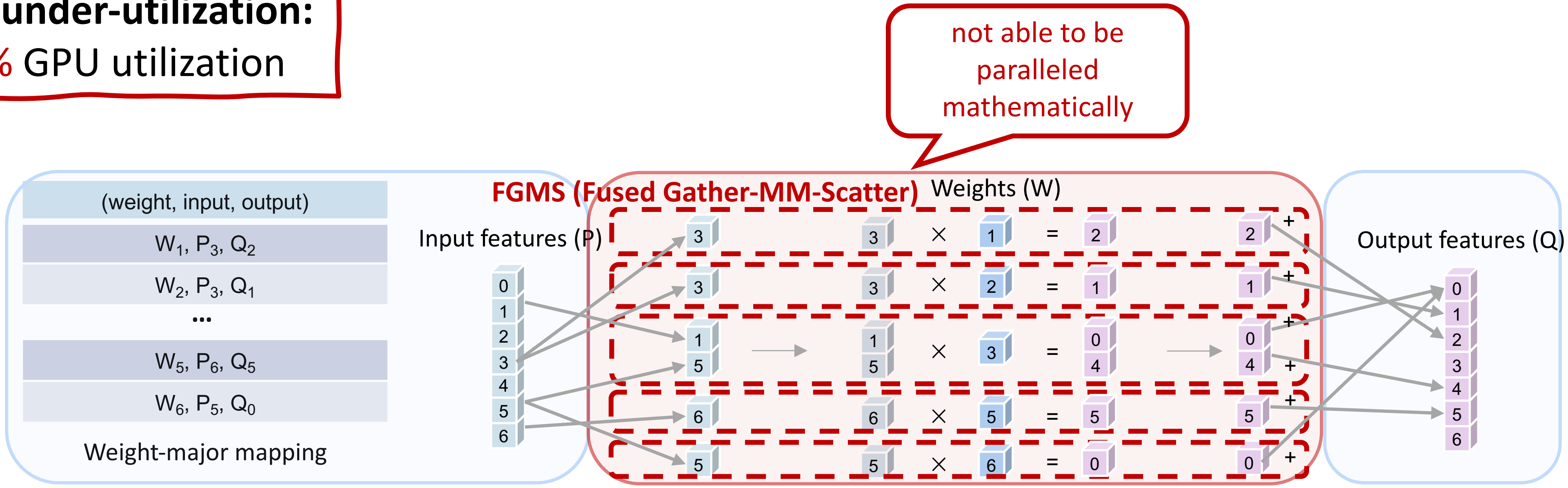
Indicator-assisted FGMS Fusion Scheme

➢ Observation:

