COLAB: Collaborative and Efficient Processing of Replicated Cache Requests in GPU

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Contribution

- **We propose Cache line Ownership Lookup tABle (COLAB), an architecture that allows replicated cache requests to be redirected and serviced efficiently within a cluster by utilizing the cache line ownership information.**
- **The incorporation of COLAB is able to reduce the GPU NoC read traffic by an average of 38% and improve the overall throughput by an average of 43% while incurring minimal overhead.**

Outline

- Introduction
- Methodology
- Experimental Results
- Conclusion
- References

Introduction

Introduction

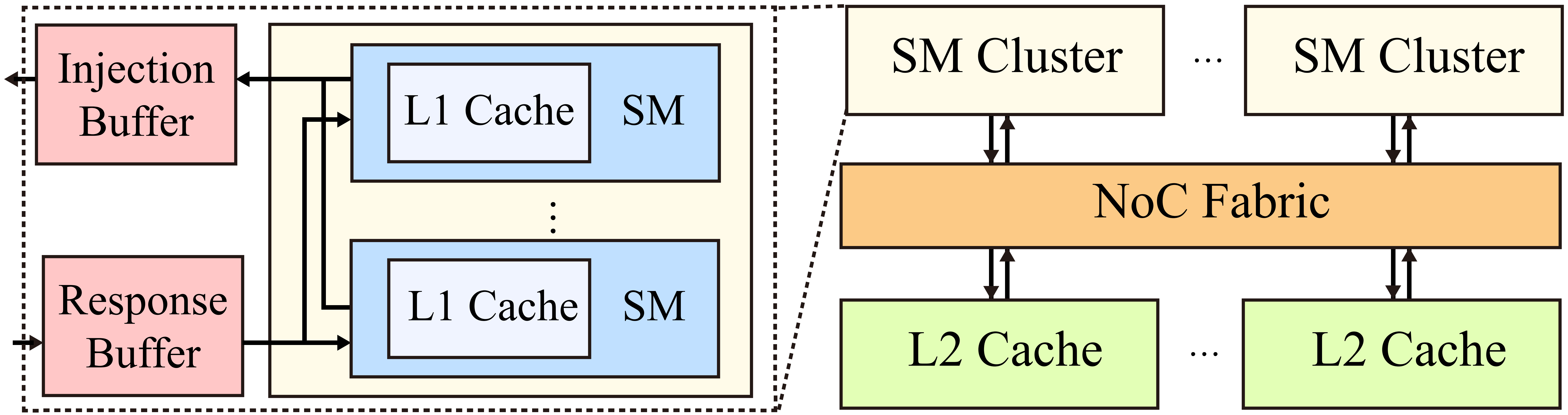
Graphics Processing Unit (GPU)

- Parallel processors that are originally built for graphics rendering.
- GPUs are increasingly utilized in general-purpose computing thanks to their:
  - Parallel processing power
  - Ease of programming
- Workloads that take advantage of GPUs' computing power:
  - Machine learning
  - Graph algorithm
  - Scientific computing

Introduction

Graphics Processing Unit (GPU) Architecture

Modern graphics processing unit (GPU) architectures feature a number of Stream Multiprocessor (SM) clusters, each of which consists of multiple SMs. [1]



Introduction

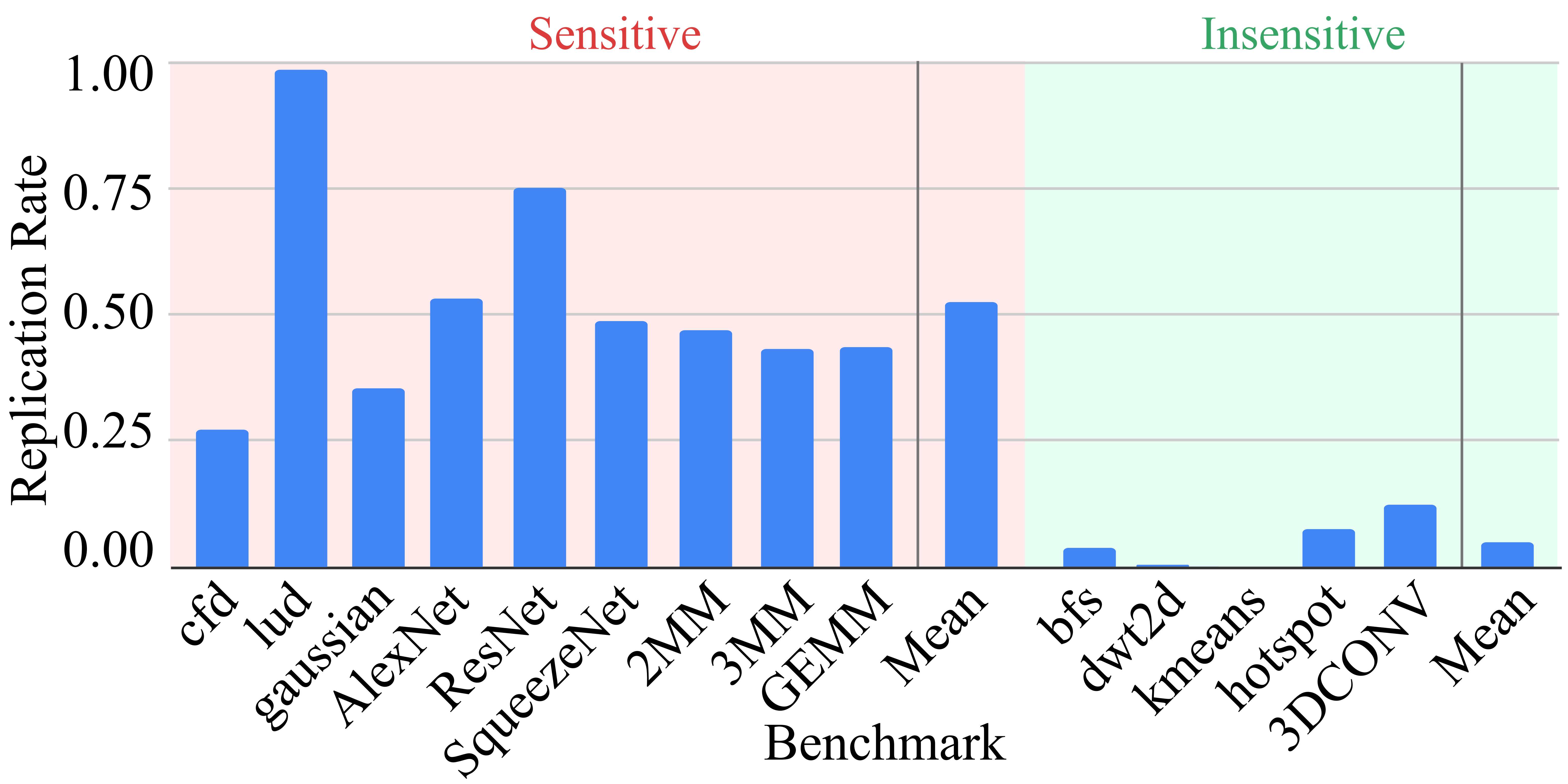
Motivation - The issue with private L1 caches

- Network-on-chip (NoC) congestion
  - The NoC fabric has become the performance bottleneck in GPUs [2]
  - NoC bandwidth is crucial for GPU performance
- Replicated cache requests:
  - Multiple SMs request for the same cache line
  - The cache line is fetched repeatedly across the NoC from L2
  - Inefficient usage of NoC bandwidth
- Replicated cache requests exacerbate NoC congestion, leading to performance degradation

Introduction

Motivation - Quantifying replicated cache requests

For replication-sensitive benchmarks, an average of 52% of cache misses could have been serviced by other SMs within the cluster.



Introduction

Aim - capturing replicated cache requests

- By capturing replicated cache requests and servicing them between SMs, we can:
  - Prevent replicated cache requests from being directed to L2 across NoC
  - Reduce NoC traffic
  - Ease NoC congestion
  - Reduce the number of stalled cycles caused by waiting for NoC
  - Improve overall GPU performance
- Given that 52% of requests can potentially be serviced within the cluster, the potential performance benefit is significant.

