SHARDS & Talus: Online MRC estimation and optimization for very large caches

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Introduction

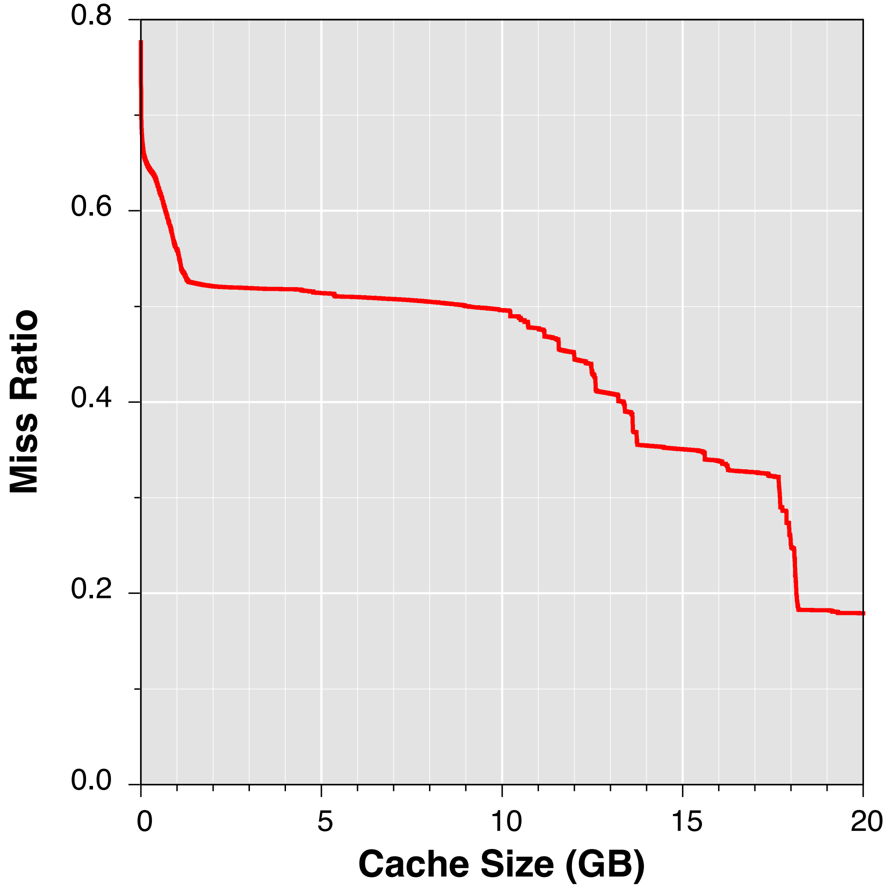
- *Efficient MRC Construction with SHARDS* – FAST’15 Waldspurger at al.
- *Talus: A simple way to remove cliffs in cache performance* – HPCA’15 Beckmann and Sanchez

- Two complementary techniques that improves cache performance
- Both techniques rely on same finding.

