RingSampler: GNN Sampling on Large-Scale Graphs with io_uring

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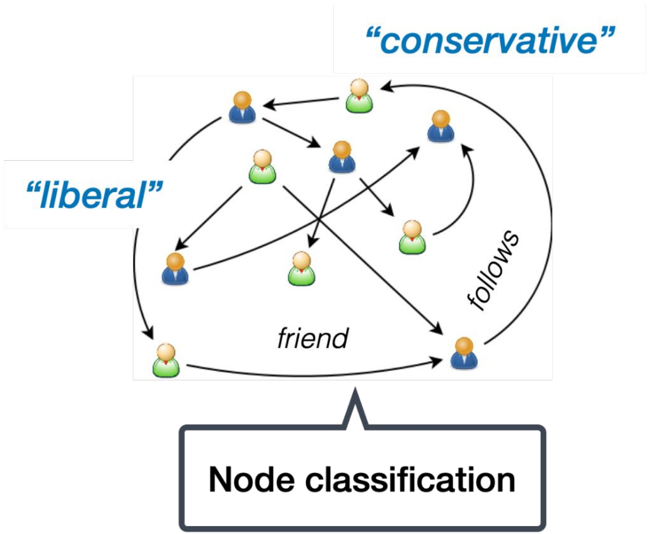
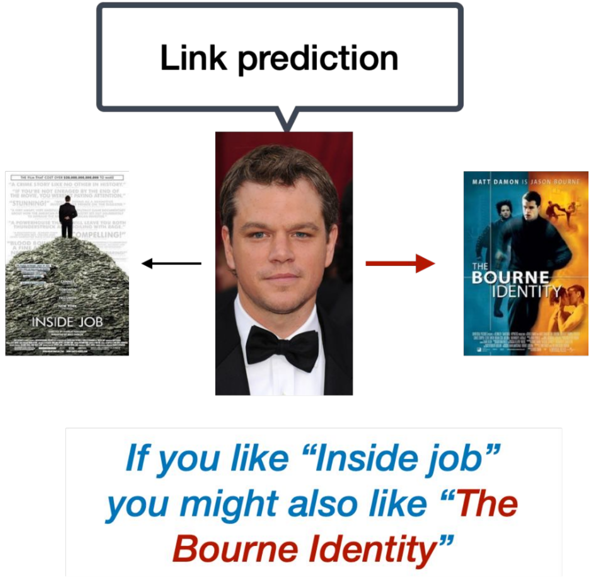
Graph Neural Networks (GNNs)

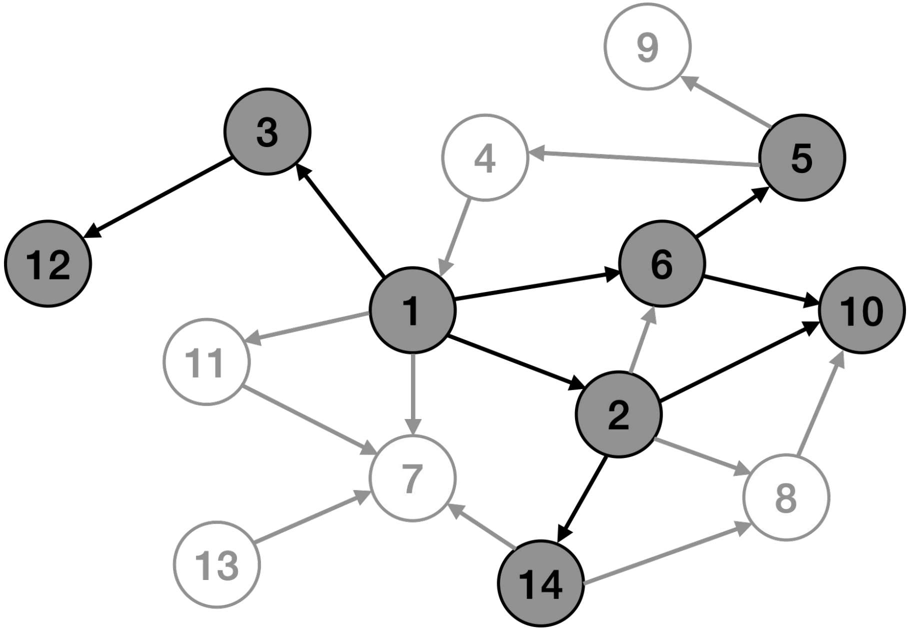
Graph Neural Networks (GNNs) are powerful models in graph learning that capture relationships and dependencies between entities in a network.





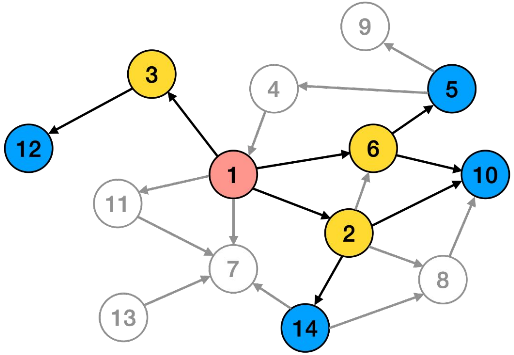
GNN Sampling

Training on the full graph can be computationally intensive and memory-heavy, so GNNs often sample a subset of the original graph that retains its key features and structure.

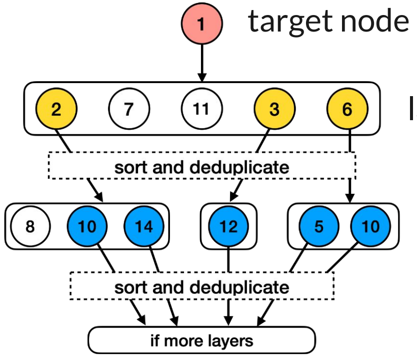


GraphSAGE Sampling

For each **target node** (i.e., a node to be trained), GraphSAGE samples a fixed number of neighbors (**fanout**) at each layer to construct the computation graph.



