GNNAdvisor: An Adaptive and Efficient Runtime System for GNN Acceleration on GPUs

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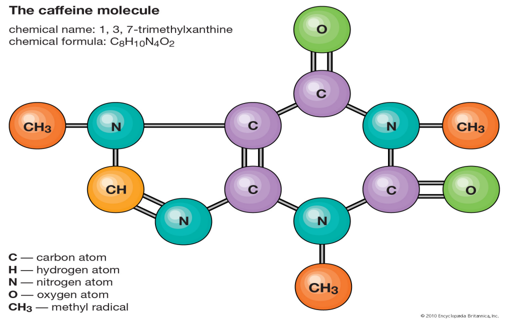
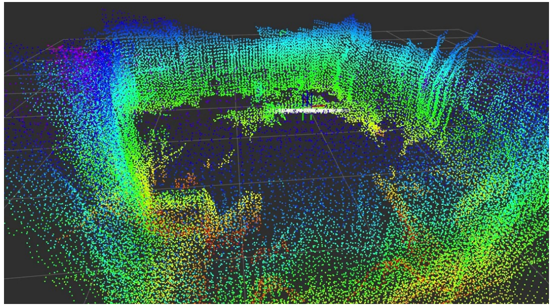
Graphs are everywhere...

Social Networks

Financial Services



Molecular chemistry



Point Cloud

Power Grid

Molecular Biology

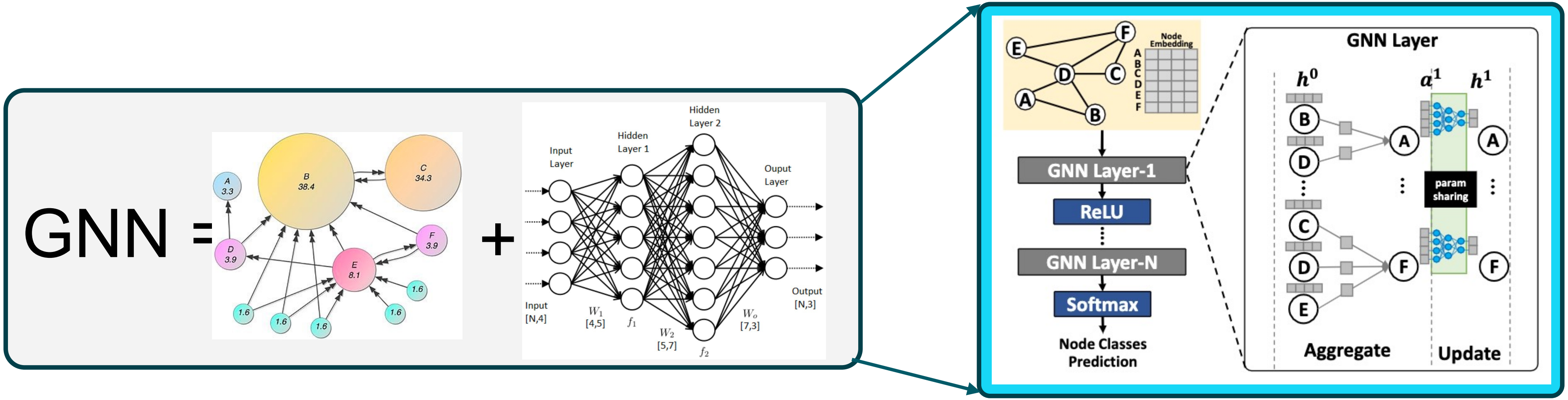
Credict: Google Image

Graph Analytics: Goals and Methods

- **Extract more insights from graphs structure.**
  - Generate the feature vectors (embeddings) for nodes, edges, and graphs.
  - **Link prediction:** friend recommendation.
  - **Graph prediction:** drug classification.
  - **Node classification:** power-grid failure detection.