Introduction

Proposed method - COLAB

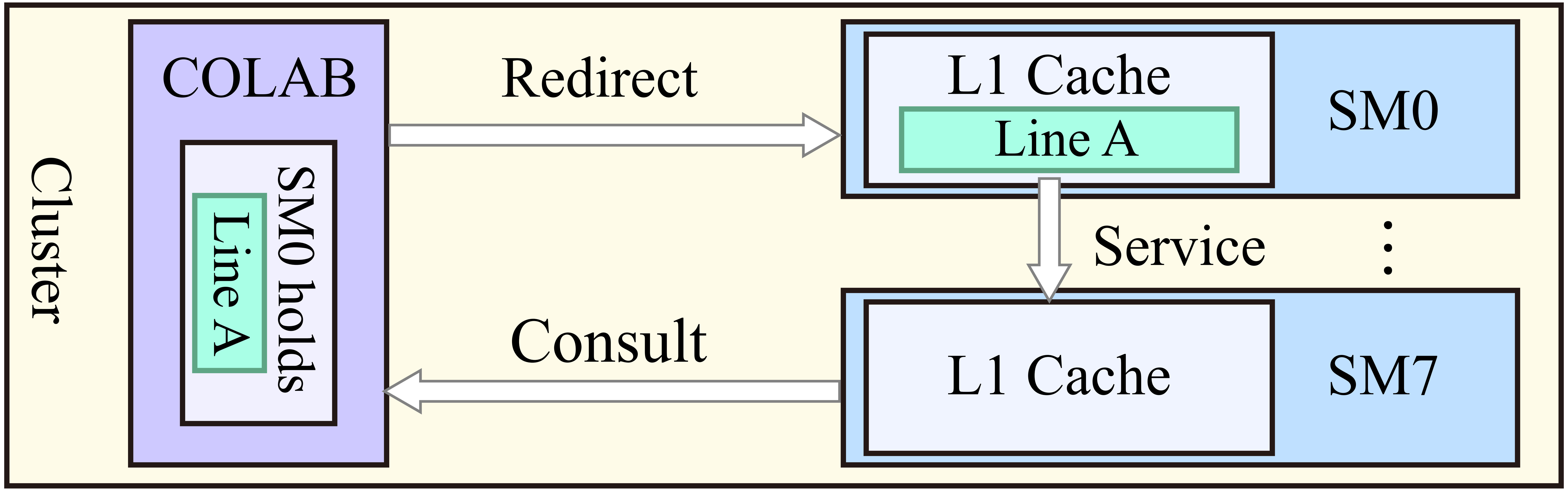
- In this work, we propose incorporating COLAB to achieve our goal of capturing replicated cache requests.
- It does so by keeping track of the ownership information of cache lines stored in the cluster.
- By consulting COLAB, a replaced cache request can know which SM within the cluster holds a copy of the requested line.
- COLAB can redirect the request to one of the SMs according to the information it stores

Methodology

Methodology

Overview

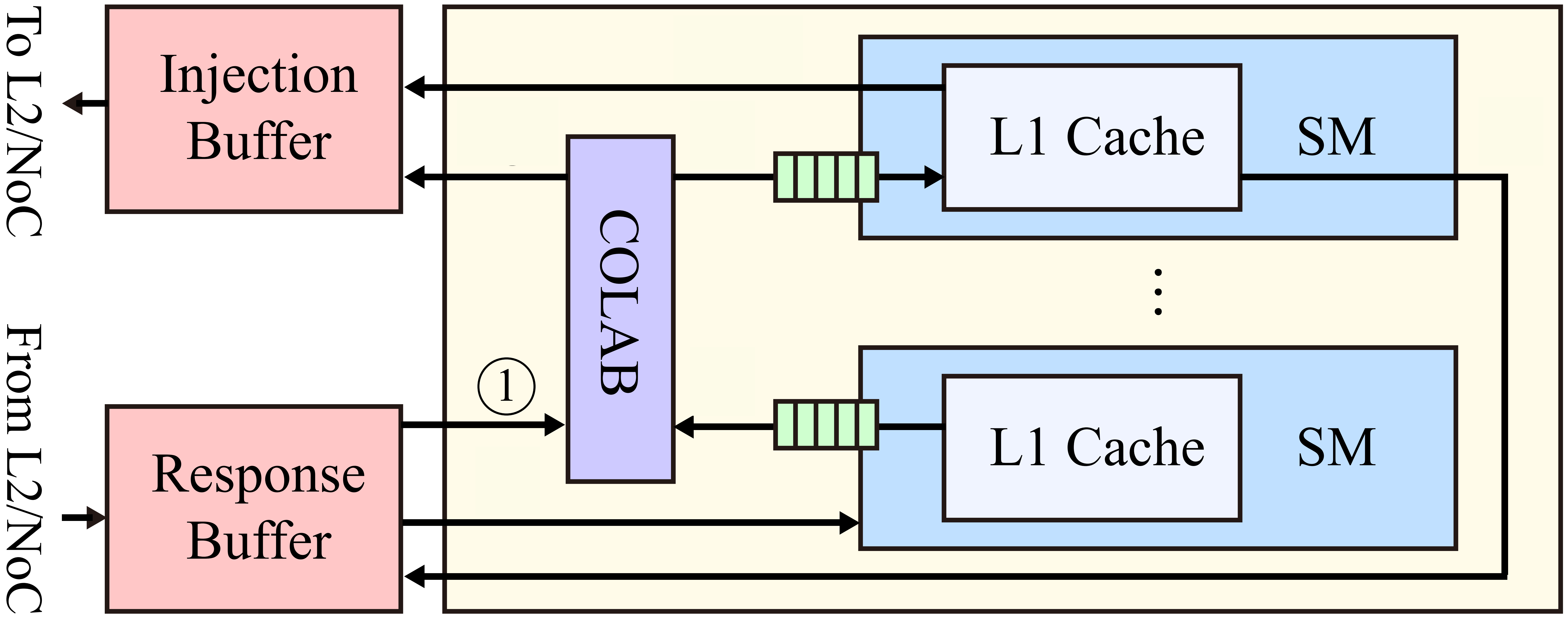
- **COLAB keeps track of the ownership information of cache lines**
- **By consulting COLAB, a cache request can be redirected.**



Methodology

Workflow - Updating COLAB

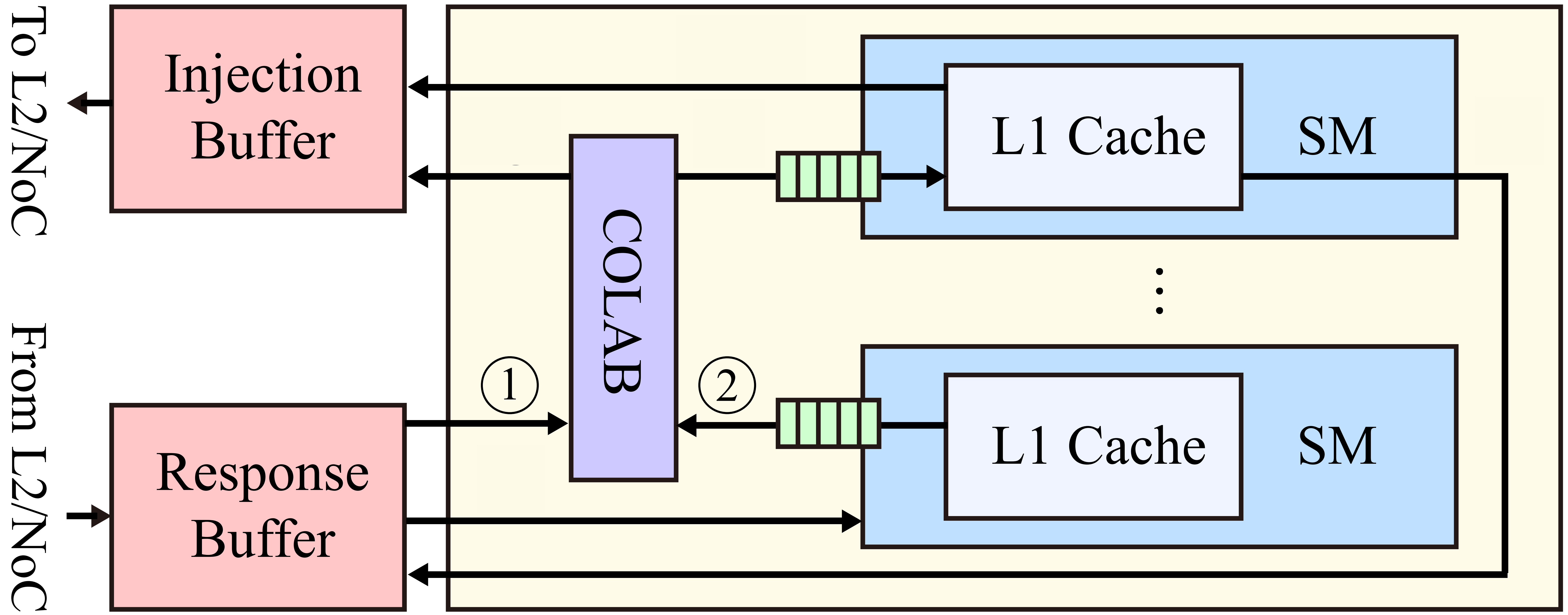
- As a cache request return from L2 via the NoC, COLAB is updated to associate the cache line with the requesting SM.