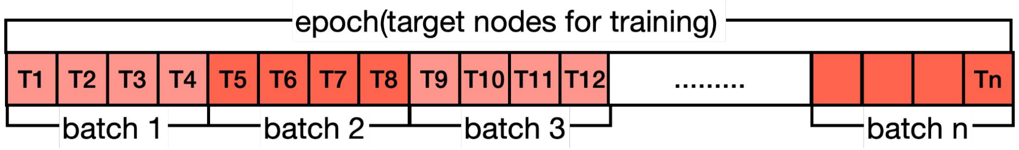
a. sample input graph



b. node-wise sampling workflow

GraphSAGE 2 layer sampling

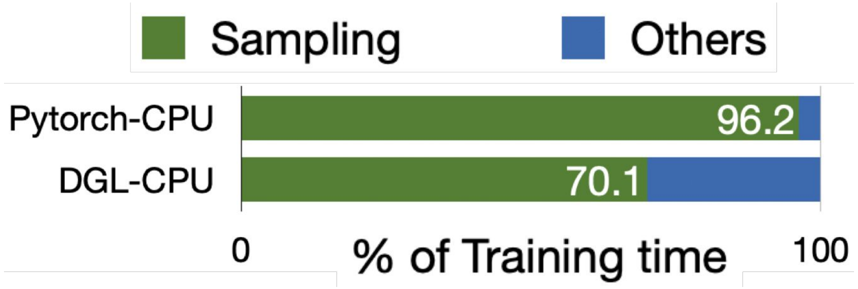
Epoch is split into mini-batches to efficiently process large datasets



GNN Sampling is a Critical Bottleneck

Neighborhood sampling can consume 50–90% of total training time

— gSampler (OSDI '23), GIDS (ICDE '23), Ginex (OSDI '22), NextDoor (VLDB '21)



How to support larger-than memory graphs?

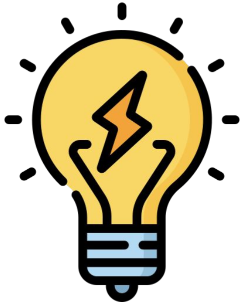
Datasets	#Nodes	#Edges	Size
Papers100M	111M	1.62B	70GB
Hyperlink	3.5B	128B	**3.4TB**
Facebook	1.4B	1T	**8.5TB**

Graph size may exceed main memory

Related Work

System Type	CPU-based	GPU-based	SSD-based
Sampling Device	CPU	GPU	SSD
Graph Stored In	Disk(SSD)	CPU/GPU	SSD
Examples	MariusGNN (EuroSys ‘23) Ginex (EuroSys ‘21)	gSampler (SOSP ‘23) NextDoor (EuroSys ‘21)	FlashGNN (HPCA ‘24) In situ SmartSSD (DaMoN ’24)
Advantages	Able to process larger-than-memory graph	Leverage high computational power of GPUs	Avoid data movement between storage and sampling device
Limitations	- High data movement overhead between SSD and main memory - Low computation power comparing to GPU-based	- Constrained GPU memory - Sampling competes with other tasks for GPU-resources - High computation Cost - Underutilized CPU resources	- Low data transfer bandwidth - Limited adoption due to hardware customizations

Key idea behind RingSampler



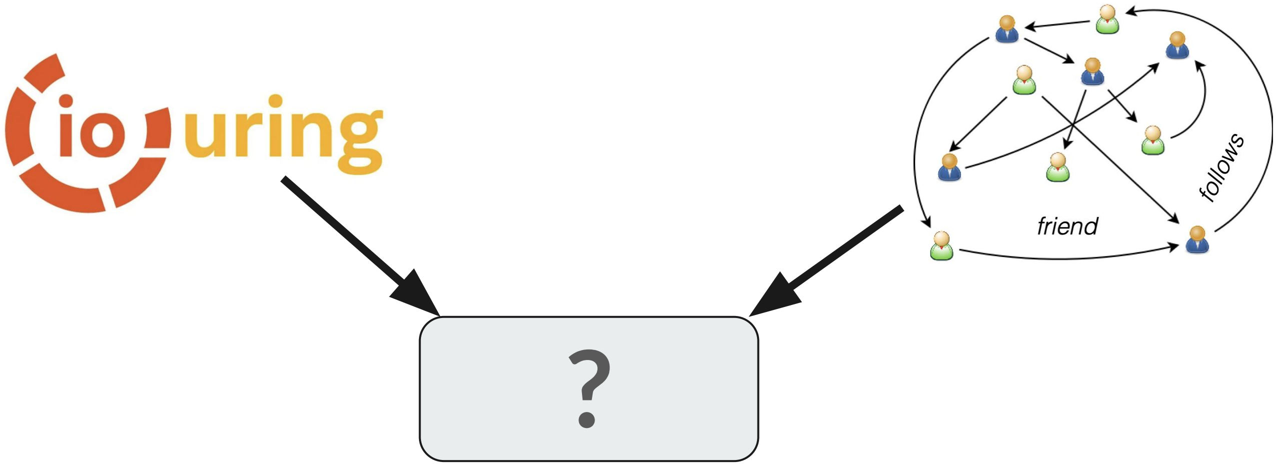
Leverage io_uring, a modern storage API, and high-bandwidth SSDs to perform sampling on larger-than-memory graphs in CPU

Why io_uring

	libaio	io_uring	SPDK
Performance (Scalability, IOPS)	❌	✅	✅
CPU Usage	✅	✅	✅
Ease of Use	✅	✅	❌
Flexibility	❌	✅	❌
Compatibility	✅	✅	❌