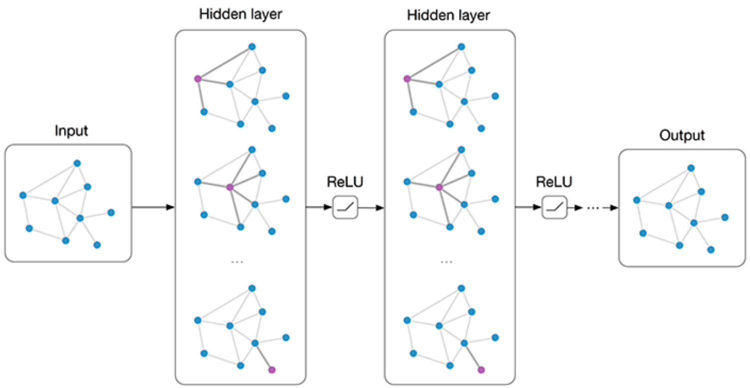
- **GNN *Vs.* Traditional graph algorithms (e.g., random walks).**
  - High classification accuracy.
  - Better generality for diverse graph inputs.
  - Lower computation complexity.
  - Ease of parallelization.

GNN: Graph Neural Networks

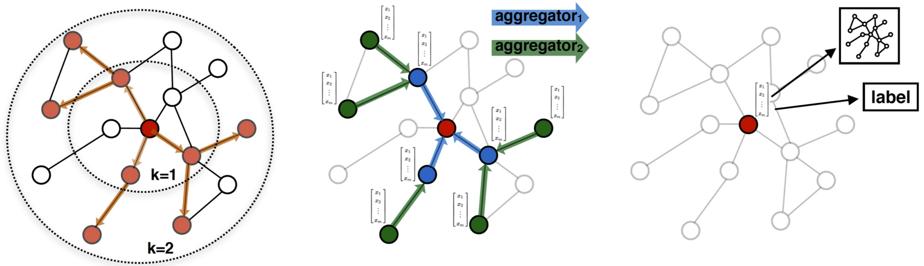


GNN: Graph Neural Networks

GCN Kipf, Thomas N., Max Welling. ***Semi-supervised classification with graph convolutional networks.*** *ICLR'17*



GraphSAGE Hamilton et al. ***Inductive Representation Learning on Large Graphs.*** *NeurIPS'17*



1. Sample neighborhood

2. Aggregate feature information from neighbors

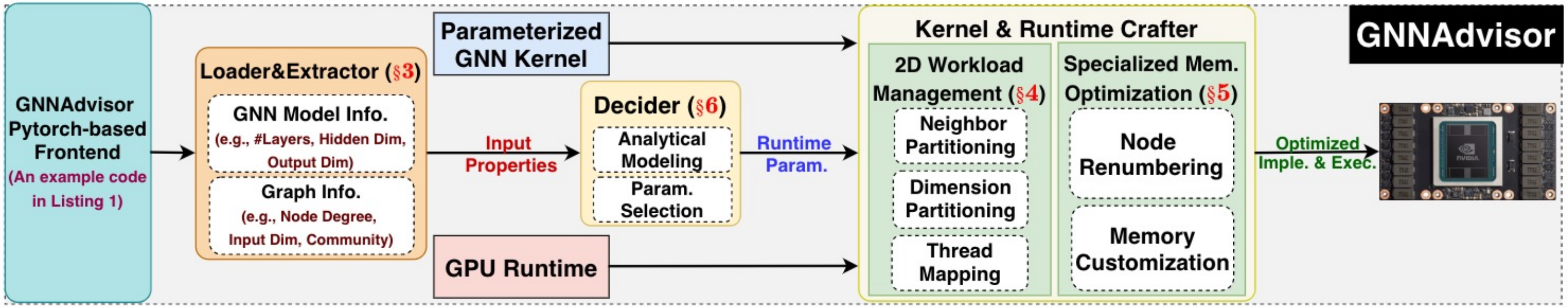
3. Predict graph context and label using aggregated information

Existing GNN Acceleration Solutions

- **Graph Processing Framework [Gunrock]:**
  - Optimizations tailored for graph algorithms.
  - Missing operators for NN computation.
  - Lack of programmability and portability.

- **Deep Learning Frameworks [PyG, DGL]:**
  - Focusing on programmability and generality.
  - Lack of efficient backend for sparse operators.
  - Hard-coded designs with poor input adaptability.