Methodology

Workflow - Accessing COLAB

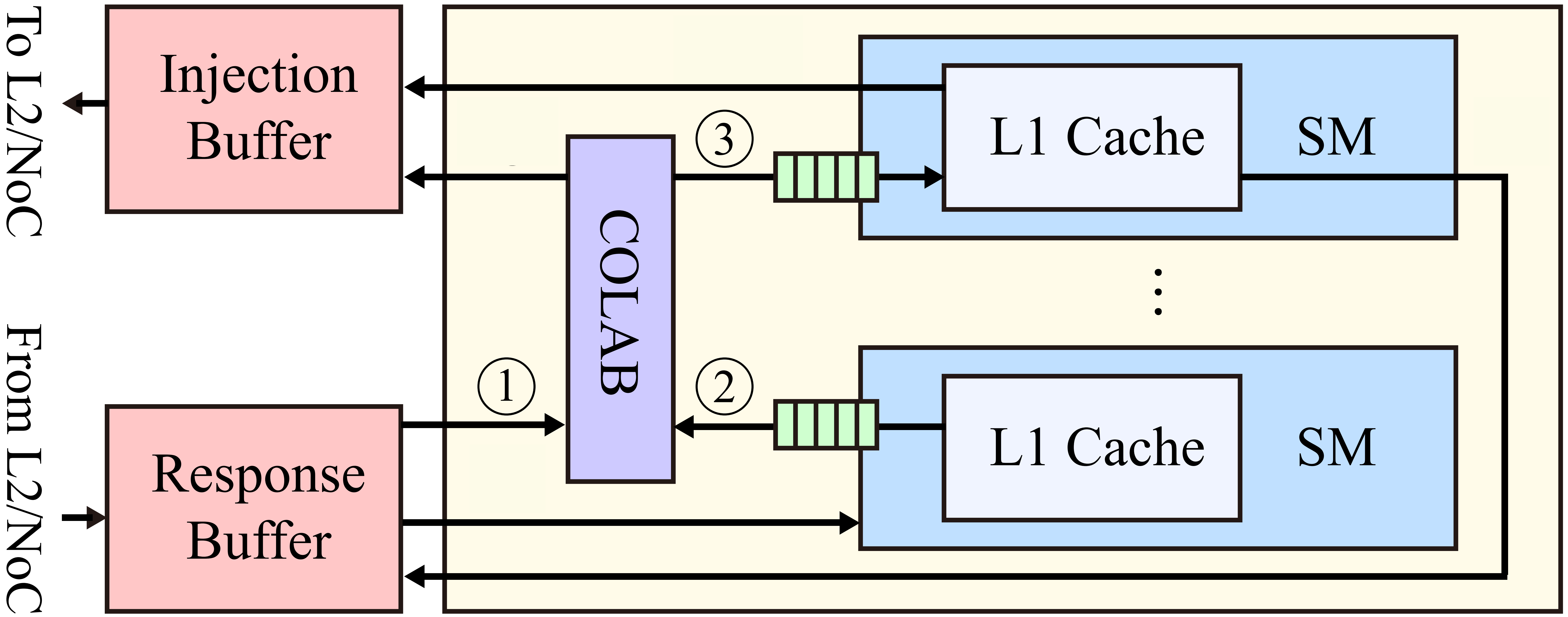
- As a cache request misses the L1 cache, it is sent to the input queue of COLAB to access COLAB.
- If input queue is full, the request is directed to the L2 cache via the NoC .



Methodology

Workflow - Redirect Request and L1 Access

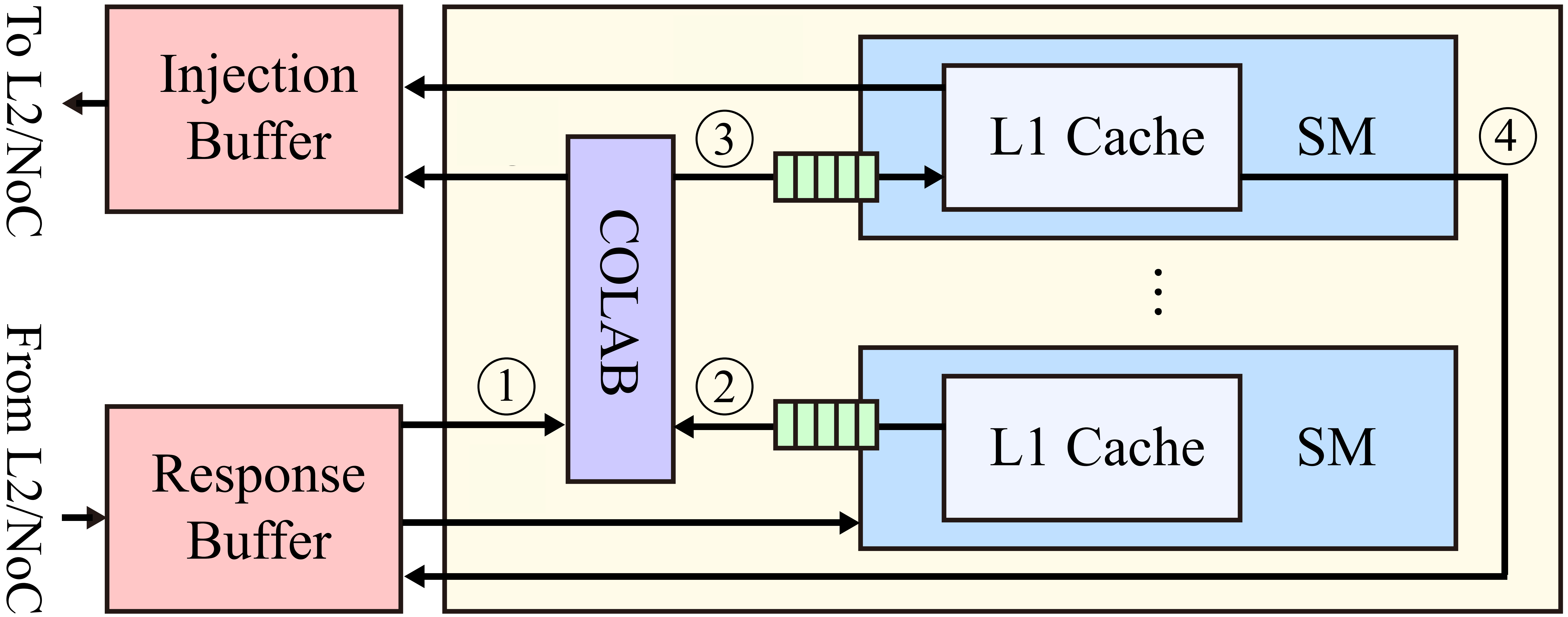
- If the request results in a hit in COLAB, it is directed to the access queue of the SM indicated by COLAB.
- A normal L1 lookup is performed.