- Sequentially computing each FGMS leads to **under-utilization**

Computation under-utilization:
Only 22.84% GPU utilization

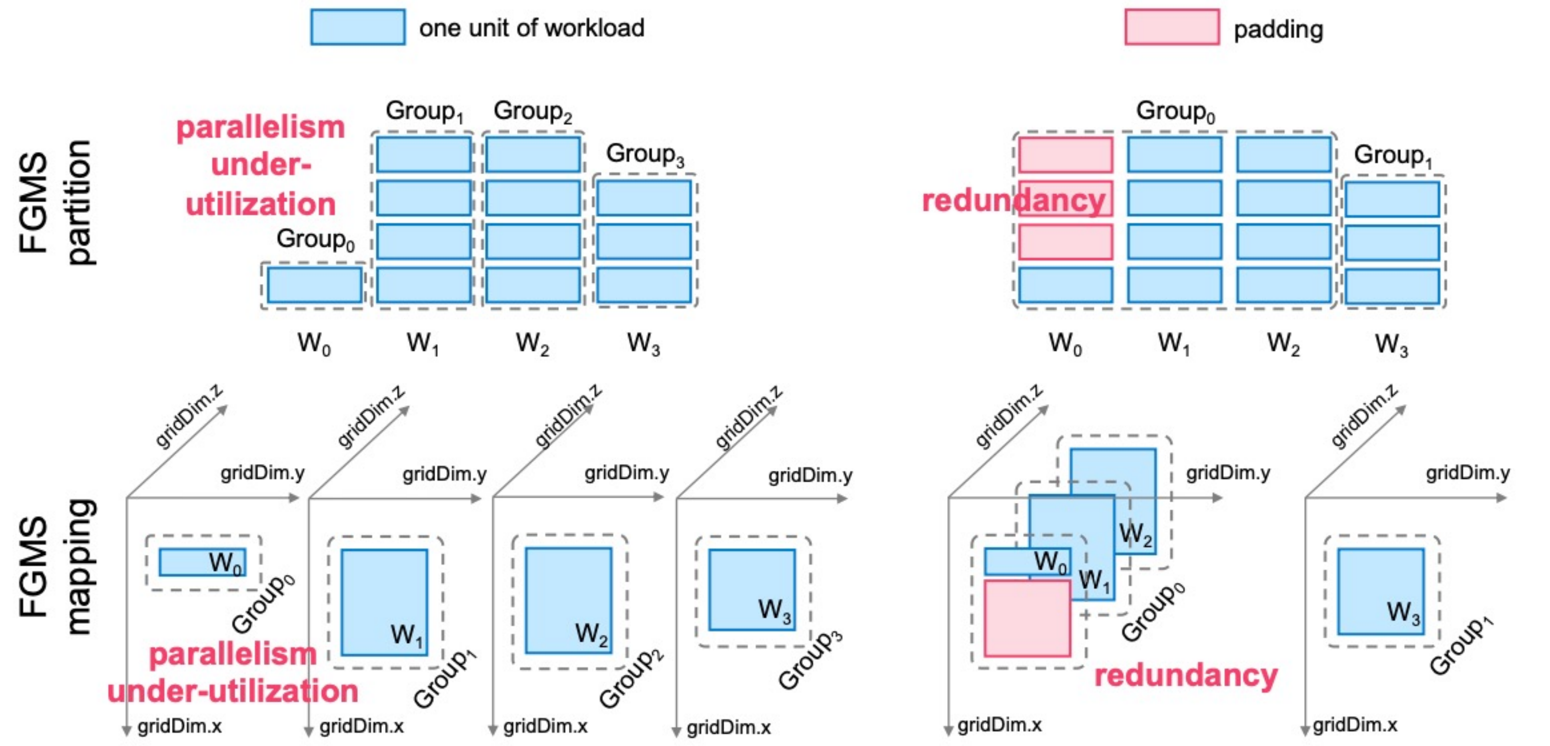
Dataflow 2
Fetch-on-Demand



Indicator-assisted FGMS Fusion Scheme

➢Observation:

- Sequentially computing each FGMS leads to **under-utilization**
- Segmented FGMSs can be paralleled through **hardware mapping strategy**
  - Batched FGMS scheme still leads to **computing redundancy** and **under-utilization**



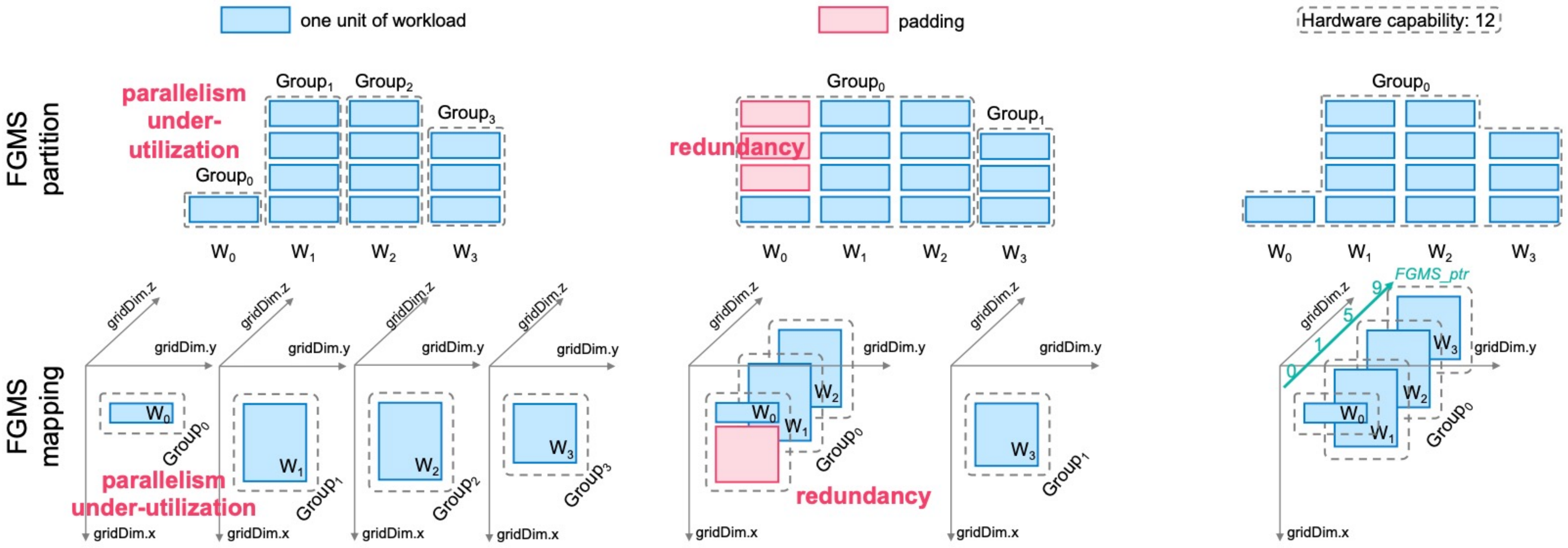
(a) Separate FGMS with parallelism under-utilization (b) Batched FGMS with redundant padding

Computation under-utilization:
Only 32.67% GPU utilization

Indicator-assisted FGMS Fusion Scheme

➢ Solution:

- Segmented FGMSs are fused with a **sparse indicator**, which indicates the mapping table address from each FGMS

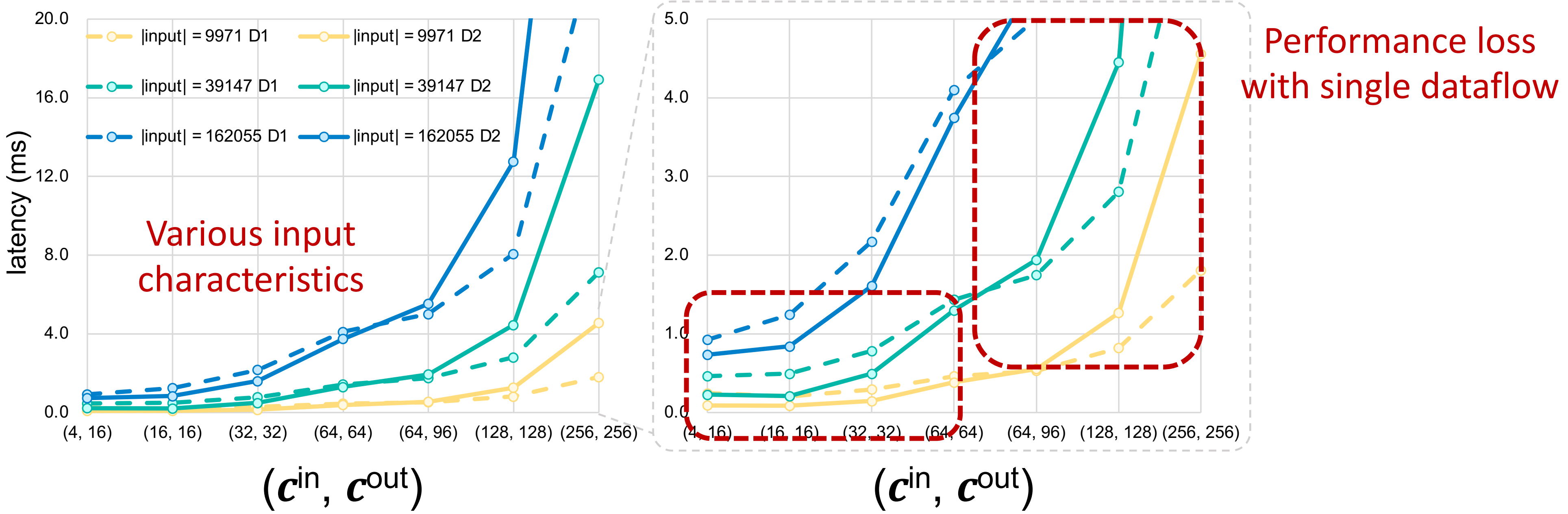


(a) Separate FGMS with parallelism under-utilization (b) Batched FGMS with redundant padding (c) Indicator-assisted segmented FGMS fusion

Heuristic Adaptive Dataflow Selection

➢Observation:

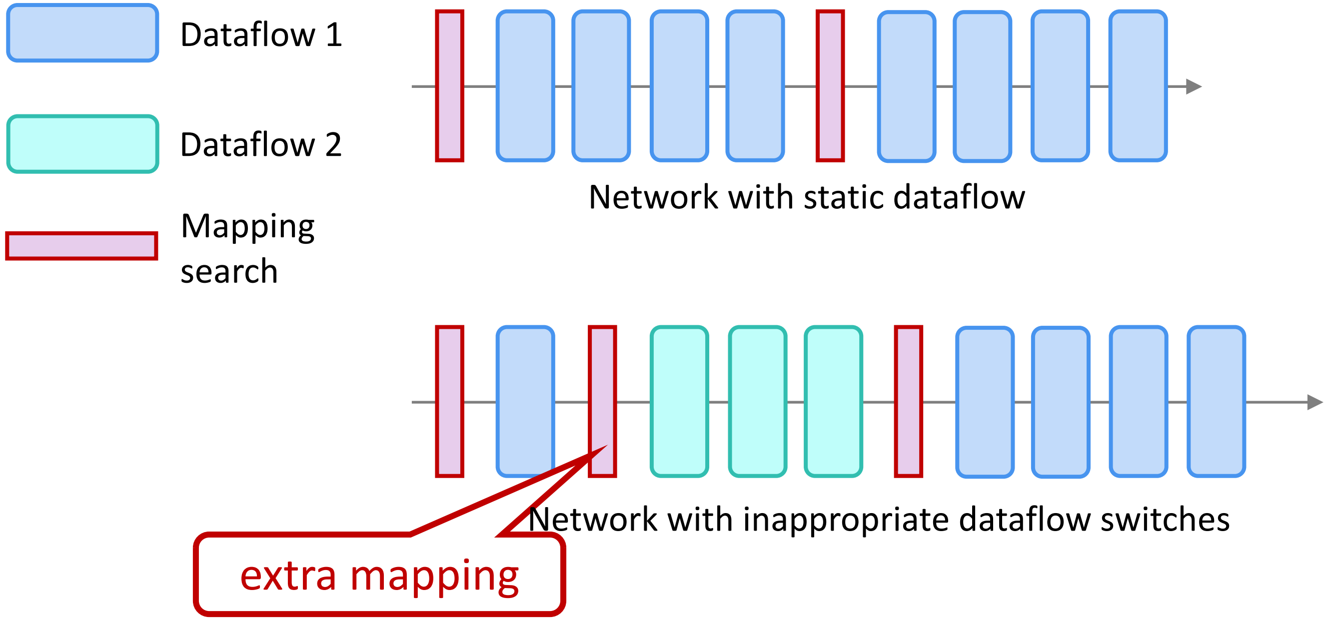
- Static dataflow brings **performance loss against input dynamics**