SHARDS

Efficient MRC Construction with SHARDS

Modeling Cache Performance

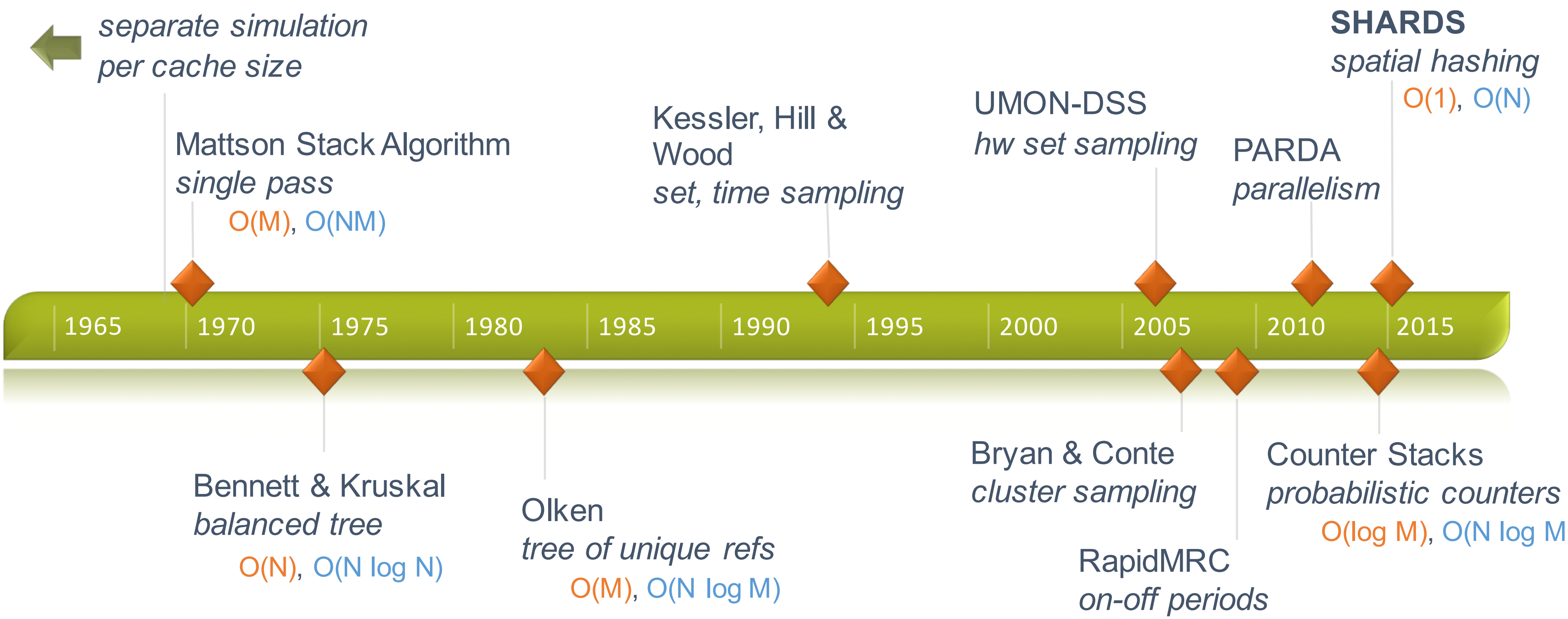


- Miss Ratio Curve (MRC)
  - Performance as *f* (size)
  - Working set knees
  - Inform allocation policy
- Reuse distance
  - Unique intervening blocks between use and reuse
  - LRU, stack algorithms

Motivation

- Cache partitioning.
- Simulation of various cache parameters.
  - Cache block size, write handling, shadow partition
- Workload partitioning.
  - By IO meta information (IO size, filesystem info, etc.)
- Problem: requires online modeling expensive
  - Too resource-intensive to be broadly practical
  - Exacerbated by increasing cache sizes