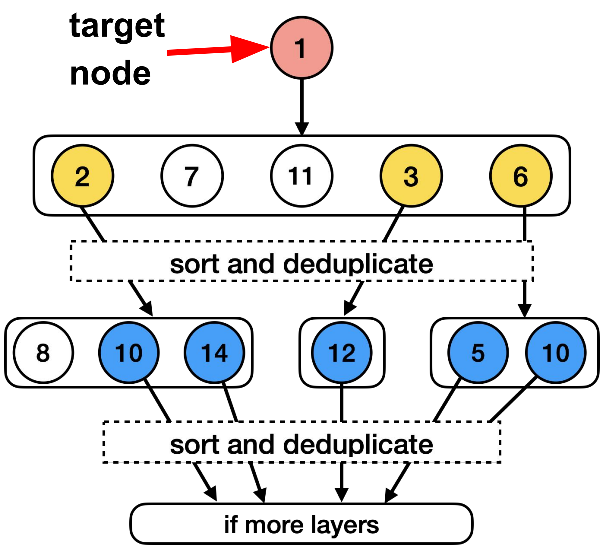
Technical Challenges

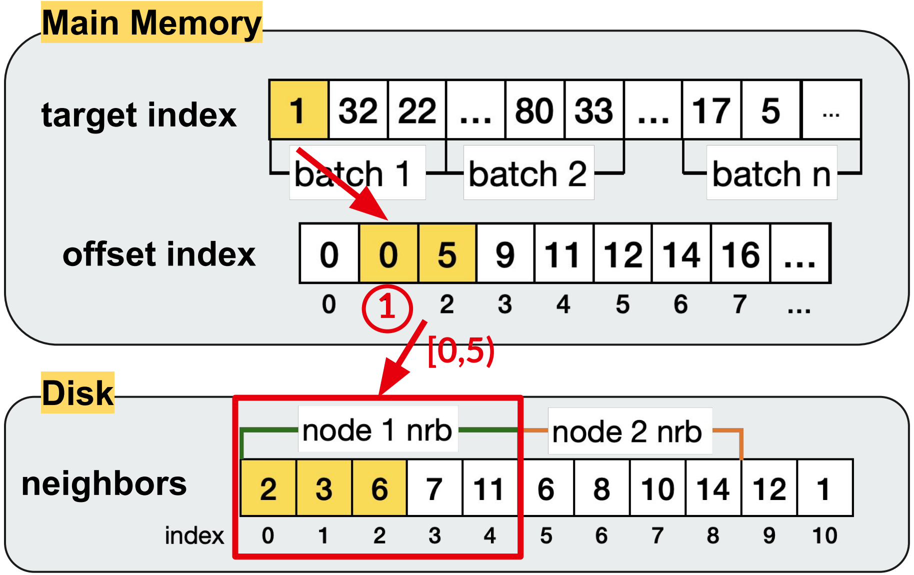
- **How to** minimize data movement between SSD and CPU?
- **How to** integrate and adjust io_uring to GNN Sampling?
- **How to** implement multi-threading to maximize CPU utilization?
- **How to** take the advantage of asynchronous I/O?



Minimize data movement

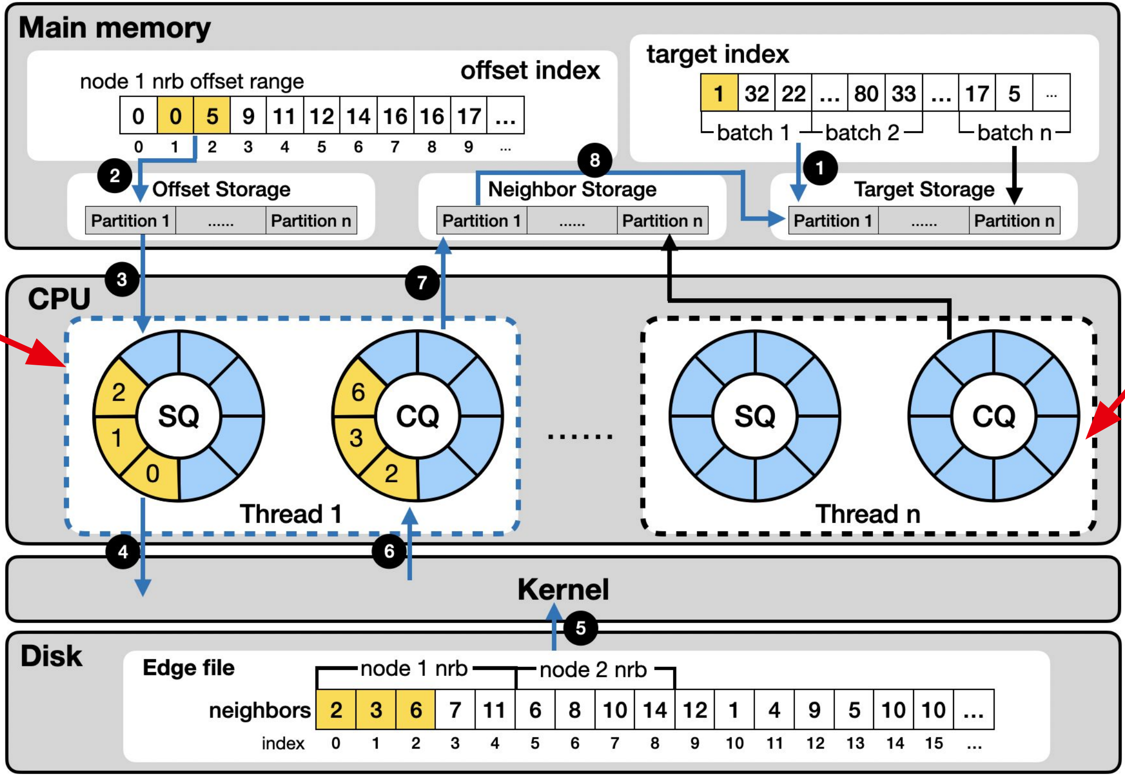
Create two indexes to efficiently select neighbor offsets, allowing direct access to sampled neighbors without loading all neighbors from disk.