Overview of GNNAdvisor

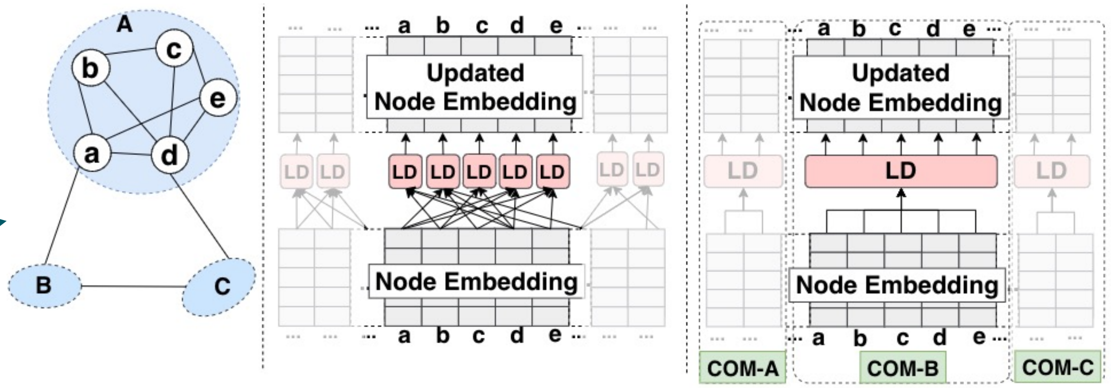


Overall, we are the first to

- ❖ Explore the benefits of input properties (e.g., GNN model architectures and input graphs).
- ❖ Give an in-depth analysis of their importance in guiding system optimizations for GPU-based GNN computing.

Input Extraction

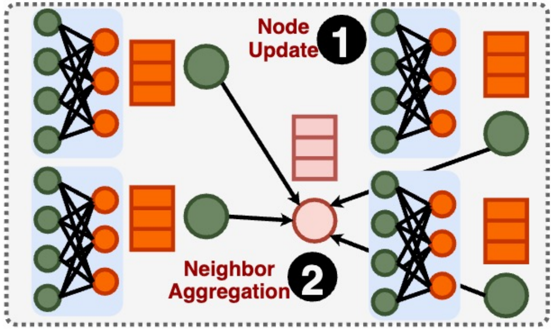
- **Graph Information.**
  1. Node Degree.
  Real-world graphs follow the power-law distribution of node degrees.
  2. Embedding Dimensionality.
  GNN input graphs demonstrates various node embedding size.
  3. Graph community
  Skewed edge distribution widely exists many real-world graphs.



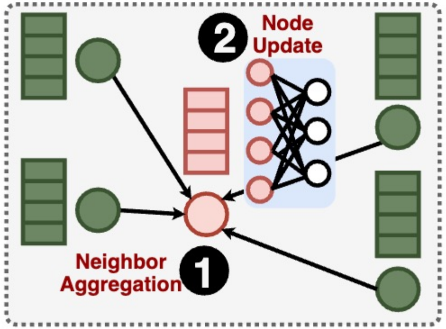
(a) Graph Community (b) Loading without Community (c) Loading with Community

Input Extraction (cont'd)

- **GNN model information.**
  - The order of neighbor aggregation and node update.
  - The tyes of aggregation method, such as sum, mean.

