Performance and Scalability of Storage Systems
Per3s 2025

Bridging Local Efficiency and Global Cost: Two Complementary ICN Caching Strategies

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Outline

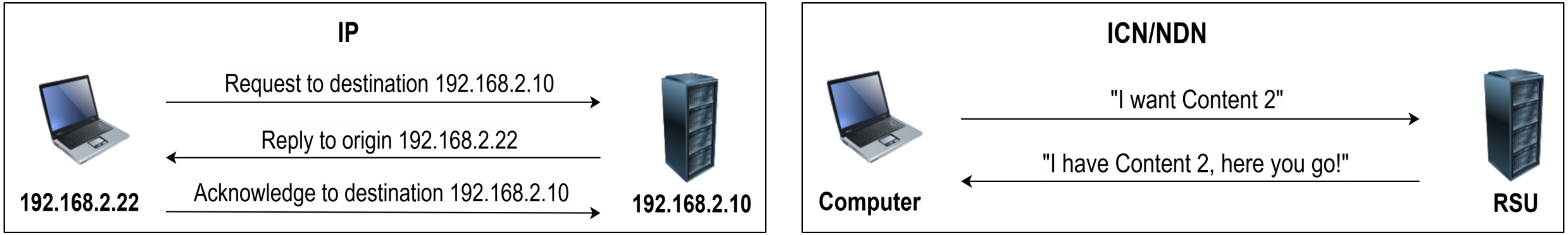
1. Context
2. Problems Statements
3. Solution
4. Evaluation
5. Conclusion and Perspective

Outline

Context
Data Explosion and the Shift to ICN

- 149 ZB of data created in 2024 ➜ Projected 394 ZB by 2028 [1].
- Traditional IP networks struggle with Scalability and Efficiency [2, 3].
- ICN (Information-Centric Networking) [4] addresses this via:
  - Content-based addressing **&** In-network caching

→The need for **caching strategies** to improve performance & scalability



Same references as in the paper

Context

Caching Challenges: Node and Network Perspectives

Node-side (Centralized Strategies):

- Storage demand grows faster than deployment capacity [7].
- Multi-tier architectures (DRAM, SSD, HDD) complicate caching due to varying costs, lifespans, and performance [8-10].
- User-specific Service Level Agreements - SLAs define performance expectations [4], but most caching approaches ignore per-user QoS [5].

Network-side (Distributed Strategies):

- High energy and bandwidth costs associated with data movement [11].
- QoS constraints (latency, throughput …) via SLAs.
- Caching strategies overlook QoS, limiting overall efficiency.

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Problems Statements

1. How do we design a multi-tier cache for applications that require different quality of service ?

2. How can we design a distributed caching strategy that reduces redundancy and cost?

State of the art

Why Current Caching Falls Short: Node and Network Perspectives

Category	Centralized				Distributed			
Criteria	Recency	Frequency	QoS	Heterogeneity	Cost	Redundancy	Popularity	Energy
LRU	✓	✗	✗	✗	✗	✗	✗	✗
LFU	✗	✓	✗	✗	✗	✗	✗	✗
LIRS [12], ARC [13], LeCar [26], LHD [14],autocache [27], CALC [15], ML-LIRS [28],Cacheus [16], SS-LRU [17], GL-Cache [29],Baleen [18]	✓	✓	✗	✗	✗	✗	✗	✗
Flashield [30]	✓	✓	✗	✓	✗	✗	✗	✗
QM-ARC [19]	✓	✓	✓	✓	✗	✗	✗	✗
LCE/LCD [20]	✗	✗	✗	✗	✗	✓	✓	✗
MPC [31], MAGIC [32], CPCCS [23],PDPU [24], CPCache [25]	✗	✗	✗	✗	✗	✓	✓	✗
CL2SM	✓	✓	✓	✓	✓	✓	✓	✓