Methodology

Workflow - Returning Requested Line

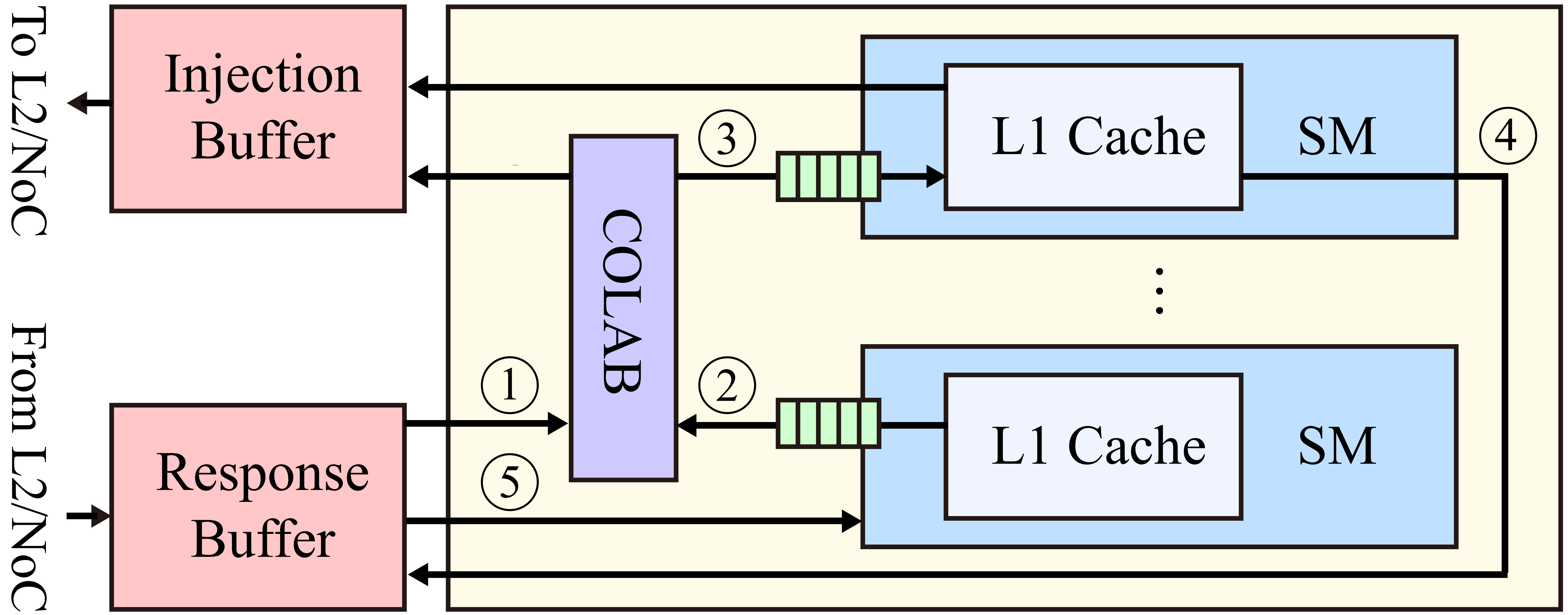
- **If the L1 lookup results in a hit, the requested cache line is pushed to the tail of the response buffer to be sent to the requesting SM.**



Methodology

Workflow - Service of Replicated Request

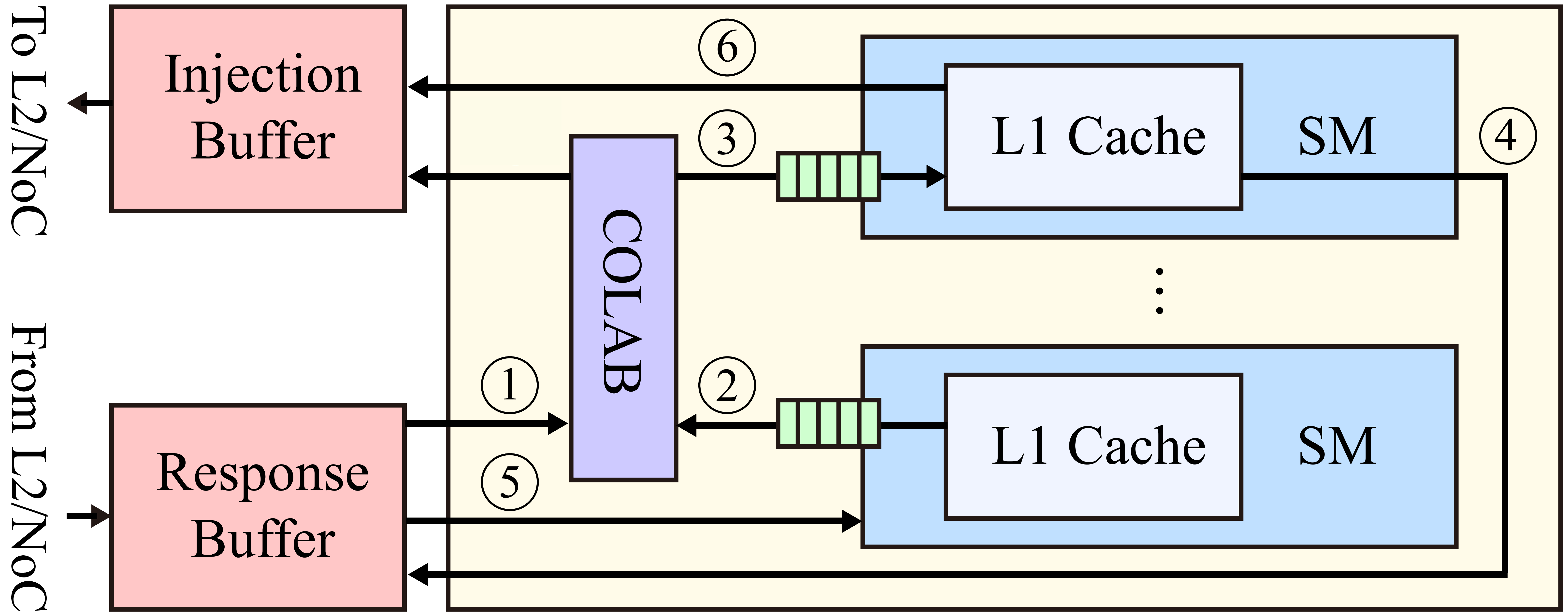
- As the request reaches the head of the response buffer, it is sent to the requesting SM, completing the inter-SM access process.
- The requested line is not cached by the requesting SM.



Methodology

Workflow - In Case of A L1 Miss

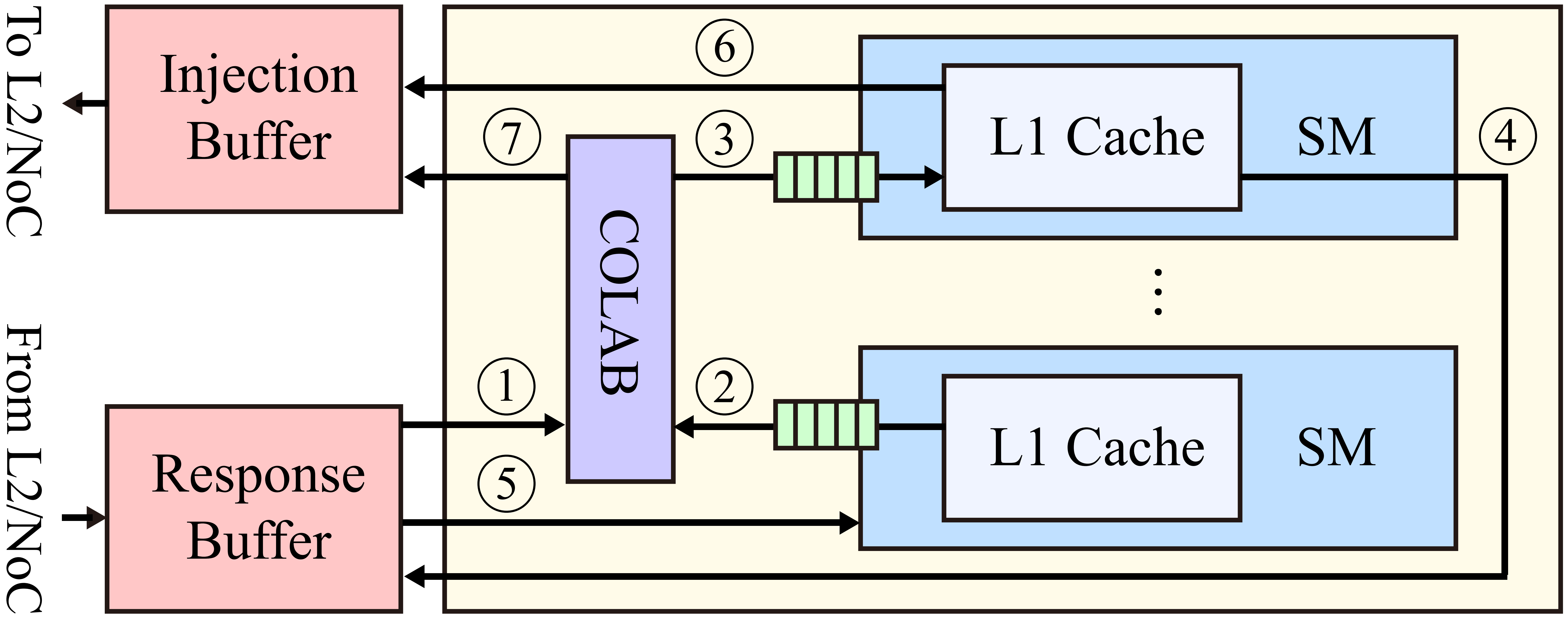
- **If the L1 access result in a miss due to outdated information in COLAB, the request is sent to the L2 cache via the NoC.**