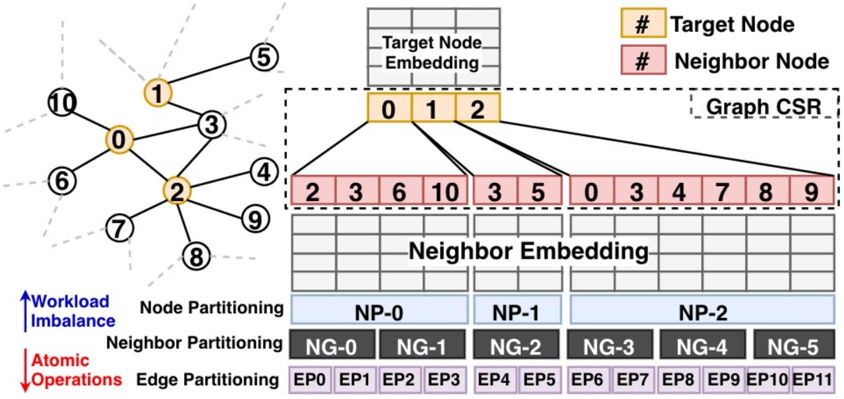


GCN Layer



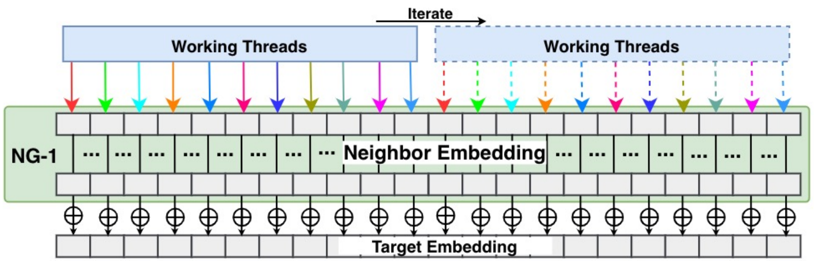
GIN Layer

2D Workload Management



➢ **Coarse-grained Neighbor Partitioning**

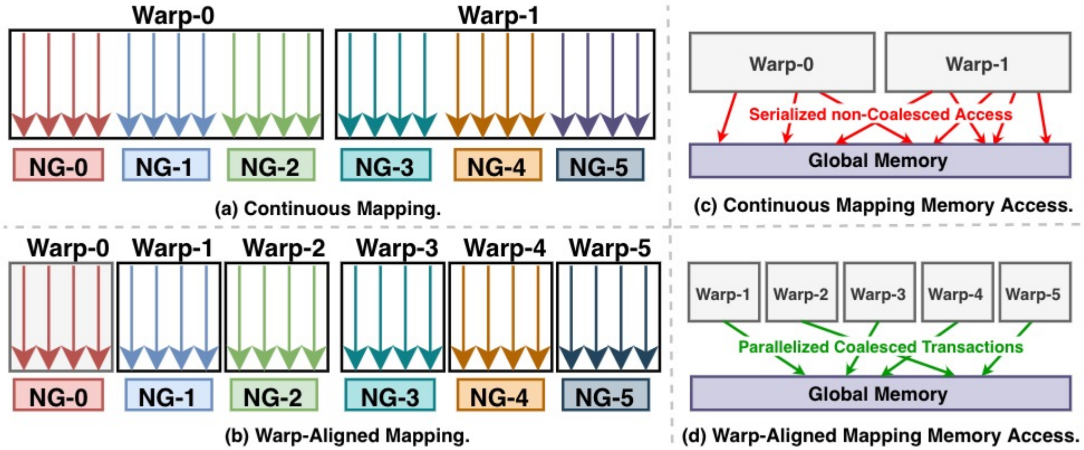
It is a novel workload balance technique tailored for GNN computing on GPUs. It aims to tackle the challenge of inter-node workloads imbalance and redundant atomic operations.



➢ **Fine-grained Dimension Partitioning**

It further distributes the workloads of a neighbor group along the embedding dimension to improve the aggregation performance.

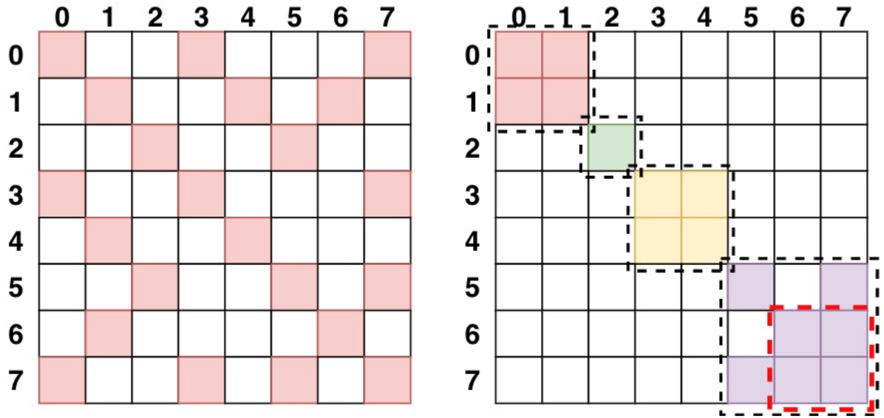
2D Workload Management (cont'd)



➢ **Warp-aligned Thread Mapping:**

This is in collaborating with our neighbor and dimension partitioning to systematically capitalize on the performance benefits of balanced workloads.

Specialized Memory Optimization



➢ **Community-aware Node Renumbering:**

We reorder node IDs to improve the temporal/spatial locality at the GNN aggregation without changing the output correctness to explore the performance benefits of graph community.