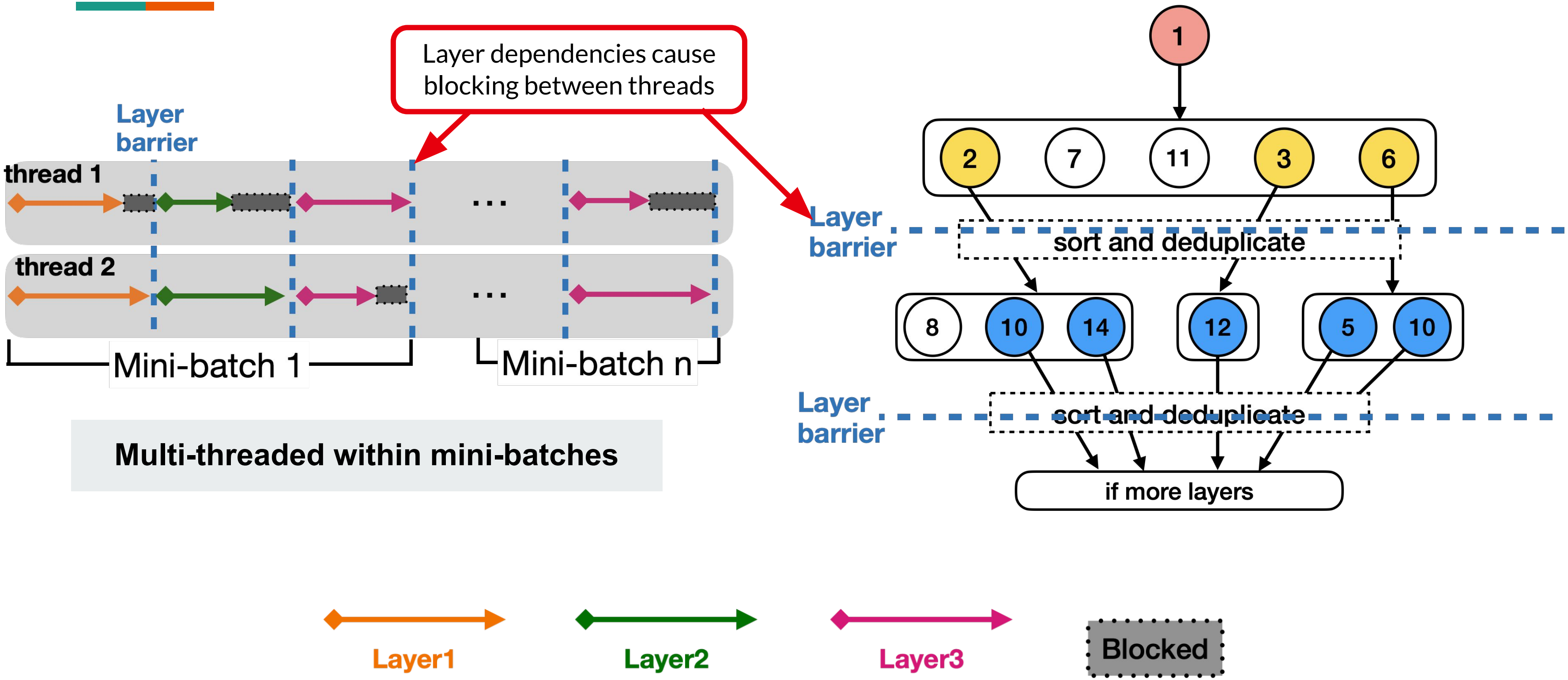
io_uring: Batched I/O Requests and High Parallelism