Methodology

Workflow - In Case of A COLAB Miss

- **If the access to COLAB results in a miss or if the access queue of the targeted SM is full, the request is sent to the L2 cache via the NoC.**



Methodology

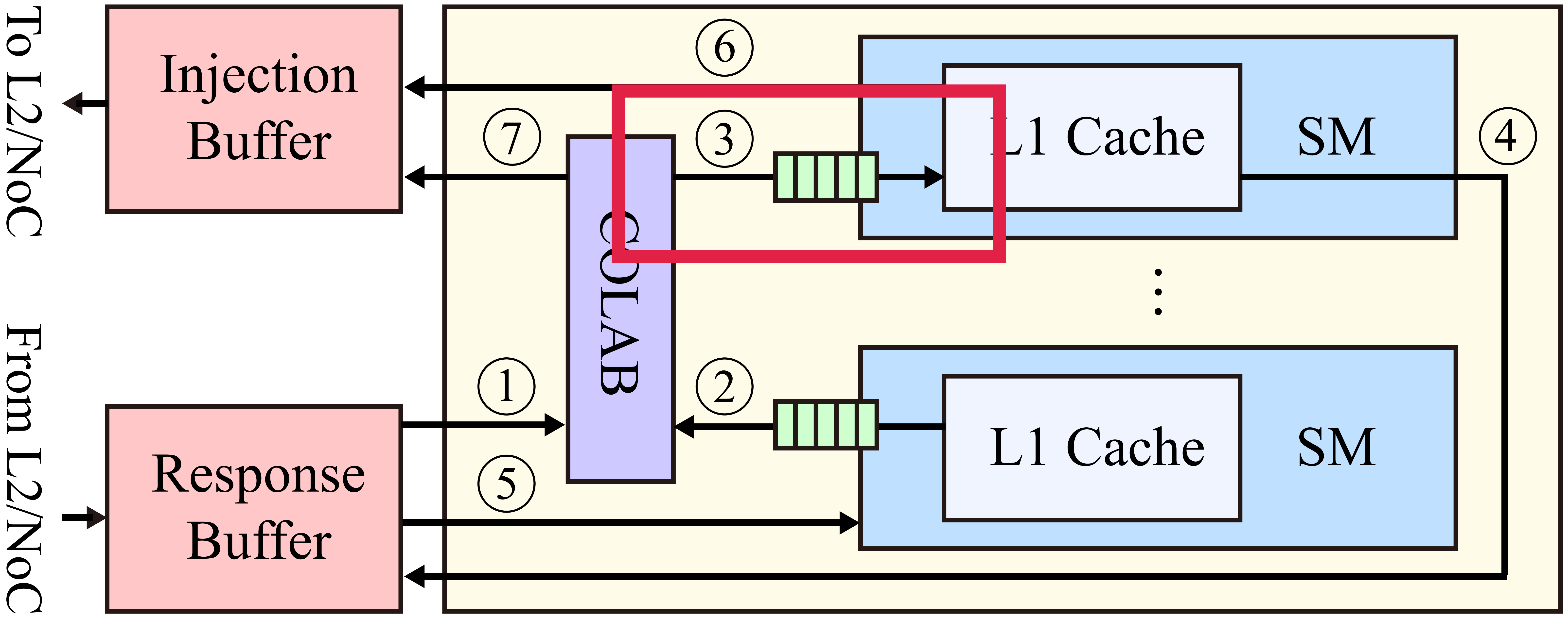
Workflow - False-Positive and False-Negative Errors

- **False-Negative:**
  - **An entry in COLAB may be evicted before its corresponding line is evicted from the L1 cache.**
  - **Miss opportunity.**
- **False-Positive:**
  - **COLAB does not update when a line is evicted from the L1 cache:**
  - **Add extra latency to cache request**
  - **Occupy L1 bandwidth**

Methodology

Workflow - Arbitration Policy between COLAB and Local L1 Requests

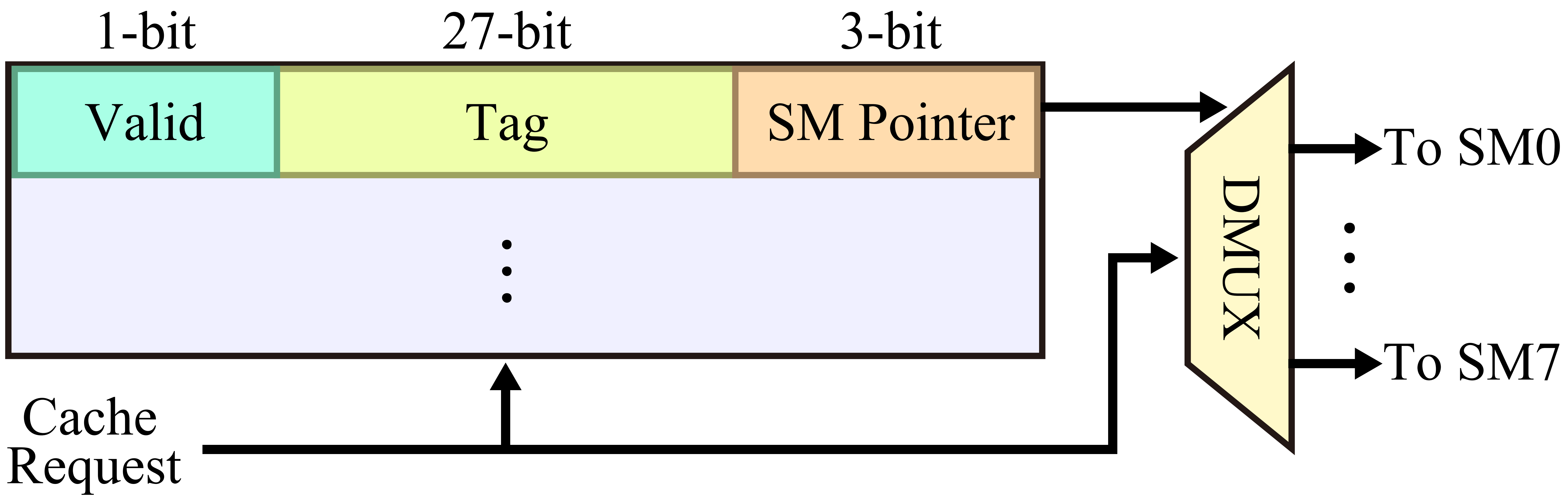
- **L1 cache access bandwidth is shared.**
- **We prioritize COLAB requests over L1 requests.**



Methodology

COLAB Organization

- **Similar to a set-associative cache**
- **Stores a SM pointer instead of the data line.**
- **Utilizes DMUX to route requests to SMs.**



Methodology

Hardware Overhead

- The number of entries in COLAB matches the total number of the L1 cache entries within a cluster.
- Each COLAB is equipped with a 32-entry input queue.
- Each SM is equipped with an 8-entry access queue.
- The total overhead is only 2% of the L1 cache capacity.