Same references as in the paper

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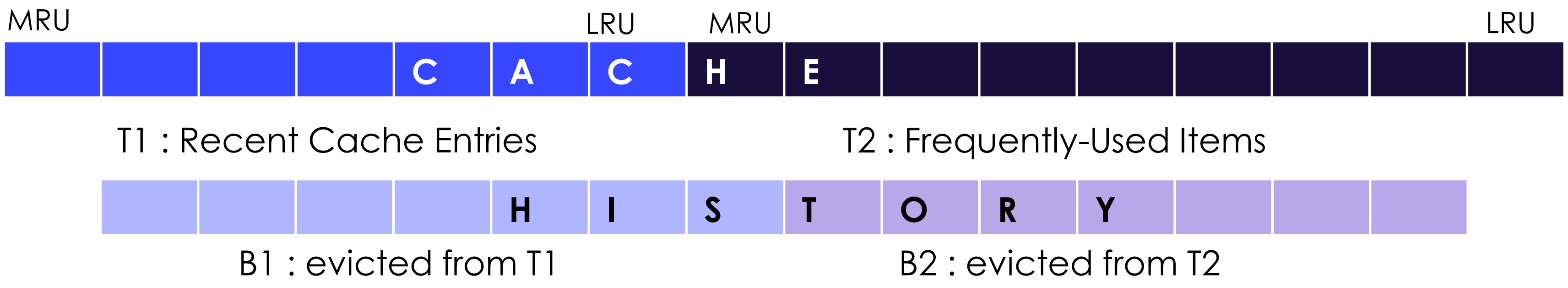
Context

ARC - Adaptive Cache Replacement

- **ARC - Adaptive Cache Replacement [6]:**
  - One of the most popular and efficient generic algorithms in the rich caching literature.
  - ARC maintains two LRU lists: T1 contains objects that have only been requested once, and T2 contains objects that have been requested at least twice.
  - ARC uses two LRU ghost lists: B1 and B2, which contain references to data that has been evicted from T1 and T2, respectively.
  - Cache miss → Insert in Most Recently Used-MRU position in T1.
  - Hit in T1, T2, B1, B2 → Promote data to MRU position in T2.
  - ARC dynamically adapts P, the size of the list T1 (size of T2 = cache size - P). Hit in B1 → Increase in P. Hit in B2 → decrease in P.
  - ARC does not take QoS into account and is originally designed for single-tier cache.