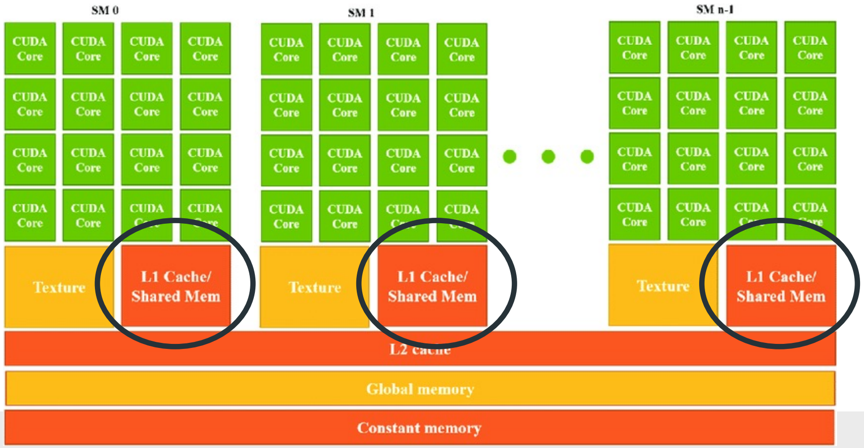
Specialized Memory Optimization (cont'd)

Algorithm 1 Warp-aware Memory Customization.

```
▷ Compute #neighbor-groups (#warps).
warpNum = neighborGroups = computeGroups(ngs);
▷ Compute the number of warps per thread block.
warpPerBlock = floor(threadPerBlock/threadPerWarp)
▷ Initialize tracking variables.
cnt = 0; local_cnt = 0; last = 0;
while cnt < warpNum do
    ▷ Warp in the front of a thread block.
    if cnt % warpPerBlock == 0 then
        warpPtr[cnt].nodeSharedAddr = local_cnt × Dim;
        last = warpPtr[cnt].nodeID;
        warpPtr[cnt].leader = true;
    ▷ Warp in the middle of a thread block.
    else
        ▷ Warp with the same target node as
          its predecessor warp.
        if warpPtr[cnt].nodeID == last) then
            warpPtr[cnt].nodeSharedAddr = local_cnt;
        ▷ Warp with the different target node as
          its predecessor warp.
        else
            local_cnt ++;
            warpPtr[cnt].nodeSharedAddr = local_cnt;
            last = warpPtr[cnt].nodeID;
            warpPtr[cnt].leader = true;
        end if
    end if
    ▷ Next warp belongs to a new thread block.
    if (++cnt)%warpPerBlock == 0 then
        local_cnt = 0;
    end if
end while
```

➢ **Warp-centric Shared Memory Optimization:**

We customize GPU shared memory layout according to the block-level warp organization pattern, therefore, significantly reducing the number of atomic operations and global memory access.



Design Optimization

$$\mathbf{WPT} = ngs \times \frac{Dim}{dw}$$

$$\mathbf{SMEM} = \frac{tpb}{tpw} \times Dim \times FloatS$$

➢ **Analytical Modeling:**

The performance/resource analytical model of GNNAdvisor has two variables, workload per thread (**WPT**), and shared memory usage per block (**SMEM**).

$$dw = \begin{cases} tpw & Dim \geq tpw \\ \frac{tpw}{2} & Dim < tpw \end{cases}$$

➢ **Parameter Auto Selection:**

To determine the value of the neighbor-group size (***ngs***) and dimension-worker (***dw***), we follow two steps.

- First, we determine the value of dw based on ***tpw*** (thread-per-warp) and ***dim*** (embedding dimension).
- Second, we determine the value of ***ngs*** based on the selected ***dw*** and the thread-per-block (***tpb***).

Evaluation

Type	Dataset	#Vertex	#Edge	Dim.	#Class
I	Citeseer	3,327	9,464	3703	6
	Cora	2,708	10,858	1433	7
	Pubmed	19,717	88,676	500	3
	PPI	56,944	818,716	50	121
II	PROTEINS_full	43,471	162,088	29	2
	OVCAR-8H	1,890,931	3,946,402	66	2
	Yeast	1,714,644	3,636,546	74	2
	DD	334,925	1,686,092	89	2
	TWITTER-Partial	580,768	1,435,116	1323	2
	SW-620H	1,889,971	3,944,206	66	2
III	amazon0505	410,236	4,878,875	96	22
	artist	50,515	1,638,396	100	12
	com-amazon	334,863	1,851,744	96	22
	soc-BlogCatalog	88,784	2,093,195	128	39
	amazon0601	403,394	3,387,388	96	22

- **GNN Models.**

❖ **Graph Convolutional Network (GCN):**
2 layers with 16 hidden dimensions.