Module	# of entries	Size/Entry	Total size
COLAB	$64\,(set) \times 6\,(way) \times 8\,(SM) = 3,072$	31 bits	11.625KB
Queues	$32\,(input) + 8\,(access) \times 8\,(SM) = 96$	8 bytes	0.75KB

Experimental Results

Experimental Results

Experimental Setup - Tools

- The GPU architecture is simulated using GPGPU-sim [6]
- The power consumption and latency of COLAB are estimated conservatively using CACTI [7]
- The power consumption of the rest of the GPU components is calculated using GPUWattch [8]
- The benchmarks used in our experiments are selected from the Rodinia [9], Tango [10], and Polybench [11] benchmark suites

Experimental Results

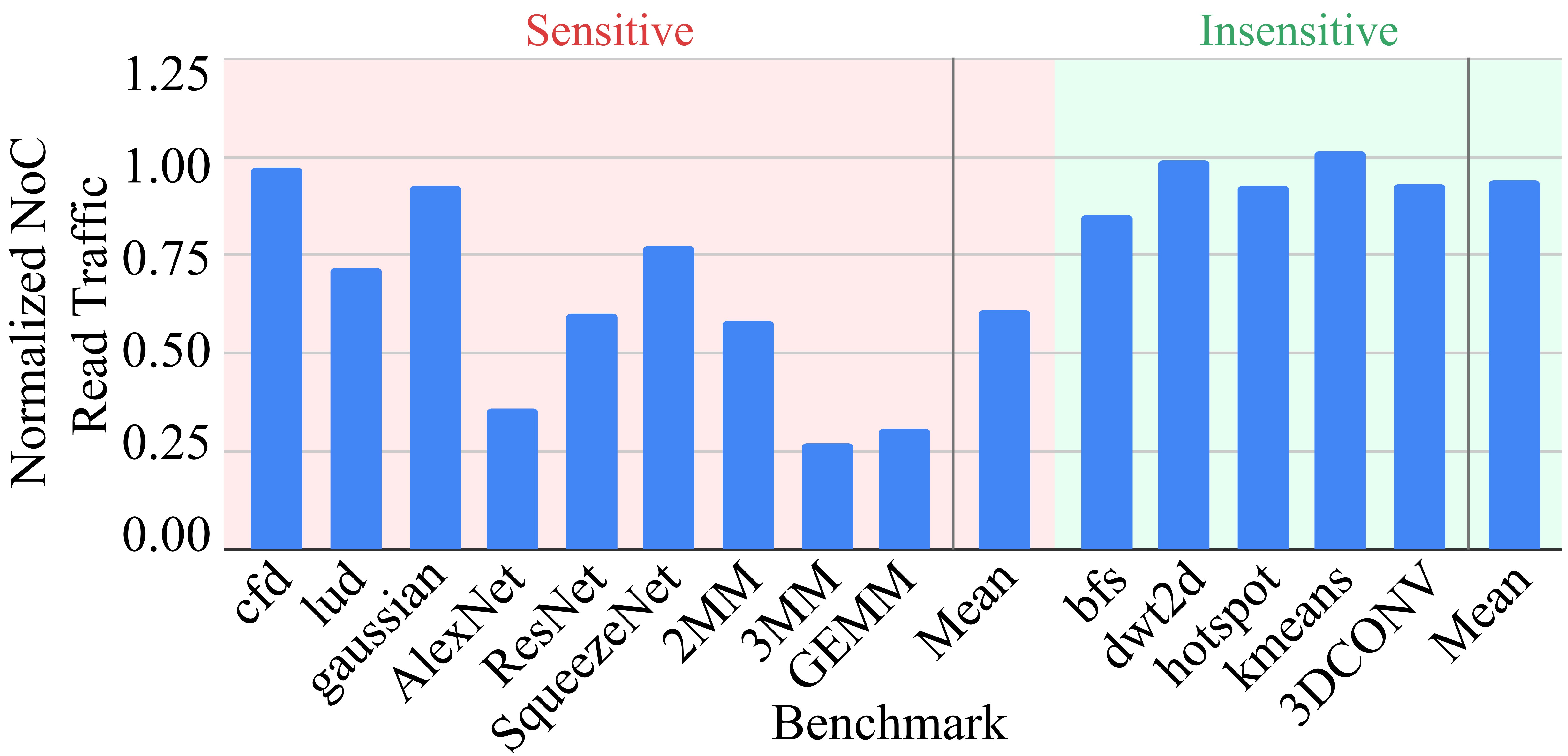
Experimental Setup - GPU Configuration

# of SMs	80, 8 per cluster @1,481MHz
Resources/SM	96KB shared memory, 64KB register, Max. 2048 thread Max. 32 thread blocks.
L1 Caches/SM	Data: 48KB, 6-way, latency=28 cycles, Texture: 48KB, 24-way. Constant: 12KB, 2-way. Instruction: 4KB, 4-way.
L2 Cache	128KB 16-way/Channel (2.75MB total), 128 bytes per line, Latency=120 cycles.
NoC	10×22 crossbar @2,962MHz
DRAM	11 partitions of GDDR5 @2,750MHz. Hynix GDDR5 timing
COLAB	Per-cluster 64-set 48-way lookup table latency=8 cycles

Experimental Results

Experimental Results - NoC Read Traffic Reduction

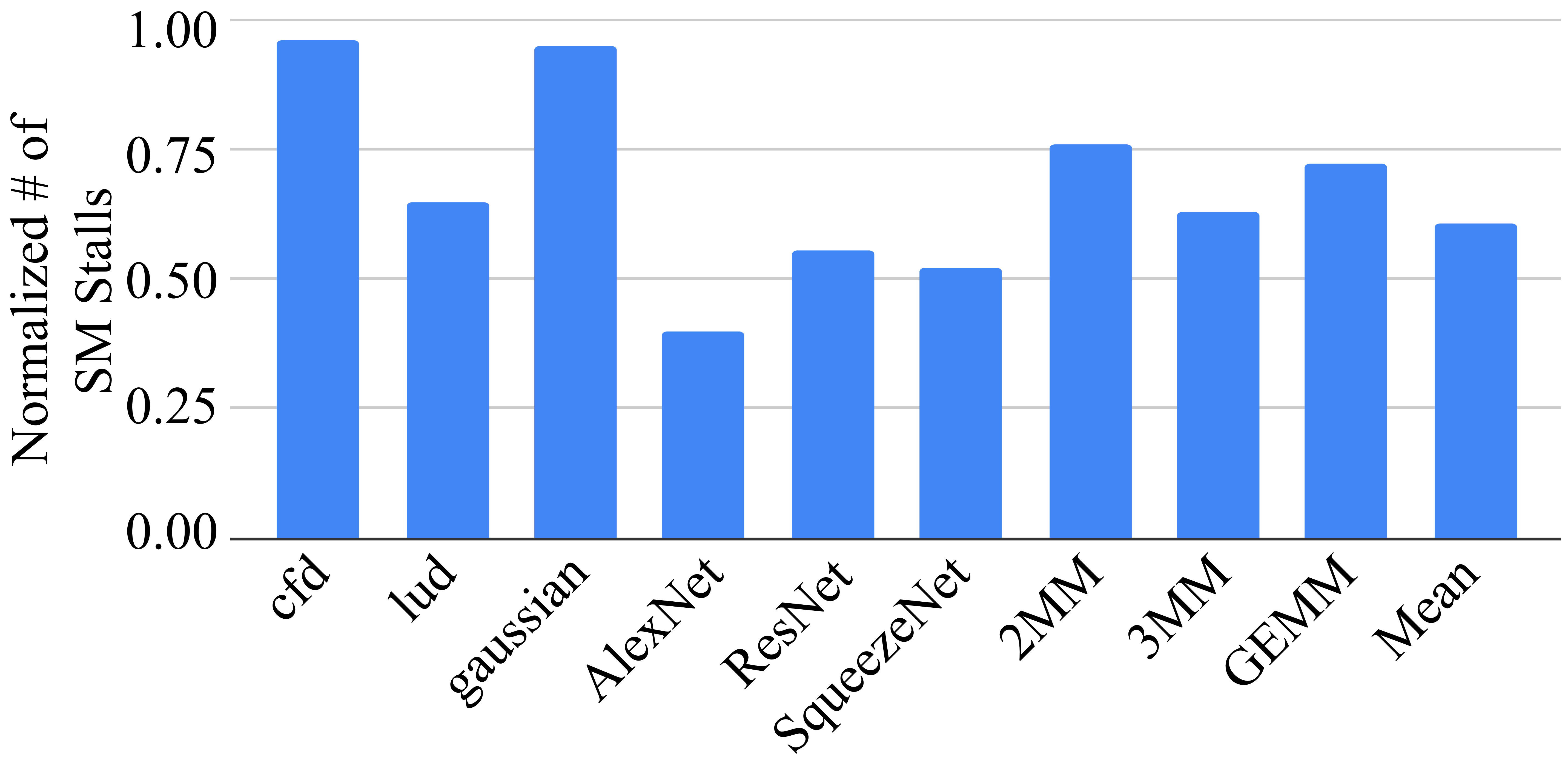
On average, the incorporation of COLAB can reduce 38% of NoC read traffic for replication-sensitive benchmarks by capturing replicated cache requests.