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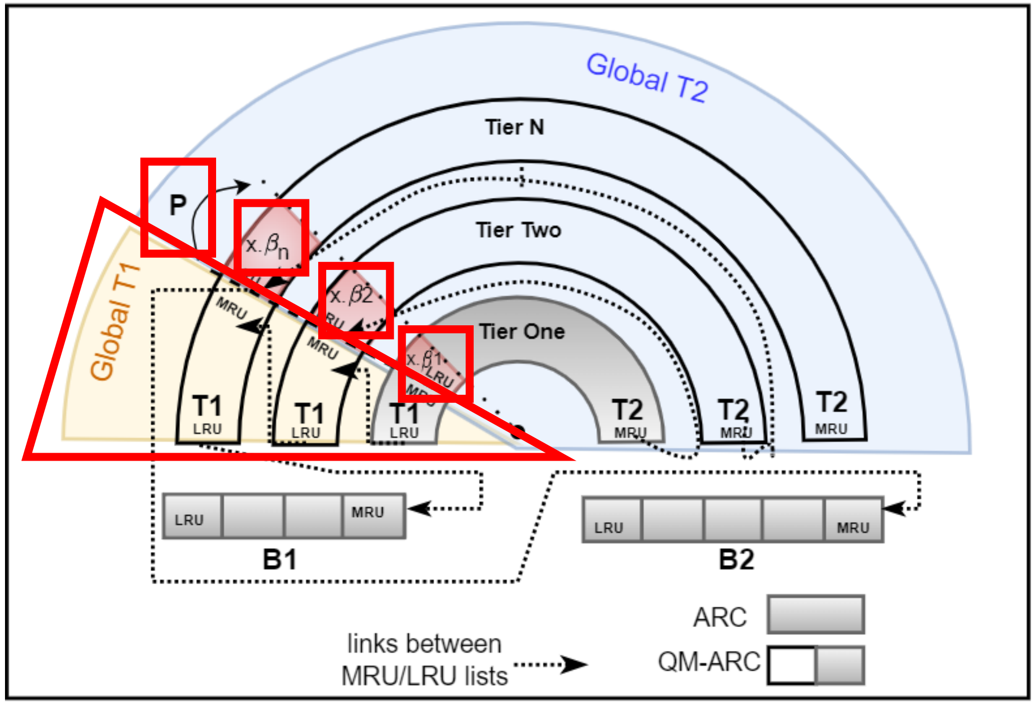
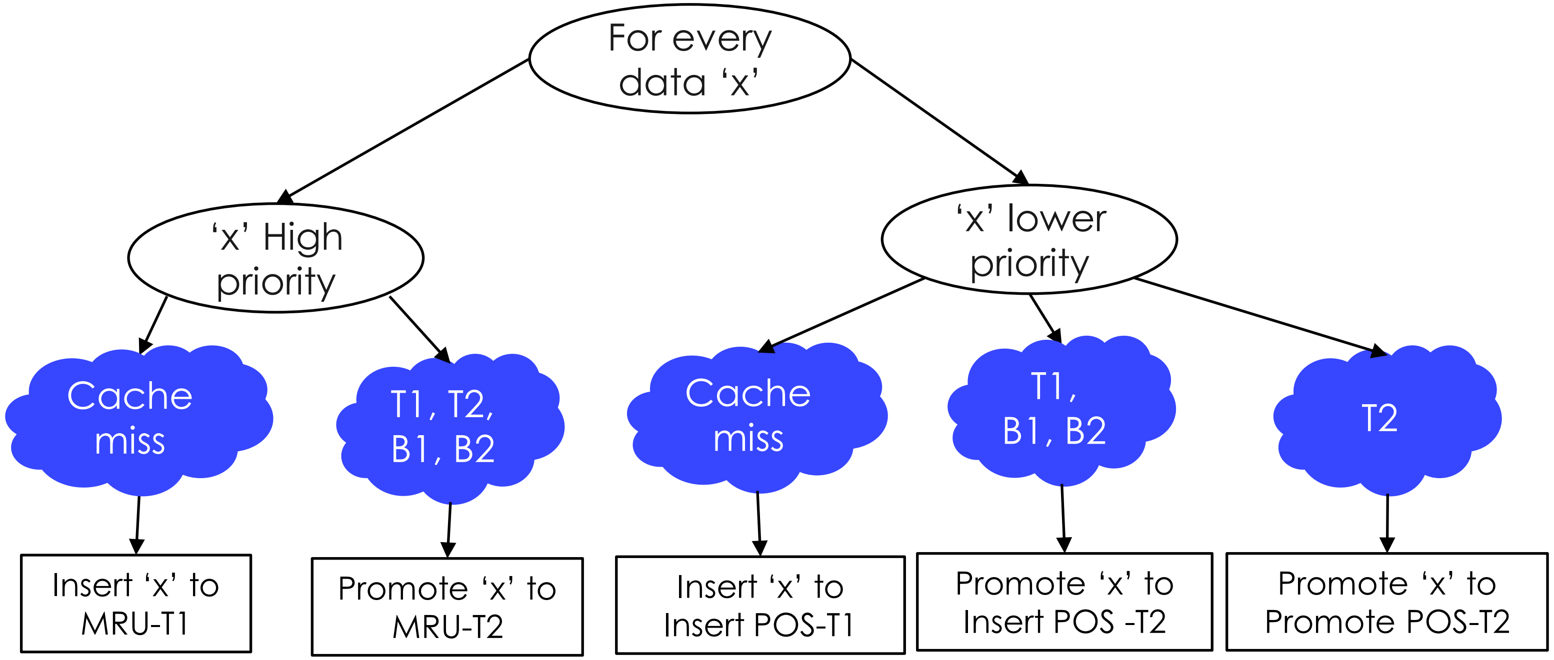
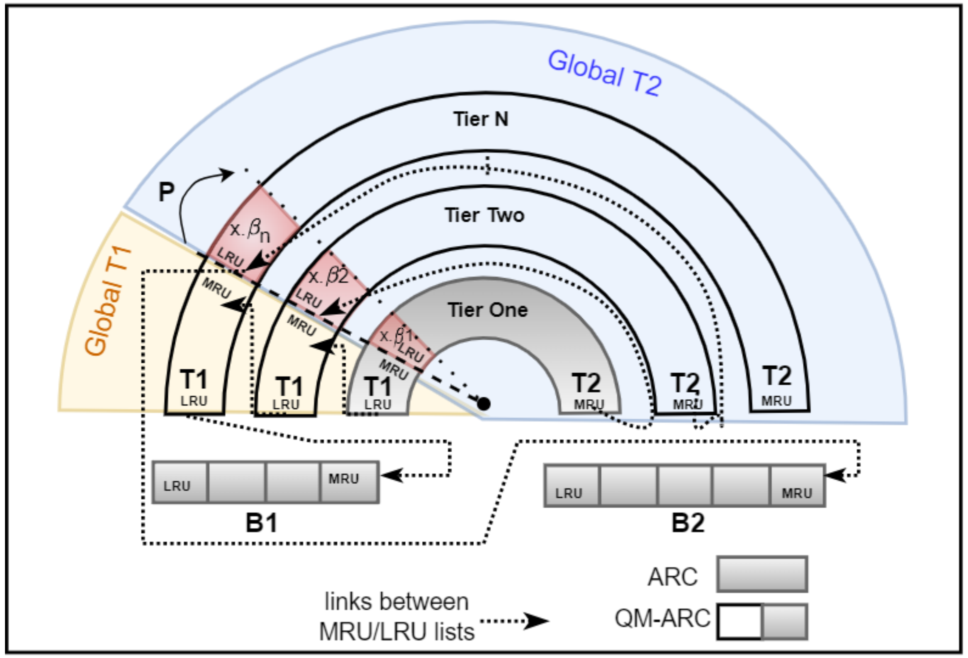
QM-ARC
QoS-aware, Multi-tier ARC policy