Submitting multiple requests in a single system call

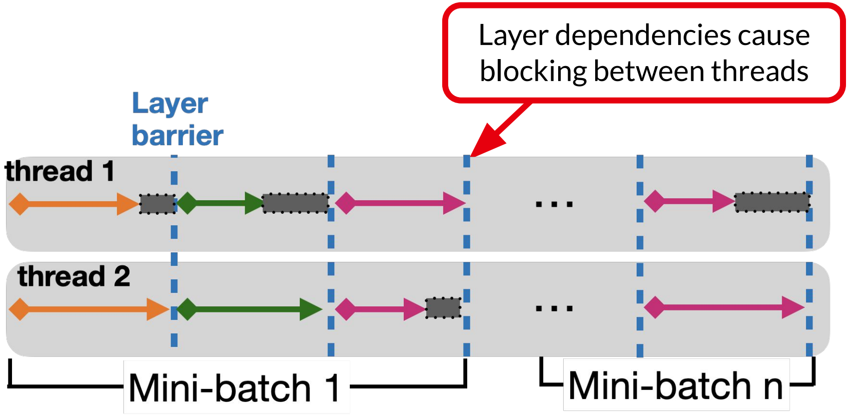


Each thread has its own pair of ring buffers

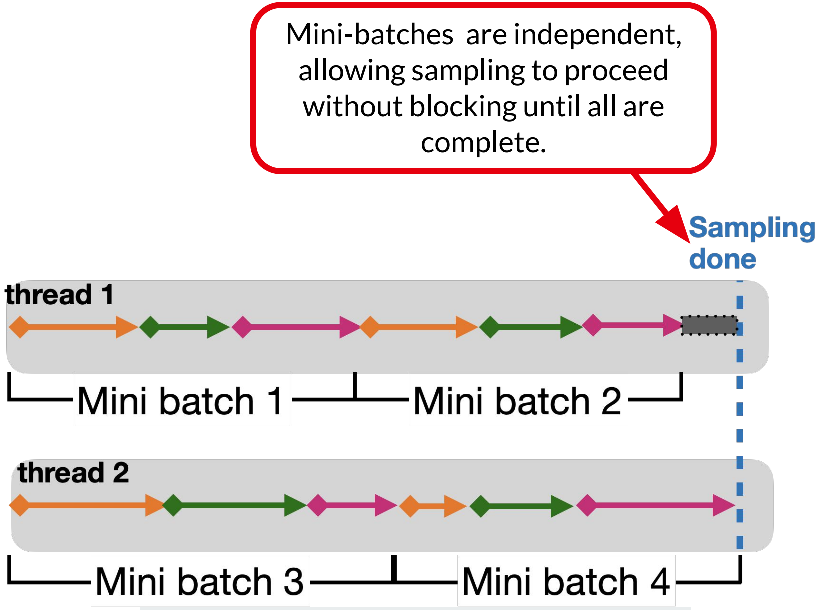
Parallel Design



Parallel Design

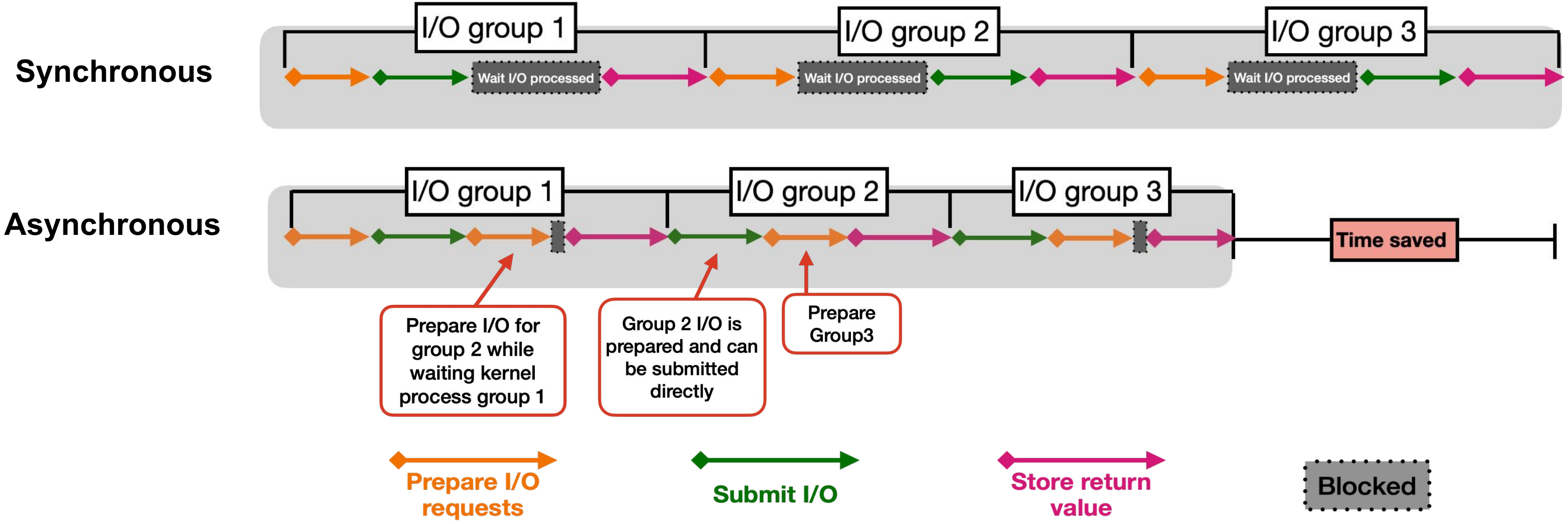


Multi-threaded within mini-batches

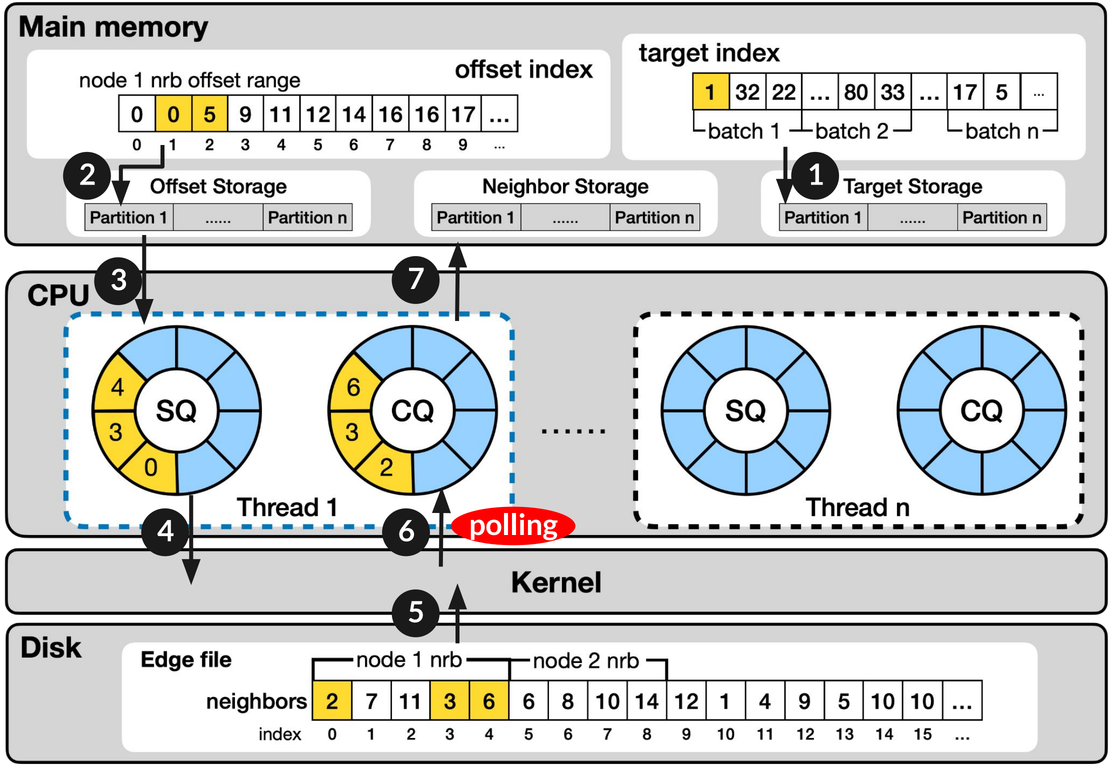


Equally distribute mini-batches across threads to process in parallel

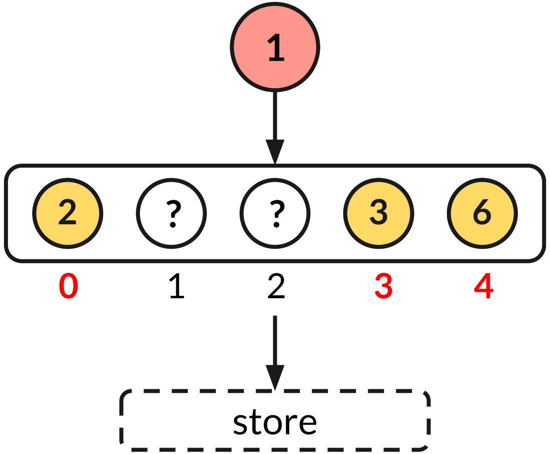
Asynchronous Design



Workflow



Main memory
node 1 nrb offset range
offset index
0 0 5 9 11 12 14 16 16 17 ...
0 1 2 3 4 5 6 7 8 9 ...
target index
1 32 22 ... 80 33 ... 17 5 ...
batch 1
batch 2
batch n
2
Offset Storage
Partition 1 ...... Partition n
Neighbor Storage
Partition 1 ...... Partition n
1
Target Storage
Partition 1 ...... Partition n
CPU
3
7
4 3 0
SQ
6 3 2
CQ
Thread 1
......
SQ
CQ
Thread n
4
6
polling
Kernel
5
Disk
Edge file
node 1 nrb
node 2 nrb
neighbors
2 7 11 3 6 6 8 10 14 12 1 4 9 5 10 10 ...
index
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 ...



1
2 ? ? 3 6
0 1 2 3 4
store

Experimental Configuration

Machine

- Our setup includes an AMD EPYC 7713P **64C/128T CPU**, 252GB DRAM, a 4TB **Samsung SmartSSD**, and an **NVIDIA A100 80GB GPU**. The software environment consists of Ubuntu 20.04, CUDA 12.1, PyTorch 2.3.1+cu121, and DGL v2.3.0+cu121.