❖ **Graph Isomorphism Network (GIN):**
5 layers with 64 hidden dimensions.

- **Evaluation Platform.**

A server with an 8-core 16-thread Intel Xeon Silver 4110 CPU and a Quadro P6000 GPU. Also study on the DGX-1 system with Tesla V100 GPU .

Evaluation (cont'd): *Overall Performance*

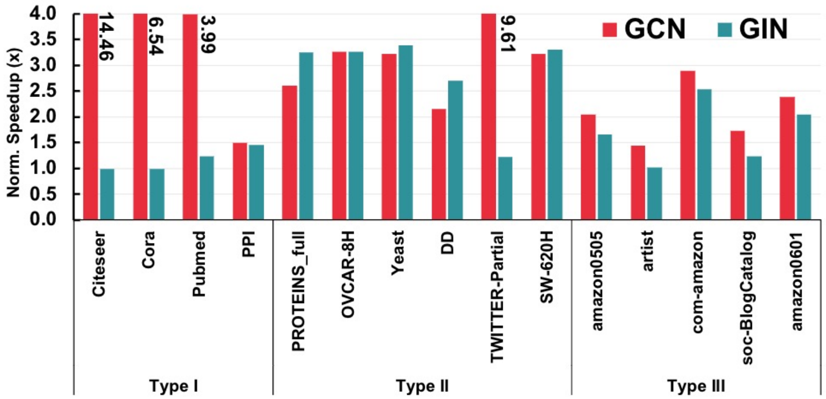


Figure 8: Speedup over DGL for GCN and GIN.

Averaged 4.03x and 2.02x speedup in comparison with DGL on GCN and GIN in inference.

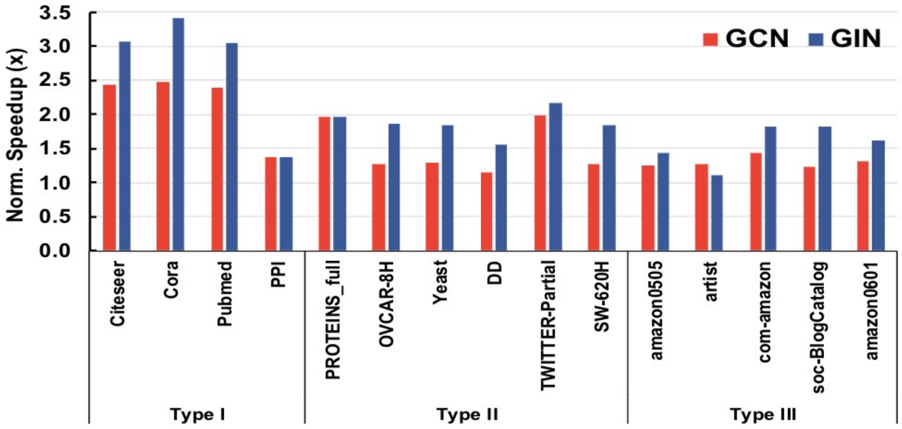
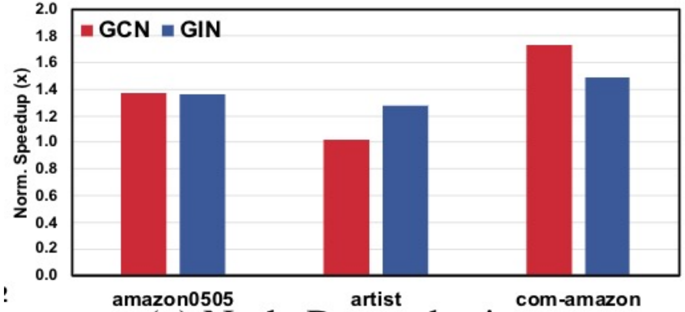


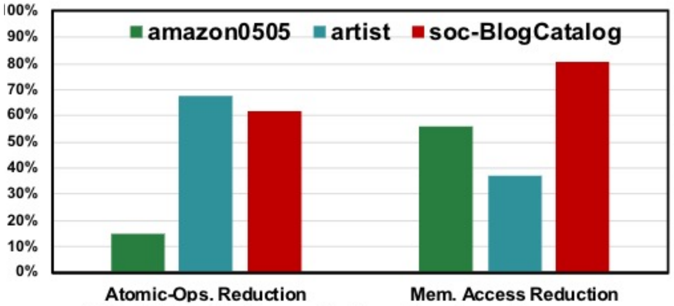
Figure 9: Training comparison with DGL on GCN and GIN.