- QM-ARC improves upon ARC in two key areas:
  - **Multi-Tier Caches**: QM-ARC supports heterogeneous memory systems through dynamic local and global cache list size adjustments across the tiers using β_i.
  - **QoS-Based Caching**: QM-ARC integrates QoS by adopting SLA and penalty-based management, from the Cloud, using priority levels to calculate the index for insertions and promotions using γ_k.



QM-ARC
Explained





- Index calculation for insertion and promotion based on QoS using $\gamma_k = \mathrm{Penalty}_k \ / \ \mathrm{Penalty}_0$
- Proportional size adjustment of the global lists, distributed between tiers using $\beta_i = |\mathrm{tier}_i| \ / \ |\mathrm{tier}_1|$

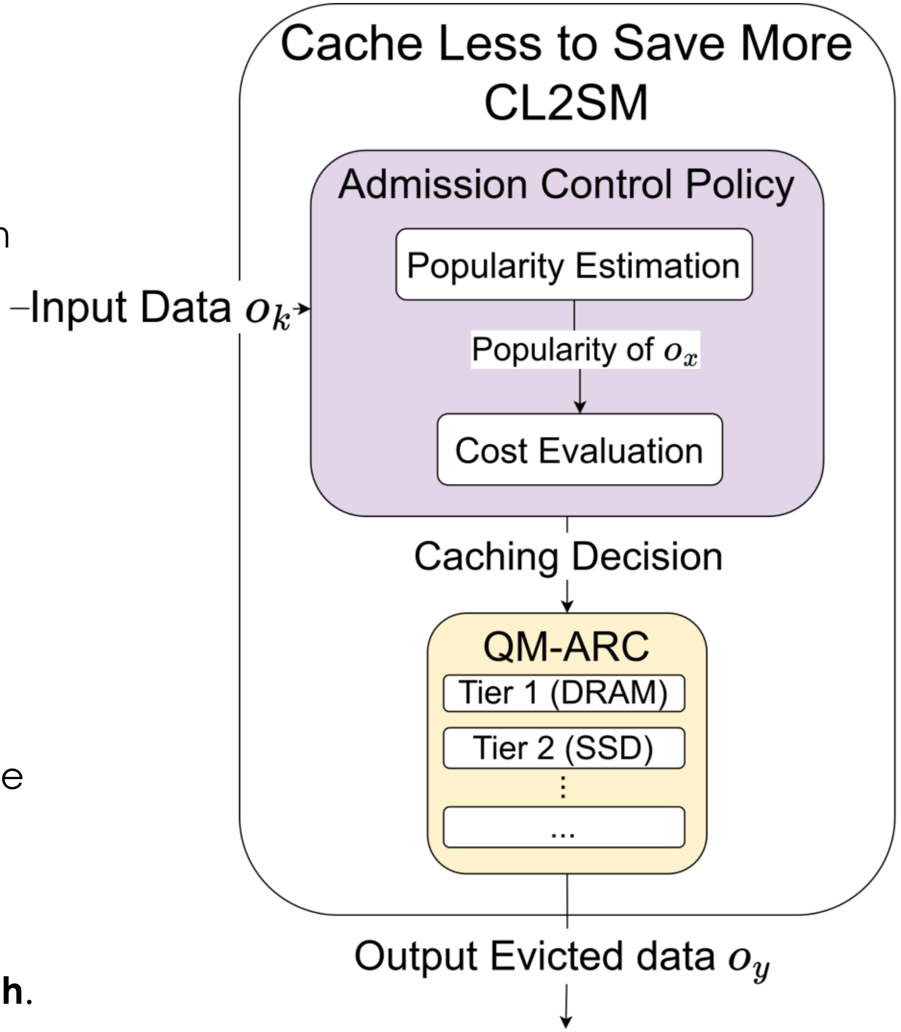
CL2SM
Cache Less to Save More

- Our proposed CL2SM caching strategy is composed of **three** core modules:

1. **Popularity Estimation:**
   - Each node maintains per-item request counters that are incremented with every request (even if not cached)
   - Popularity is calculated only for cached items:

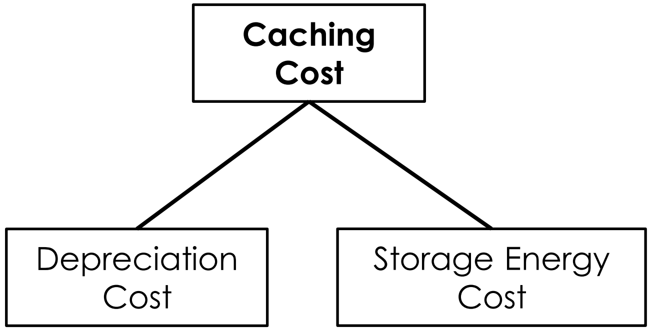
$$\text{Popularity(k)} = \frac{\text{Requests for data k}}{\text{Requests for all data in current node}}$$

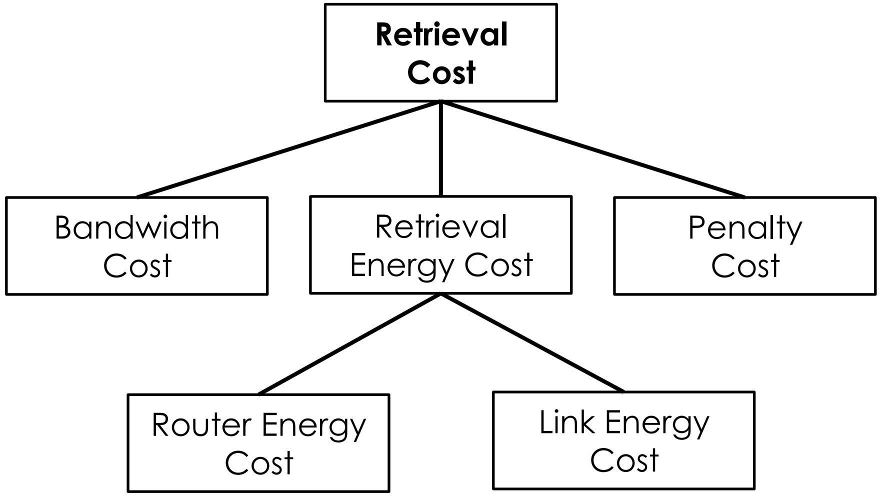
2. **Cost Evaluation:**
   - Determines the benefit of caching each item based on a **Gain vs. Loss** principle:
     - **Gain** = (Local Popularity) × (**Retrieval Cost** Saved by Caching)
     - **Loss** = (**Caching Cost** of the Item) + (Cost of Evicting an Existing Item)
   - If **Gain > Loss**, the item with the lowest gain in the cache is evicted to make space.
3. **Enhanced QM-ARC:**
   - Evicts data based on both **recency** and **retrieval cost**.
   - From the least recently used 10%, we remove the **cheapest item to re-fetch**.



CL2SM
Cost Model

- **Caching cost**: The cost incurred when storing data locally, including device depreciation and the energy consumed during read and write operations.
- **Retrieval cost**: The cost of fetching data from remote nodes when it is not cached locally. This includes band-width usage, energy for routing and forwarding, and potential penalties for SLA violation.