Model Configuration

- **3-layer GraphSAGE** model with a fanout of {20, 15, 10} and a mini-batch size of 1024.

Baselines

- **DGL v2.3 (Deep Graph Library)**: In-memory CPU/GPU-based
- **gSampler (SOSP '23):** In-memory GPU-based
- **MariusGNN (EuroSys '23)**: Out-of-memory CPU-based
- **In-situ SmartSSD (DaMoN '24)**: SSD-based

Datasets Used For Evaluation

Dataset	Vertices	Edges	Raw Size (GB)	Bin Size (GB)
ogbn-papers	111M	1.6B	24.1	6.8
Friendster	65M	3.6B	30.1	13.5
Yahoo	1.4B	6.6B	66.9	35.3
Synthetic	134M	8.2B	140.8	31.7

ogbn-papers and Friendster: Fit in memory; used to evaluate in-memory sampling performance.

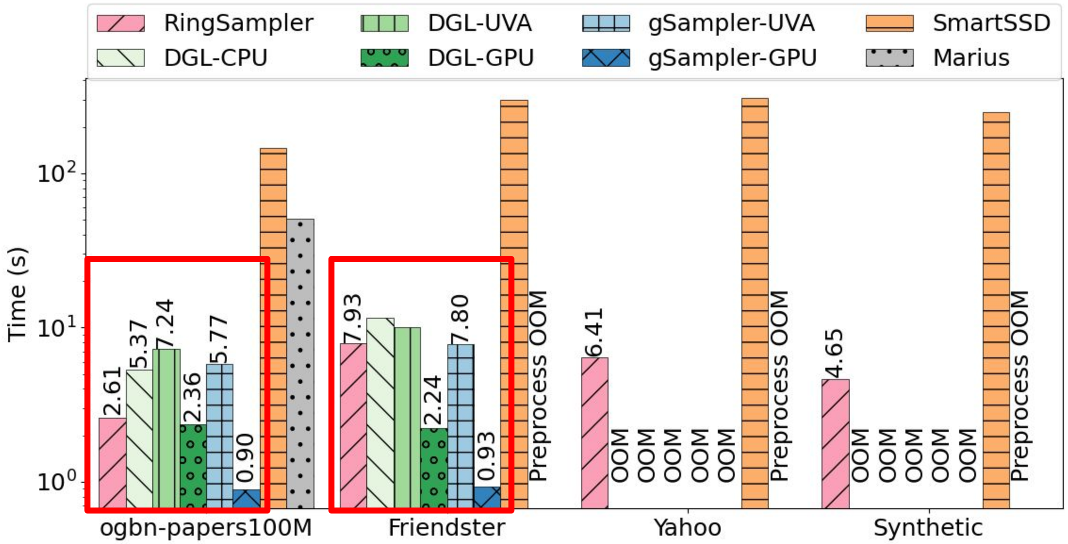
Yahoo and Synthetic: Extremely large graphs that do not fit in memory; used to test the system's ability to handle larger-than-memory graphs.

Faster Than In-Memory CPU Systems, Competitive with GPU Solutions

DGL-CPU: Graph stored and sampled on CPU

DGL-GPU, gSampler-GPU: Graph stored and sampled on GPU

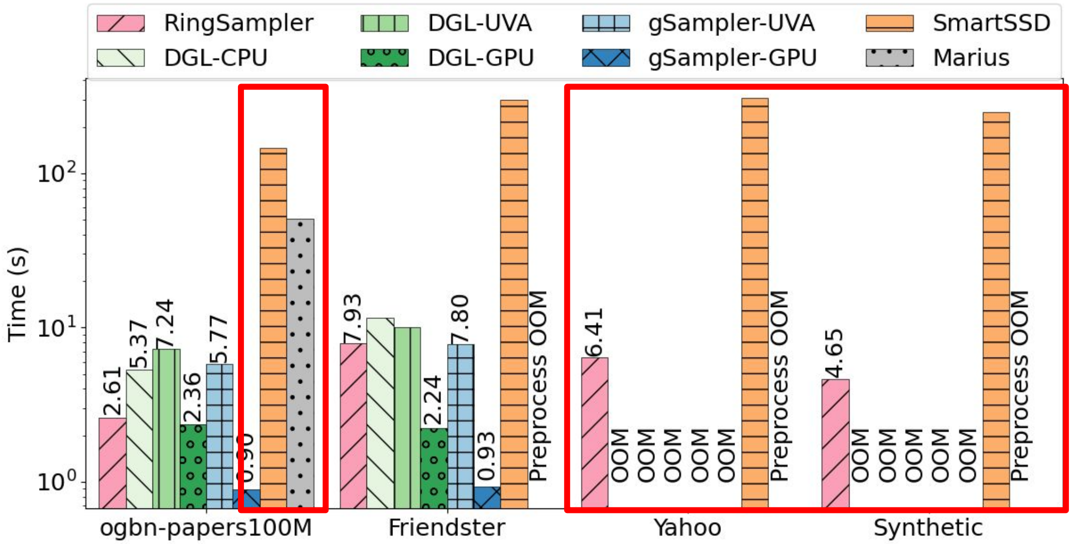
DGL-UVA, gSampler-UVA: Graph stored on CPU, sampled on GPU using Unified Virtual Addressing (UVA) to access data