Averaged 1.61x and 2.00x speedup in comparison with DGL on GCN and GIN in training.

Evaluation (cont'd): *Optimization Analysis*



(c) Node Renumbering.

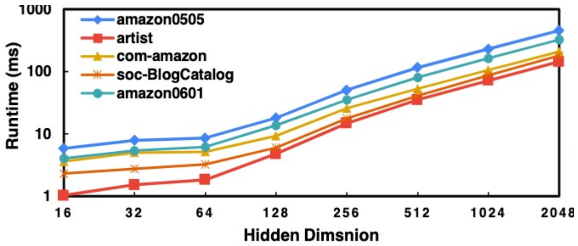


(d) Block-level Optimizations.

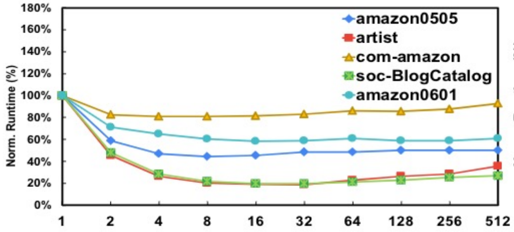
up to 1.74x and 1.49x speedup in GCN and GIN, respectively.

average 47.85% and 57.93% reduction in atomic operations and DRAM access, respectively

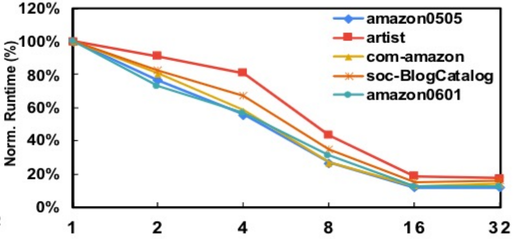
Evaluation (cont’d): *Additional Studies*



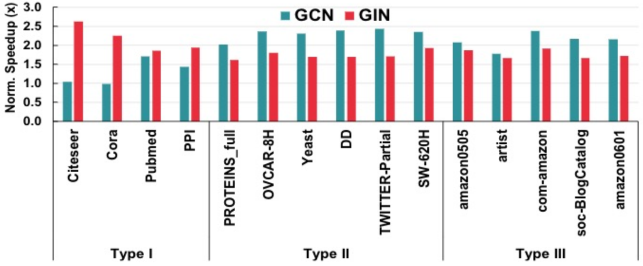
(a) Dimension Analysis on GCN.



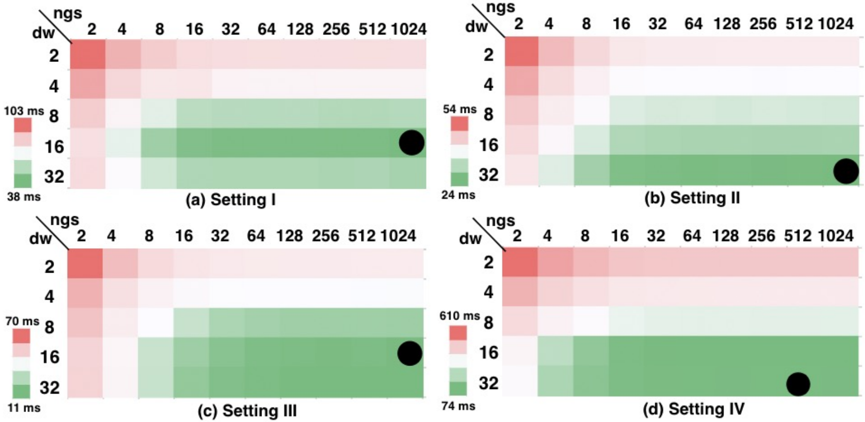
(a) Neighbor Group.



(b) Dimension Worker.



(c) Performance Quadro P6000 Vs. Tesla V100.



Key Focus & Contributions

- ☑ Efficient sparse kernel design for GNN computation on GPUs
- ☑ Design flexibility for handling different inputs.
- ☑ Seamless integration with the existing NN frameworks.

- ➢ 2D workload management.
- ➢ Specialized memory optimization.

GNN Input propertities (e.g., graph structure, node embedding size) for guiding system-level optimizations.

PyTorch-based front-end design with high programmability and portability.

Thank You

Q & A

[Github] https://github.com/YukeWang96/OSDI21_AE.git