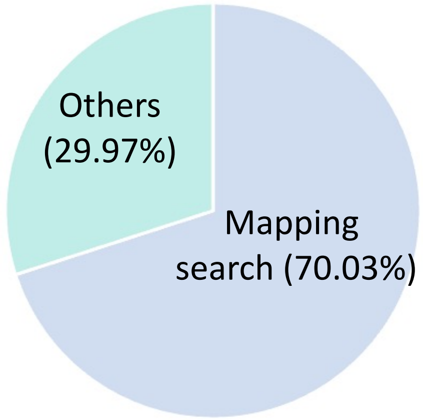


Heuristic Adaptive Dataflow Selection

➢Observation:

- Static dataflow brings **performance loss against input dynamics**
- Different mapping patterns are used in different dataflows, which may lead **extra mapping searches upon dataflow switches**
  - Mapping reuse can be exploited based on network structure



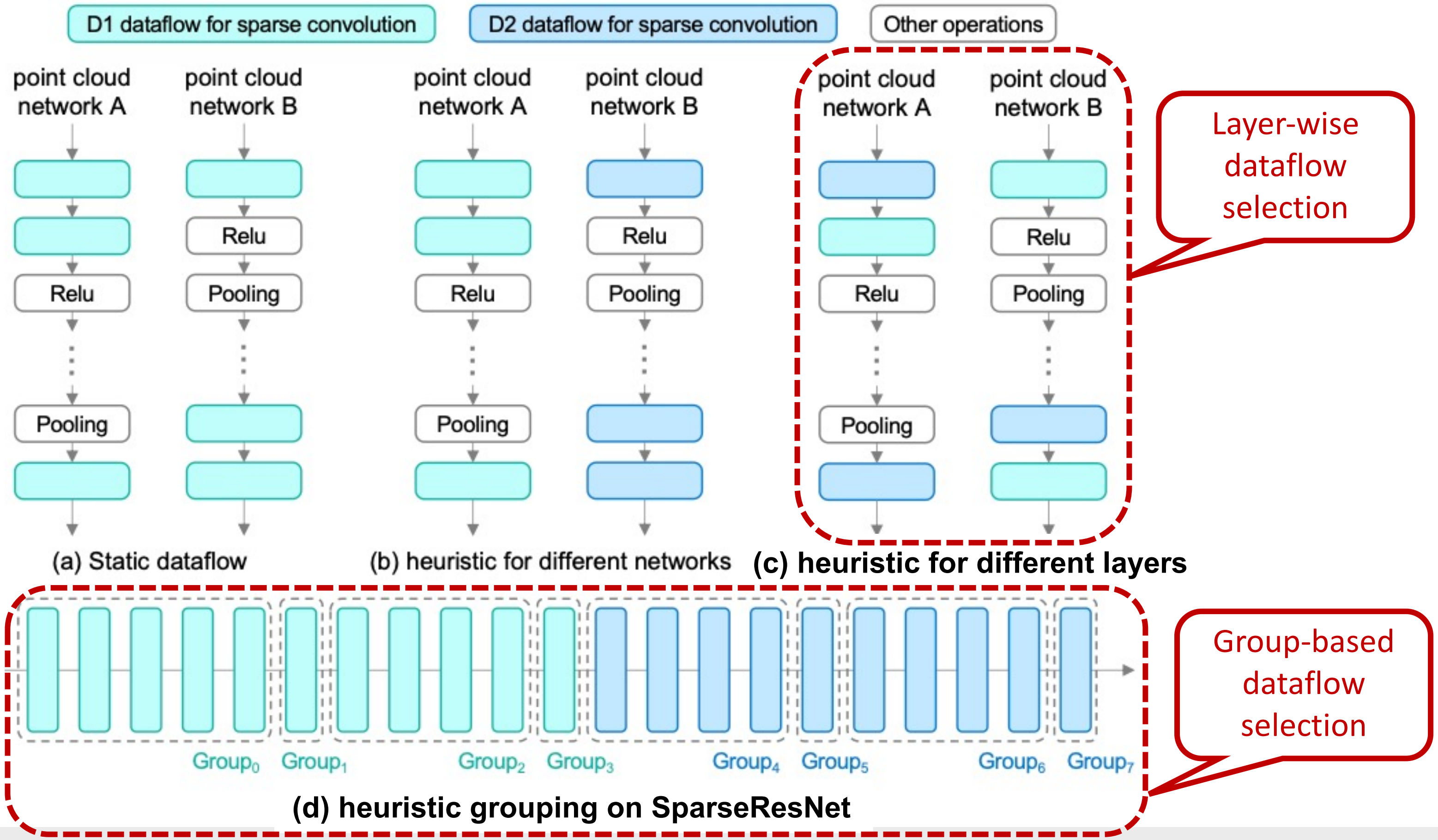


Runtime breakdown of a strided sparse convolutional layer

Heuristic Adaptive Dataflow Selection

➢Solution:

- **Layer-wise dataflow selection** to exploit network performance improvement
- **Group-based dataflow selection** to avoid extra mapping searches



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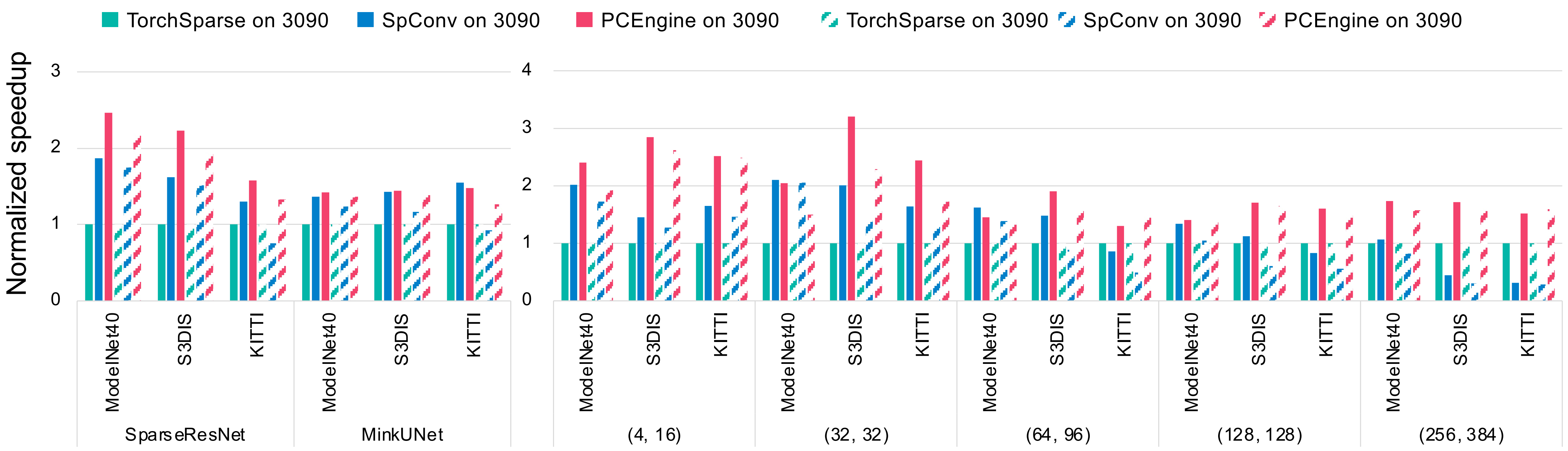
Experiment Settings

- Baselines:
  - TorchSparse v2.0.0 [https://github.com/mit-han-lab/torchsparse]
  - SpConv v2.2.3 [https://github.com/traveller59/spconv]
- Models:
  - SparseResNet [21 sparse convolutional layers]
  - MinkUNet [42 sparse convolutional layers]
- Datasets:
  - ModelNet40 [classification]
  - KITTI [detection]
  - S3DIS [segmentation]

Dataset	Size	Density
ModelNet40	~25k	1.59%
KITTI	~40k	0.04%
S3DIS	~10k	6.92%

- Platforms
  - A 10-core 20-thread Intel Xeon Silver 4210 CPU running @ 2.2GHz
  - An NVIDIA **RTX 3090** GPU and an NVIDIA **RTX 2080** GPU with CUDA 11.1.

Experiment: End-to-End



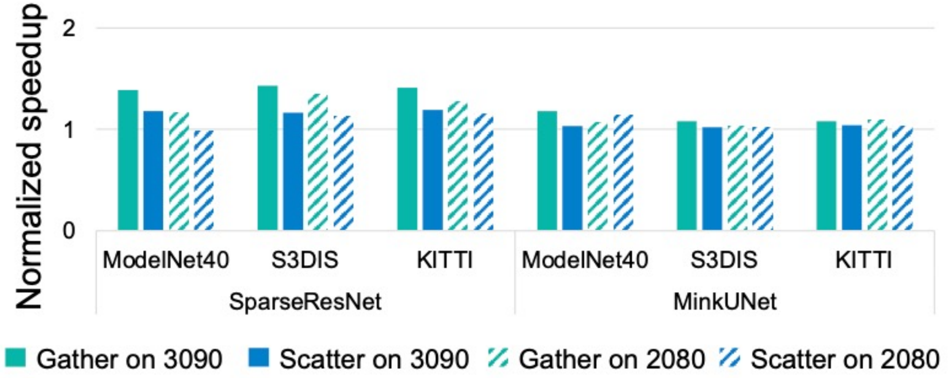
(a) end-to-end performance

(b) kernel performance

End-to-end: 1.64x, 1.23x speedup over TorchSparse, SpConv on average
Sparse convolution: 1.81x, 1.76x speedup over TorchSparse, SpConv on average