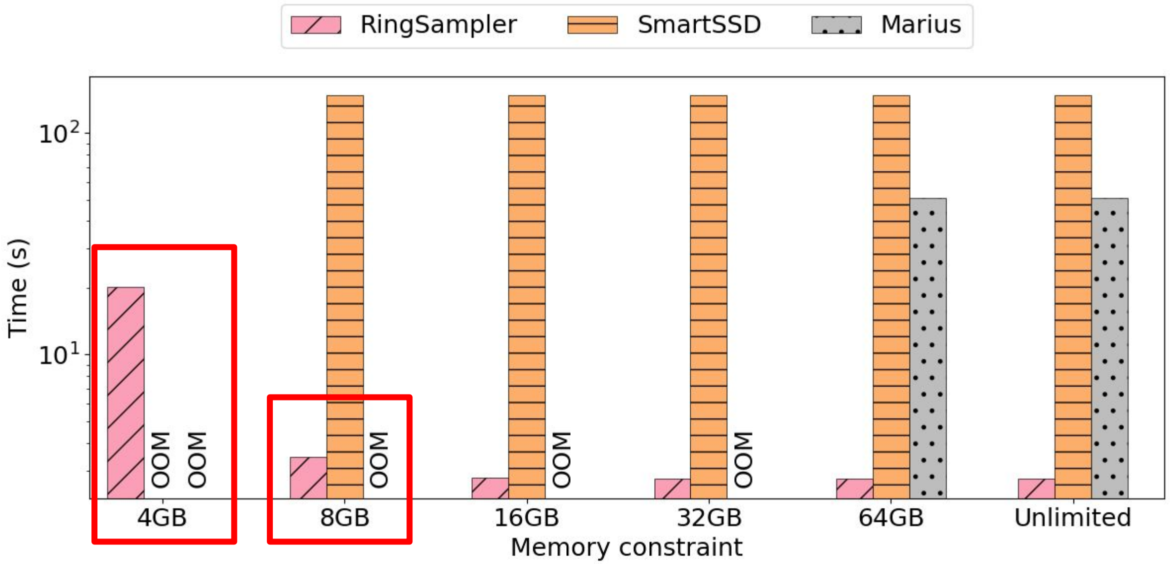
Scales to Large Graphs and Outperforms Baseline

MariusGNN: Graph stored on SSD and partially loaded into memory for CPU-based sampling

SmartSSD: Graph stored and sampled directly on SSD using FPGA

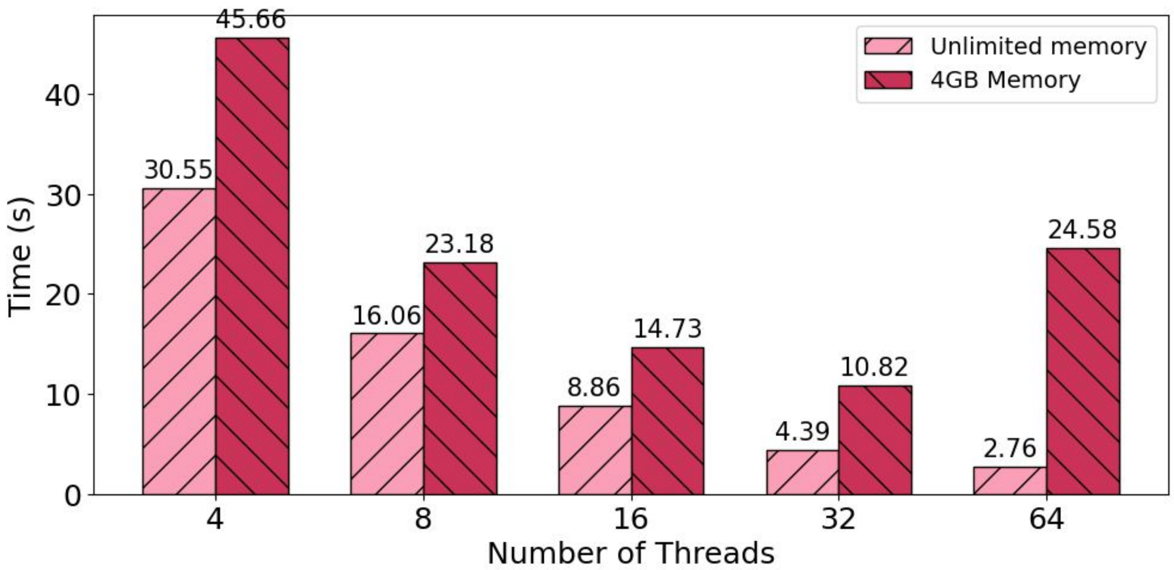


Low Memory Requirement for Large-scale Sampling



Only 4 GB of memory is needed to sample a billion-edge graph (ogbn-papers)