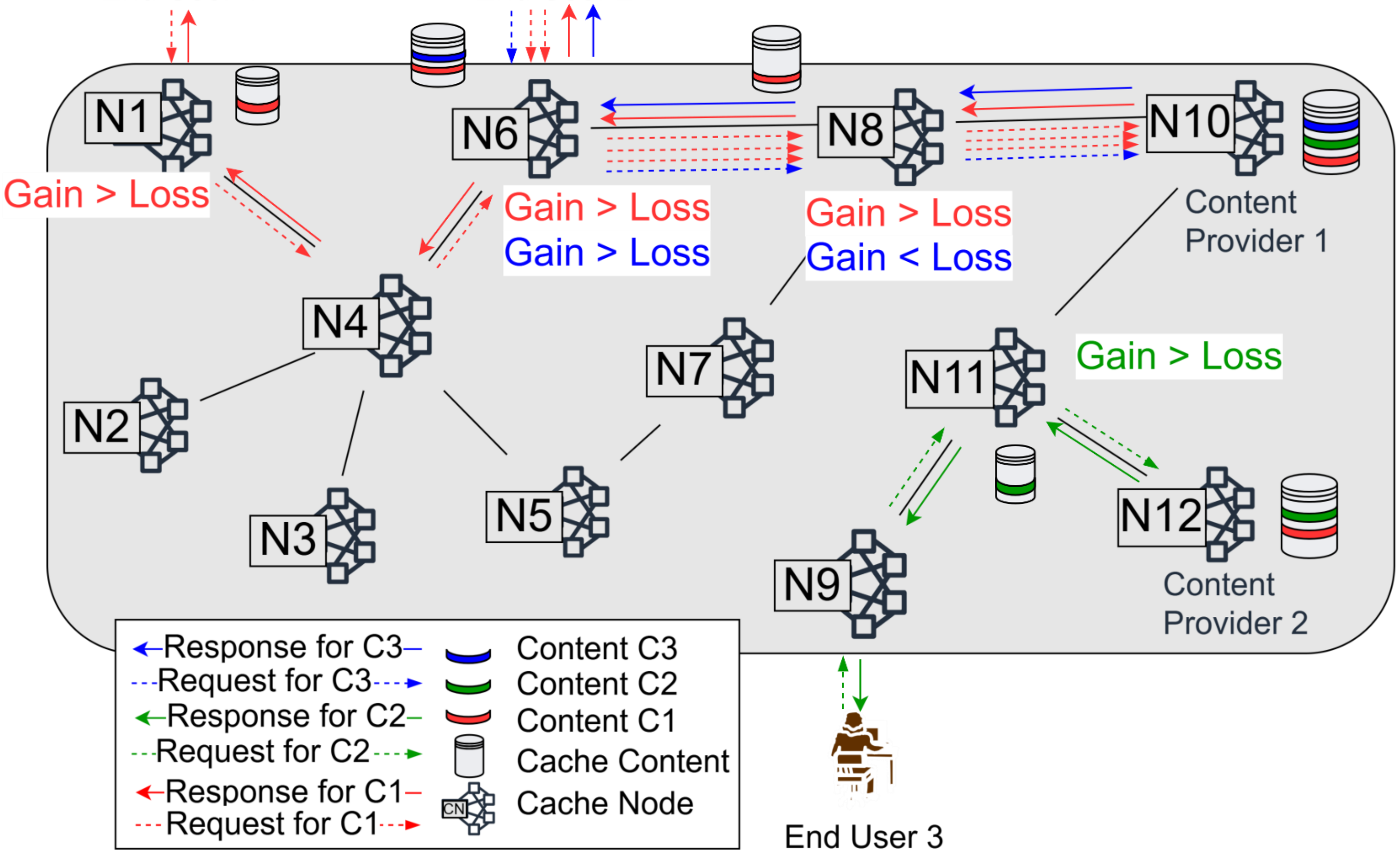




CL2SM
Recapitulative

ICN Architecture

Cache Node N8		
Content Name	Request Counter	Cache Gain
C1	3	0.9
C3	1	0.2



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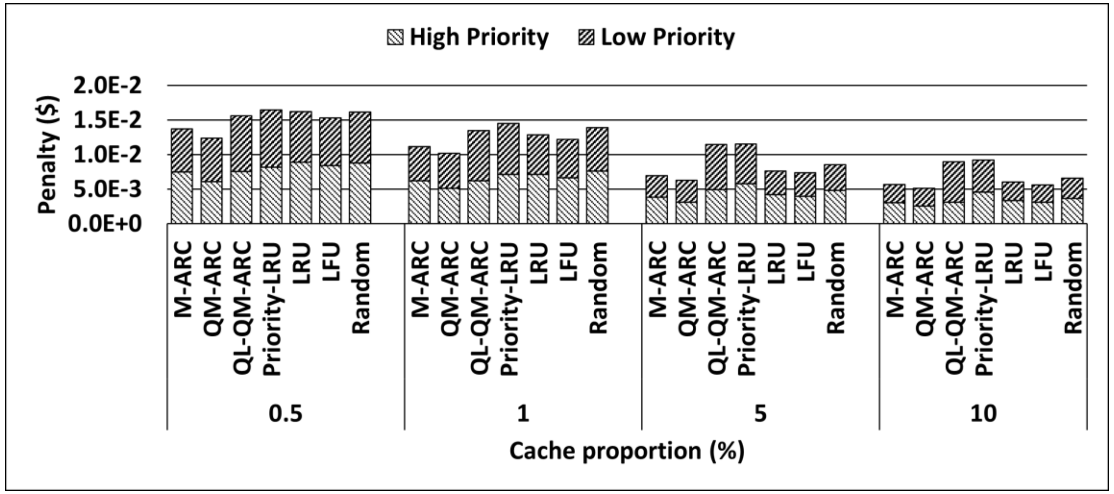
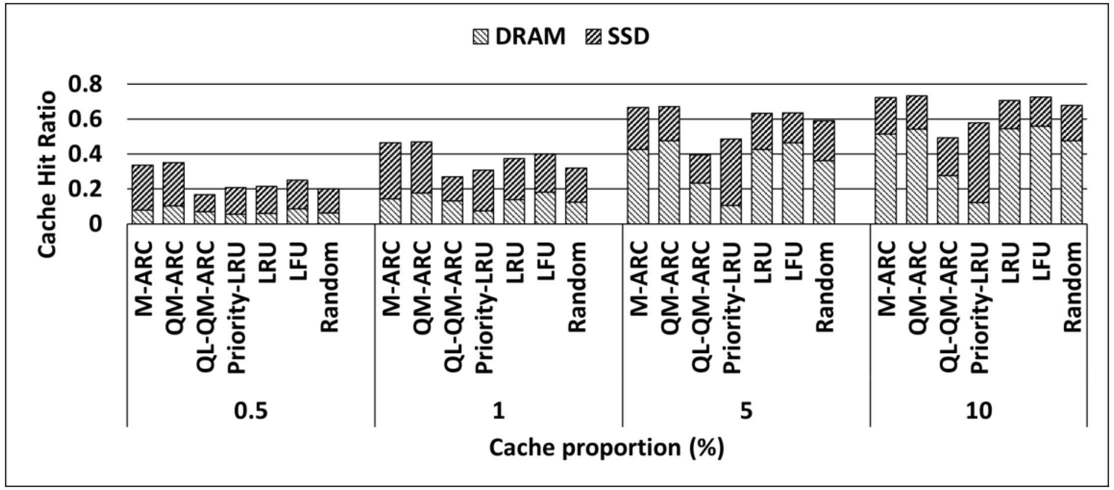
Evaluation : QM-ARC

- **Simulator:**
  - Implementation of a cache simulator with Simpy a discrete event simulation framework based on standard Python.
  - Link to the simulator: https://github.com/Multi-Tier-Cache-Simulator/MultiTierCacheSimulator

- **Methodology:**
  - **Experiment**: vary cache proportion as a function of dataset size [0.5% - 10%].
  - **Traces**: use of Zif-like synthetic and real traces (IBM and Jedi [28]).
  - **Solutions compared**: **QM-ARC** and LRU, LFU, Random, Priority-LRU[16], M-ARC.