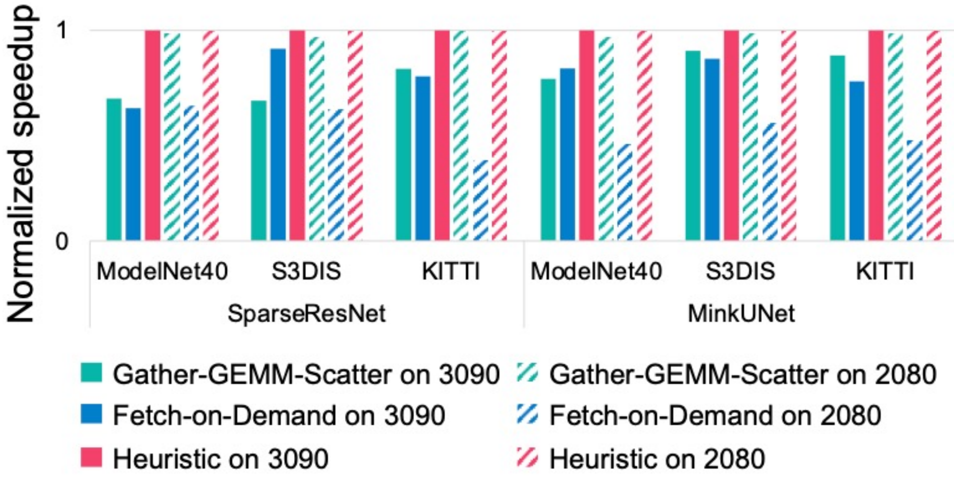
Experiment: Ablation & Additional Studies

Coded-CSR Format Mapping Storage



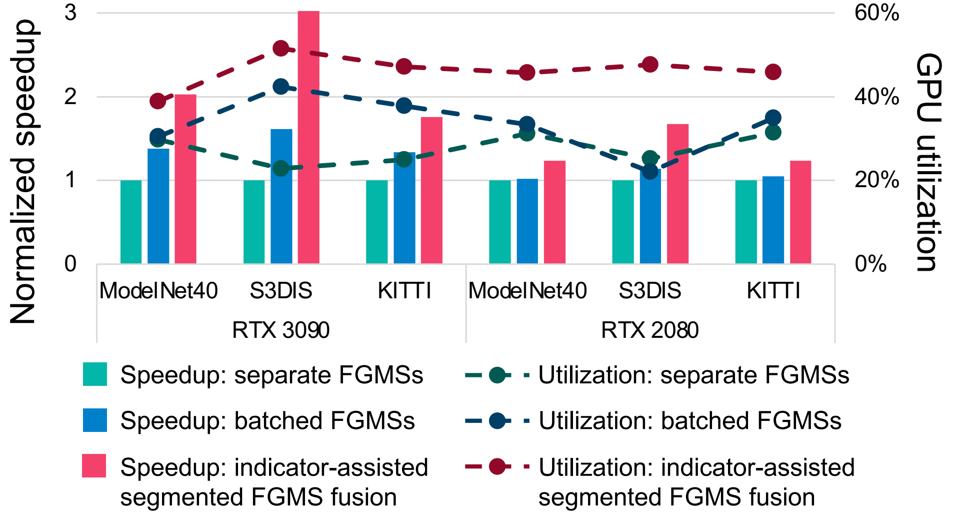
On average 1.21x/1.10x speedup, 21.18% less memory access

Heuristics Adaptive Dataflow Selection



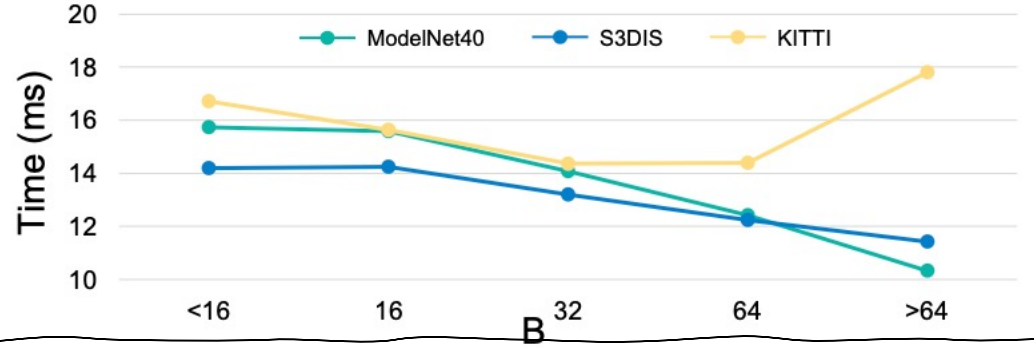
On average 1.15x/1.57x speedup over static dataflows