Experimental Results

Experimental Results - Stalls Reduction

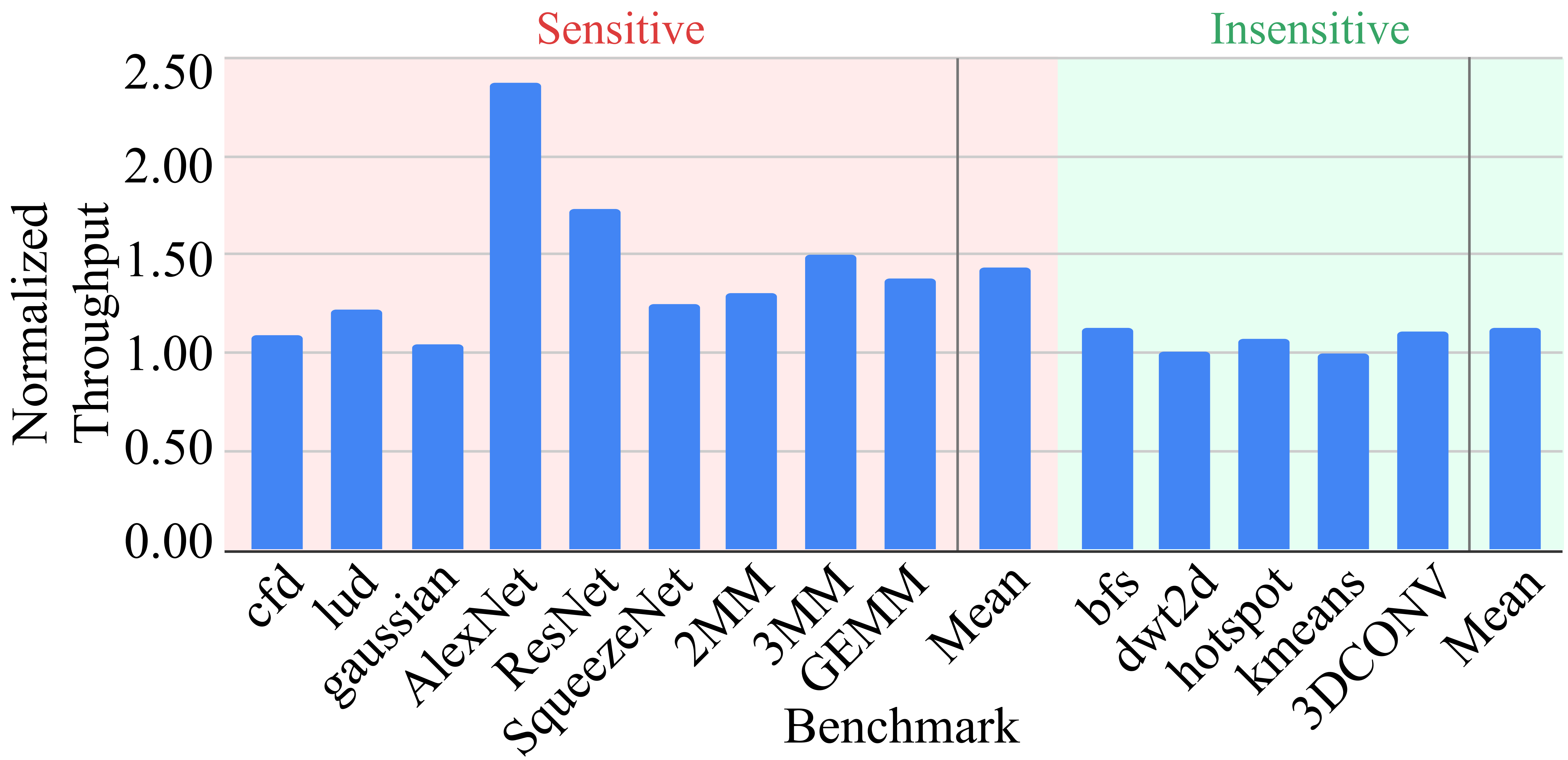
By reducing traffic, the number of stalled cycles due to NoC congestion is reduced by 40% for replication-sensitive benchmarks.



Experimental Results

Experimental Results - Performance Improvement

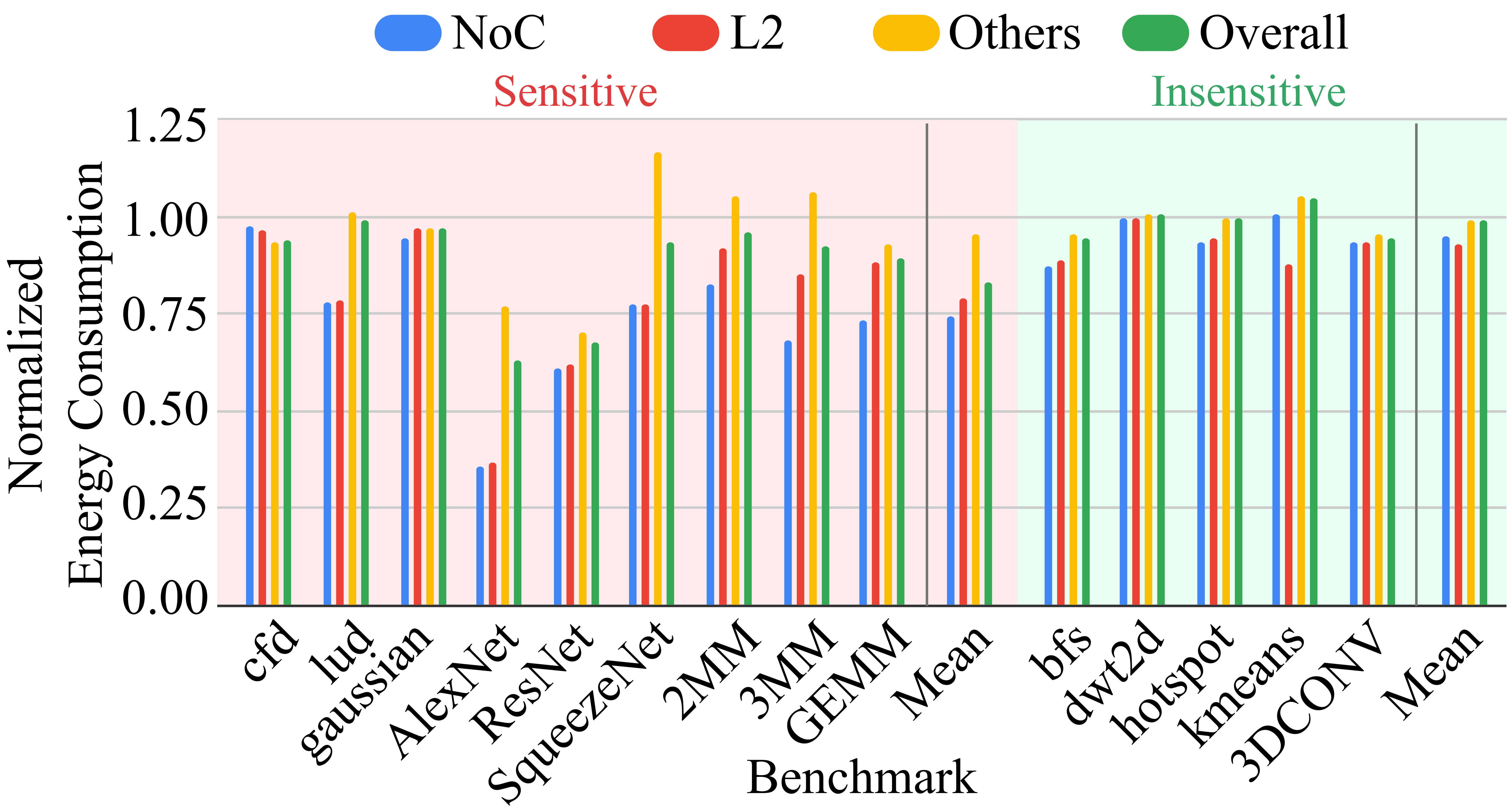
By reducing the number of stalled cycles, the computing throughput of the GPU is improved by an average of 43% for the replication-sensitive benchmarks.