  - **Evaluation criteria**: penalty, overall hit rate, hit rate per priority level
  - **Two** priority levels: **20%** of the data is high priority.
  - **System**: 2-tiers, the first one is DRAM, the second is SSD, the size of the DRAM is a fifth of the SSD

Results: QM-ARC





- **Penalty:**
  - QM-ARC cuts penalty by 80% as cache size grows.
- **Global Hit Ratio:**
  - M-ARC & QM-ARC lead with a 48% increase.
- **High-Priority Hit Rate:**
  - QM-ARC boosts hits by 67%, leveraging the fastest tier.
- **Low-Priority Hit Rate:**
  - M-ARC outperforms as QM-ARC favors high-priority data—validating its QoS strategy.

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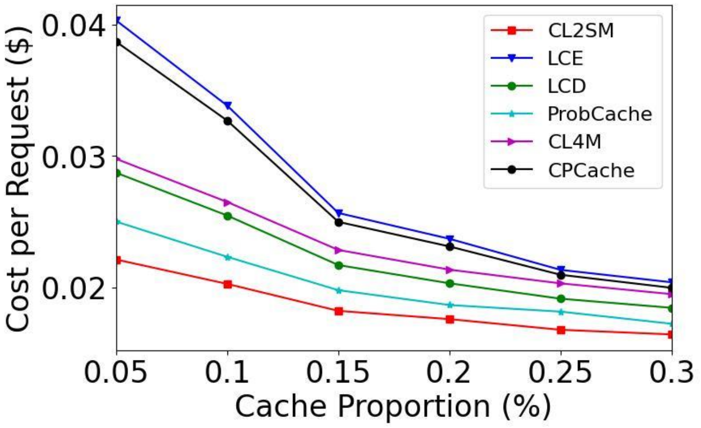
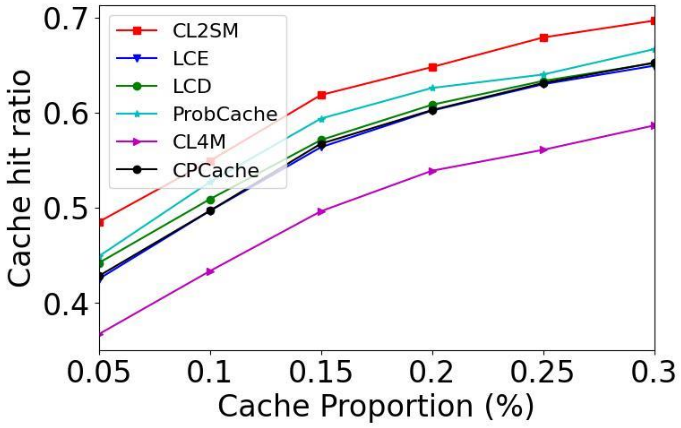
Evaluation : CL2SM