Indicator-assisted FGMS fusion scheme



On average 1.75x/1.41x speedup, 1.68x/1.40x higher utilization

Threshold choice for dataflow heuristic algorithm



Tuning *B* on different datasets brings further improvement

Key Challenges & Contributions

*FGMS: Fused Gather-MM-Scatter

✗ Redundant memory access caused by mapping storage

✓ Coded-CSR mapping storage

✗ Computation under-utilization caused by sequential FGMSs

✓ Indicator-assisted FGMS fusion scheme

✗ Input dynamics performance loss caused by static dataflow

✓ Heuristic adaptive dataflow selection

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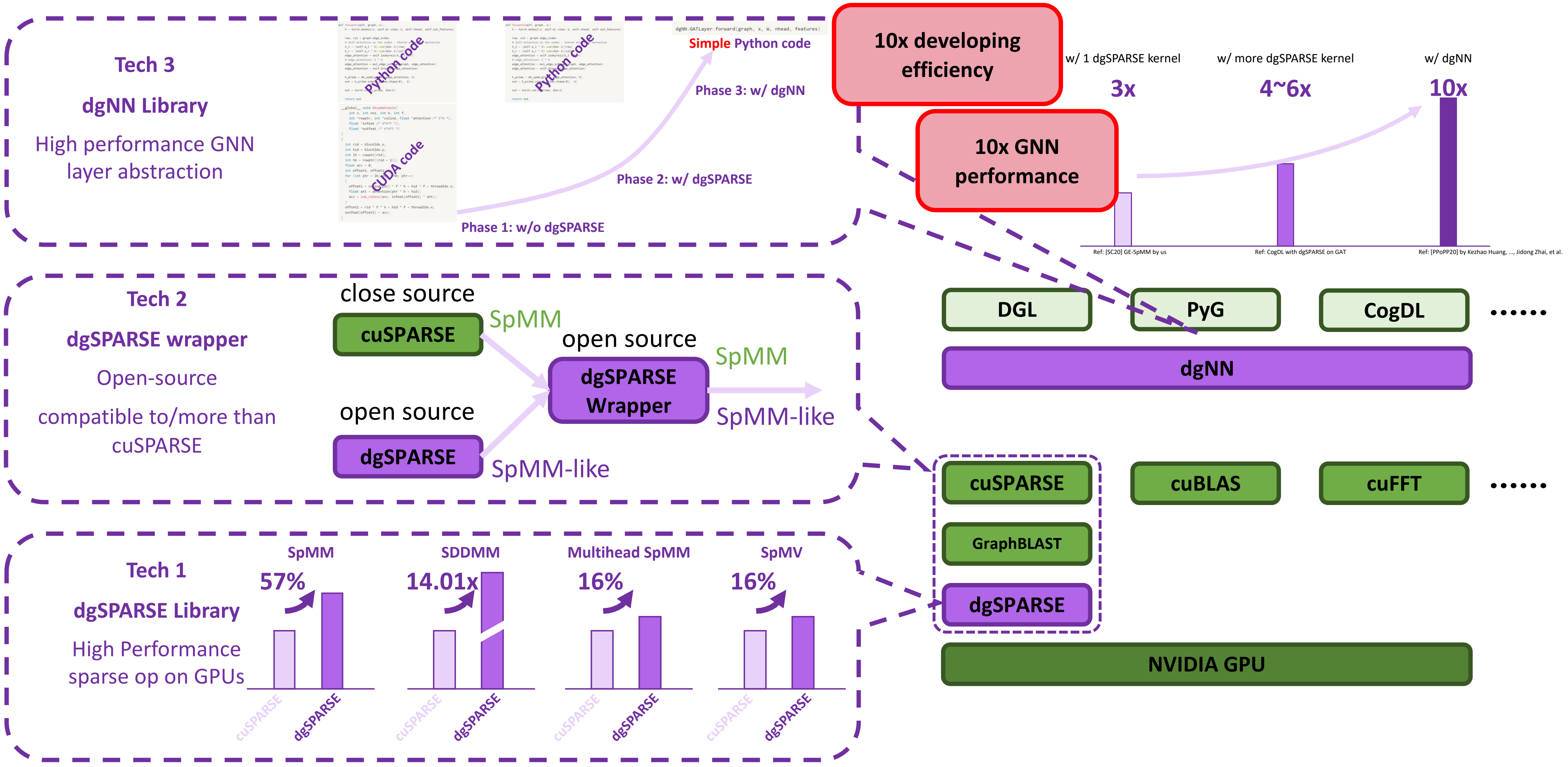
dgSPARSE