Experimental Results

Experimental Results - Energy Evaluation

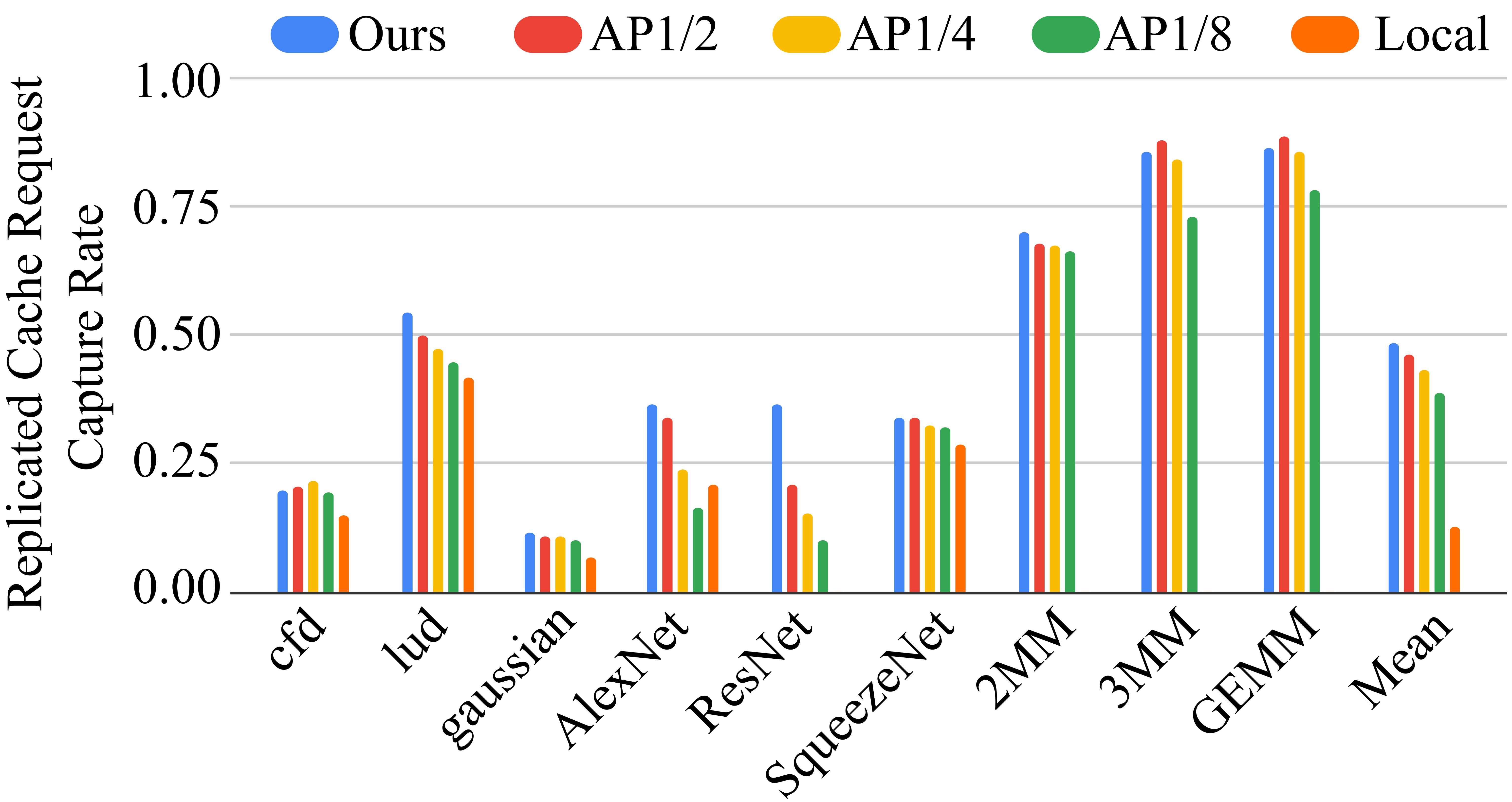
By reducing the NoC traffic and L2 accesses, COLAB can reduce the overall energy consumption of the replication-sensitive benchmark by 17%.



Experimental Results

Ablation Analysis - Arbitration Policy

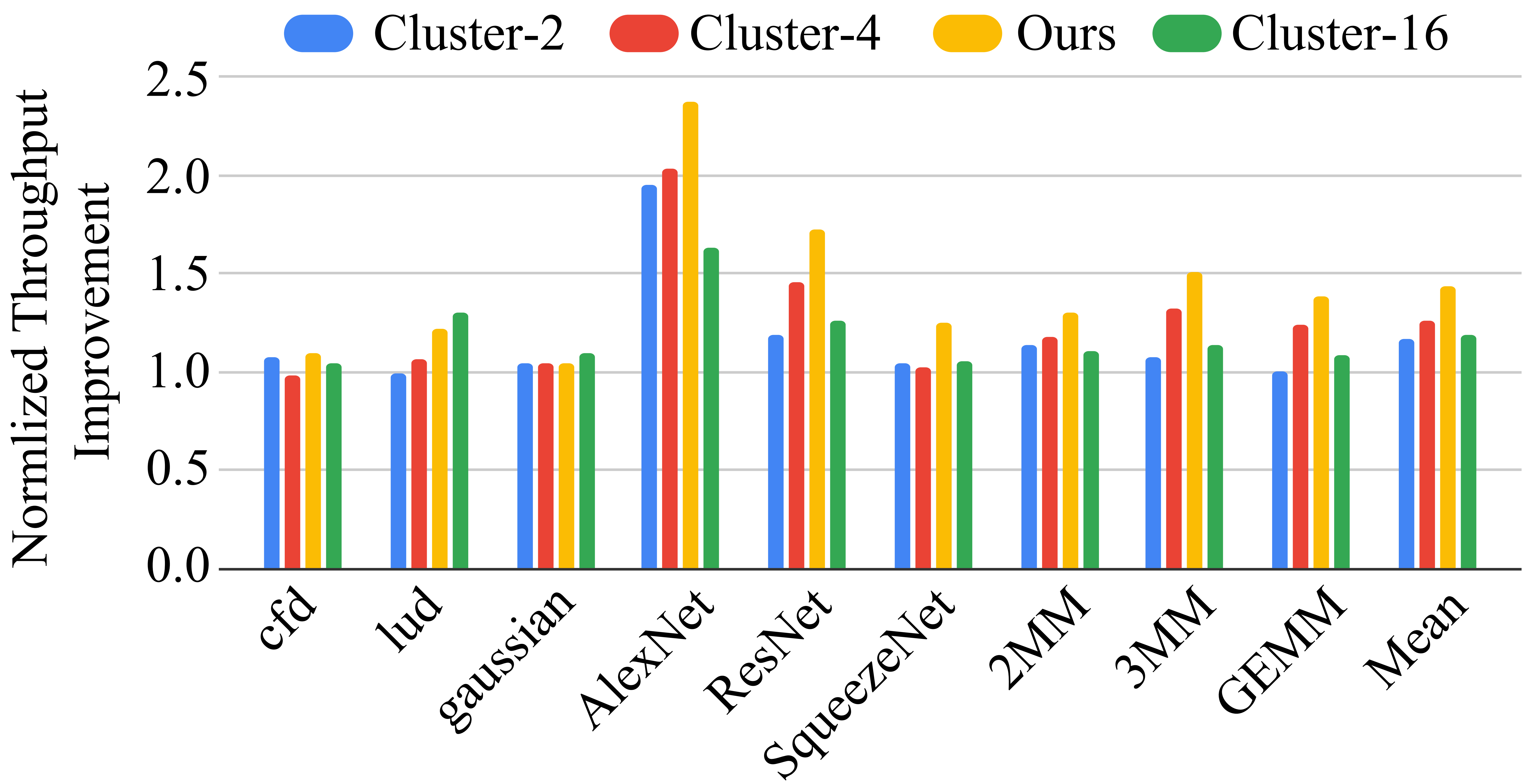
The proposed arbitration policy that prioritizes COLAB requests allows COLAB to capture the most replicated cache requests compared to other policies.



Experimental Results

Ablation Analysis - Cluster Size

COLAB is able to provide performance improvement regardless of the cluster size. However, the improvement is most significant when the cluster size is 8.



Conclusion

Conclusion

- We propose COLAB, an addition to the baseline GPU architecture that captures and redirects replicated cache requests within an SM cluster.
- By servicing replicated cache requests cooperatively within an SM cluster, COLAB is able to prevent replicated cache requests from entering the NoC network and consuming its precious bandwidth.
- Our experimental results demonstrate that COLAB can indeed reduce NoC read traffic and GPU stalled cycles and improve overall GPU performance while incurring limited hardware overhead.
- Our ablation analysis validates the design choices made while designing COLAB.

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