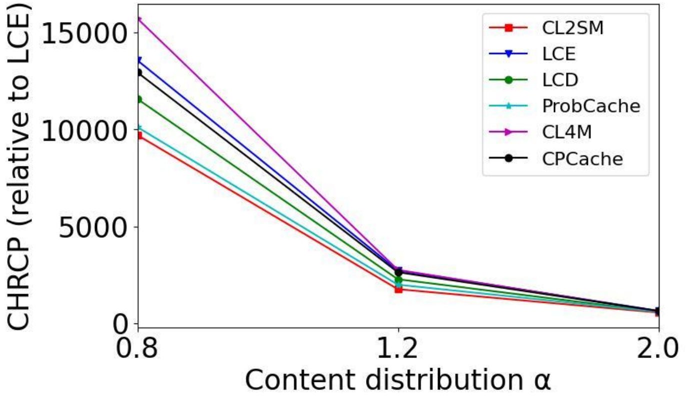
- **Simulator**:
  - Icarus[37] a Python-based discrete-event simulator developed for ICN, focusing on the performance evaluation of caching mechanisms.
  - Link to the simulator: https://github.com/LydiaNosali/icarus/tree/qmarc

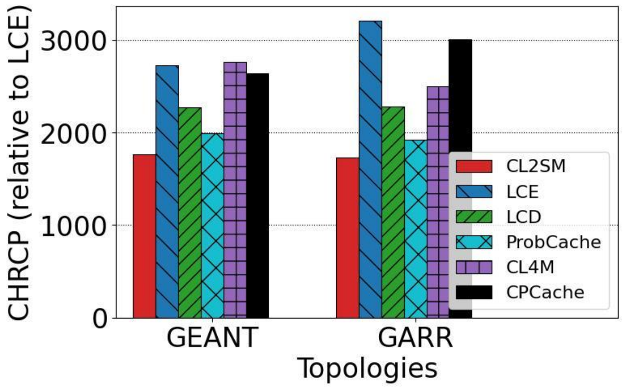
- **Methodology**:
  - **Experiments:**
    - **Experiment 1:** vary cache proportion as a function of dataset size [0.05% - 0.3%].
    - **Experiment 2:** vary content distribution alpha of the Zipf Law [0.8, 1.2, 2.0]
    - **Experiment 3:** vary topologies [GEANT and GARR].
  - **Solutions compared: CL2SM** and LCE, LCD, Prob-Cache [21], CL4M [24], CPCache [25].
  - **Evaluation criteria:** Cost per request, Global hit rate, Cache Hit Ratio Cost Product (CHRCP), Latency
  - **Two** priority levels: **20%** of the data is high priority.
  - **System**: 2-tiers, the first one is DRAM, the second is SSD, the size of the DRAM is a fifth of the SSD

Results: CL2SM









- CL2SM balances caching and retrieval costs, offering a trade-off between storage overhead and access efficiency.
- Caching more does not necessarily mean better performance.
- Strong performance at moderate skew ($\alpha = 1.2$), where both **cost** and **popularity** are relevant.
- **CL2SM** adapts effectively to diverse network structures as CHRCP is stable.

Outline

Conclusion and Perspective

Summary:

- Design of **CL2SM**, a unified caching algorithm for ICN that:
  - Integrates **centralized** and **distributed** caching strategies
  - Uses **content popularity** + **cost model** (energy, transmission, SLA penalties)
- Supports **multi-tier storage** with the use of **QM-ARC** as a replacement strategy

Benefits:

- **Adaptive & cost-efficient**
- **QoS-aware**, models real device behavior
- Promotes **performance & sustainability**

For future work:

- Reduce **carbon footprint** of caching

Thank you for your attention !

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