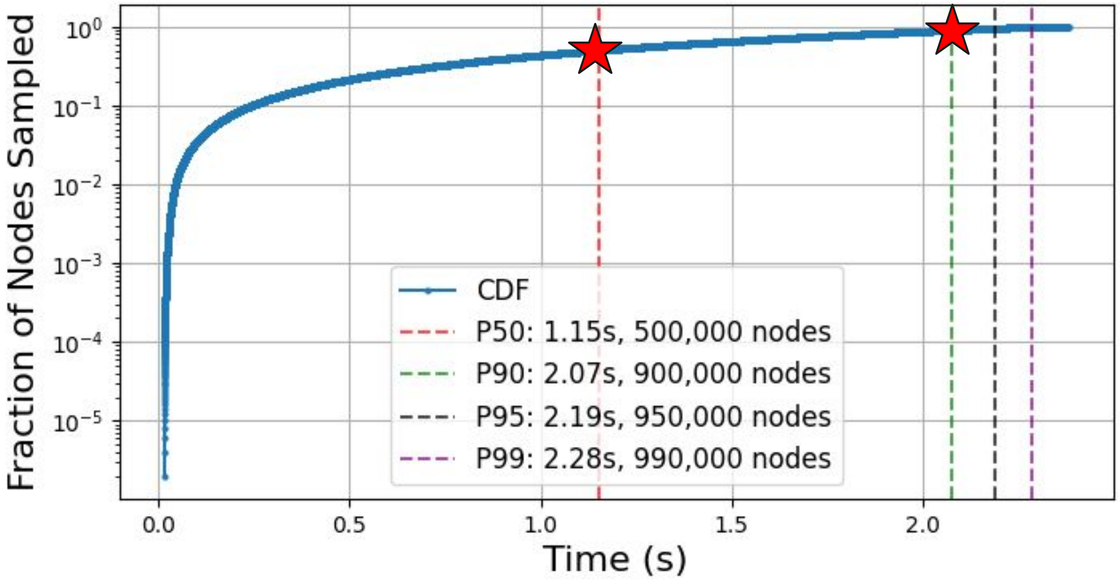
Linear Scalability with No of Threads



Sampling run time decreases almost linearly with the number of threads, up to the maximum number of available cores

(ogbn-papers)

Low Latency Sampling for Real-Time GNN Inference

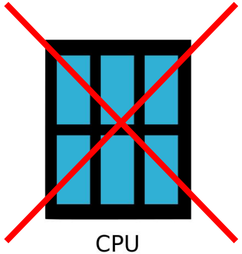


50% of sampling requests complete within 1.15s, and 90% within 2.07s

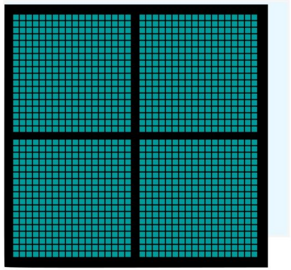
When RingSampler May Not Be the Best Choice

Large GPUs

- When GPU is large enough, GPU-based sampling Systems (gSampler) will be the best choice.



CPU
Multiple Cores



GPU
Thousands of Cores

Small Graphs

- For graphs that fit entirely in memory, the performance gains from io_uring-based sampling are minimal

Future Work

End-to-end implementation

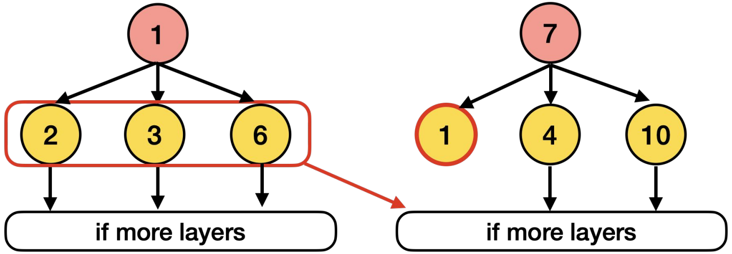
- Build an end-to-end system by integrating RingSampler into GNN frameworks like DGL to enable asynchronous CPU-based sampling alongside GPU-based feature aggregation.

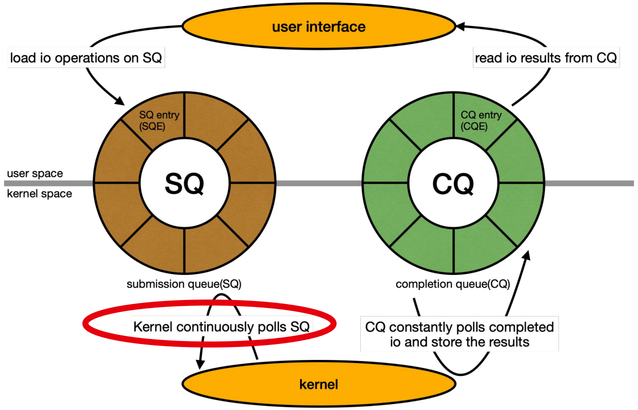
Exploiting caching strategy and sampling reuse

- Due to our parallel design, threads do not share states, which can result in reading the same nodes multiple times.

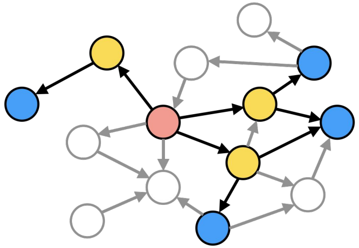
io_uring kernel polling mode

- Kernel polling mode auto-submits I/O when the submission queue is full.

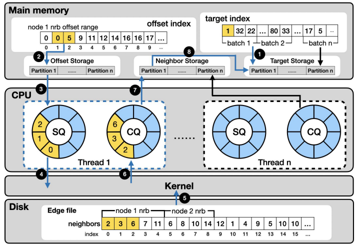




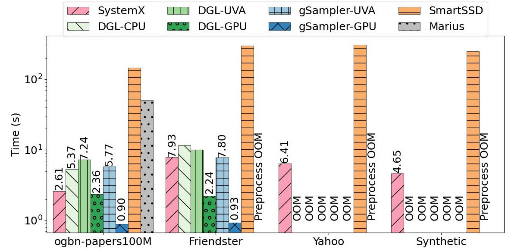
RingSampler



As graph data scales to terabyte sizes, out-of-memory challenges arise, making **efficient sampling** difficult



A CPU-based GNN system **leveraging io_uring** for asynchronous, batched I/O, and multi-threading to maximize CPU utilization



Efficiently handles larger-than-memory graphs and outperforms existing baselines.

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RingSampler

https://github.com/CASP-Systems-BU/RingSampler