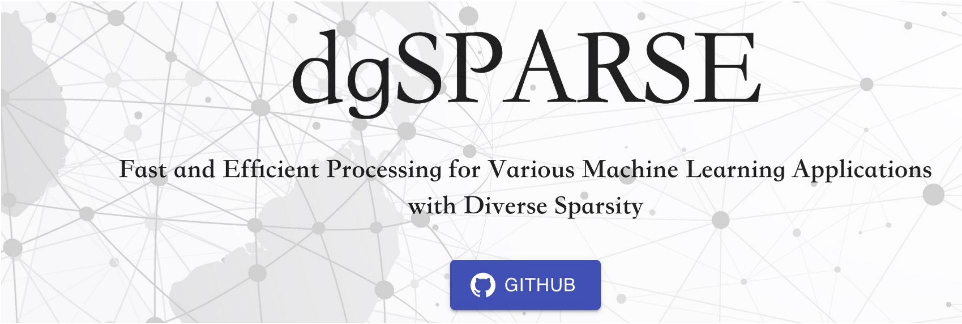


Tech 3
dgNN Library
High performance GNN layer abstraction
Python code
CUDA code
Python code
Simple Python code
Phase 1: w/o dgSPARSE
Phase 2: w/ dgSPARSE
Phase 3: w/ dgNN
10x developing efficiency
10x GNN performance
w/ 1 dgSPARSE kernel
3x
w/ more dgSPARSE kernel
4~6x
w/ dgNN
10x
Ref: [SC20] GE-SpMM by us
Ref: CogDL with dgSPARSE on GAT
Ref: [PPoPP20] by Kezhao Huang, ..., Jidong Zhai, et al.
Tech 2
dgSPARSE wrapper
Open-source
compatible to/more than cuSPARSE
close source
cuSPARSE
SpMM
open source
dgSPARSE Wrapper
SpMM
SpMM-like
open source
dgSPARSE
SpMM-like
DGL
PyG
CogDL
......
dgNN
cuSPARSE
cuBLAS
cuFFT
......
GraphBLAST
dgSPARSE
NVIDIA GPU
Tech 1
dgSPARSE Library
High Performance sparse op on GPUs
SpMM
57%
SDDMM
14.01x
Multihead SpMM
16%
SpMV
16%
cuSPARSE
dgSPARSE
cuSPARSE
dgSPARSE
cuSPARSE
dgSPARSE
cuSPARSE
dgSPARSE

dgSPARSE

➢dgSPARSE papers

- [MLSys 23] Yu, Z., Dai, G., Yang, S., Zhang, G., Zhang, H., Zhu, F., Yang, J., Zhao, J. & Wang, Y. HyperGef: A Framework Enabling Efficient Fusion for Hypergraph Neural Network on GPUs. To appear in Sixth Conference on Machine Learning and Systems (MLSys), 2023.
- [MLSys 23] Hong, K., Yu, Z., Dai, G., Yang, X., Lian, Y., Liu, Z., Xu, N., Dong, Y., & Wang, Y. Exploiting Hardware Utilization and Adaptive Dataflow for Efficient Sparse Convolution in 3D Point Clouds. To appear in Sixth Conference on Machine Learning and Systems (MLSys), 2023.
- [DAC 22] Dai, G., Huang, G., Yang, S., Yu, Z., Zhang, H., Ding, Y., Xie, Y., Yang, H., Wang, Y. Heuristic Adaptability to Input Dynamics for Sparse Matrix-Matrix Multiplication on GPUs. (Best Paper nomination)
- [MLSys 22] Zhang, H., Yu, Z., Dai, G., Huang, G., Ding, Y., Xie, Y., & Wang, Y. Understanding GNN Computational Graph: A Coordinated Computation, IO, and Memory Perspective. arXiv preprint arXiv:2110.09524.
- [ACM-SRC 21] Huang, G., Dai, G., Ding, Y., Wang, Y., Xie, Y. Efficient Sparse Matrix Kernels based on Adaptive Workload-Balancing and Parallel-Reduction. In ACM Student Research Competition (ACM-SRC), 2021.
- [ICCD 21] Yu, Z., Dai, G., Huang, G., Wang, Y., & Yang, H. Exploiting Online Locality and Reduction Parallelism for Sampled Dense Matrix Multiplication on GPUs. To appear in International Conference on Computer Design (ICCD), 2021.
- [MICRO-SRC 20] Huang, G., Dai, G., Wang, Y., & Yang, H. Towards Fast Graph Neural Network Training with Efficient and Framework-Compatible Sparse-Dense Matrix Multiplication. In MICRO-53 Student Research Competition (MICRO-SRC), 2020.
- [SC 20] Huang, G., Dai, G., Wang, Y., & Yang, H. GE-SpMM: General-purpose Sparse Matrix-Matrix Multiplication on GPUs for Graph Neural Networks. In International Conference for High Performance Computing, Networking, Storage and Analysis (SC), pp. 1-12, 2020.



https://dgsparse.github.io/

Thank you
Q&A

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