MRC Algorithm Research

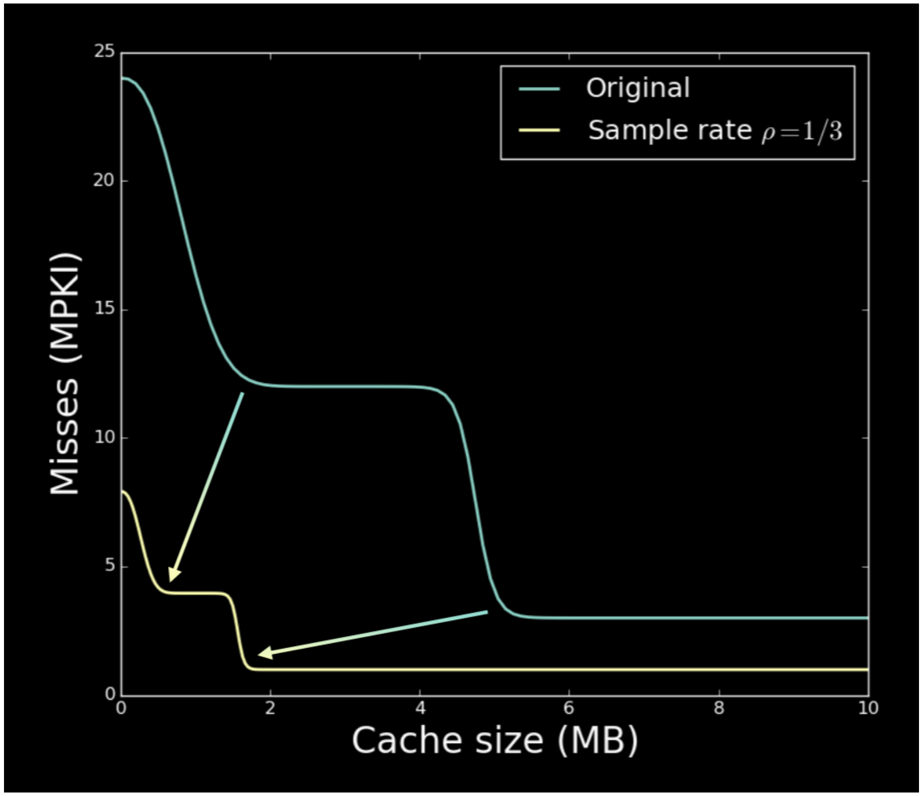


Space, Time Complexity

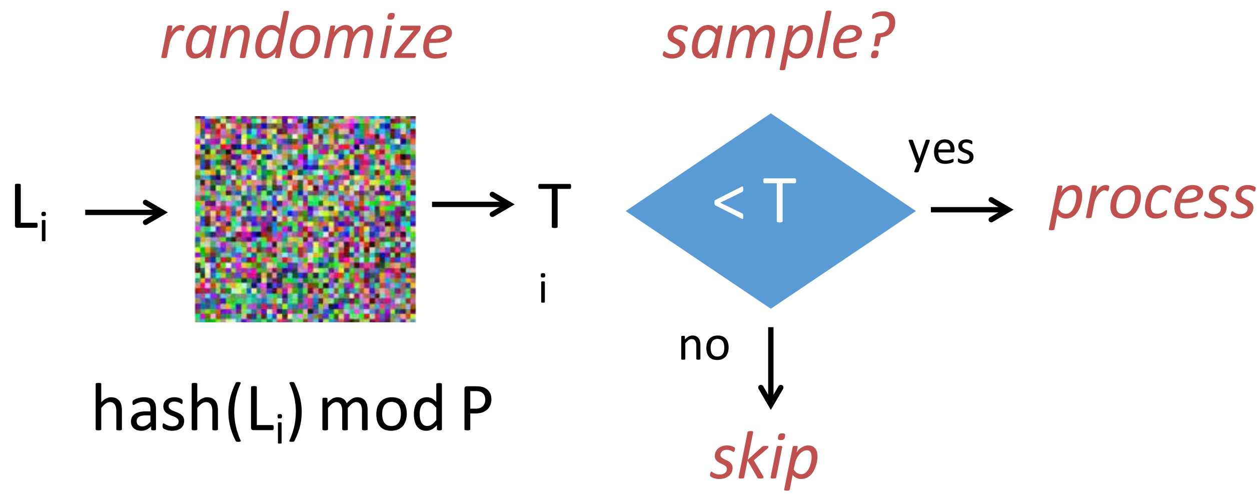
N = total refs, M = unique refs

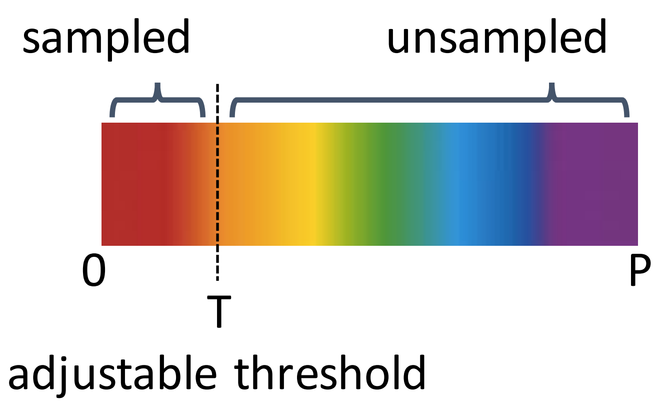
Key Idea

- Random spatial sampling results in a smilar MRC scaled by the sampling rate.



Spatially Hashed Sampling

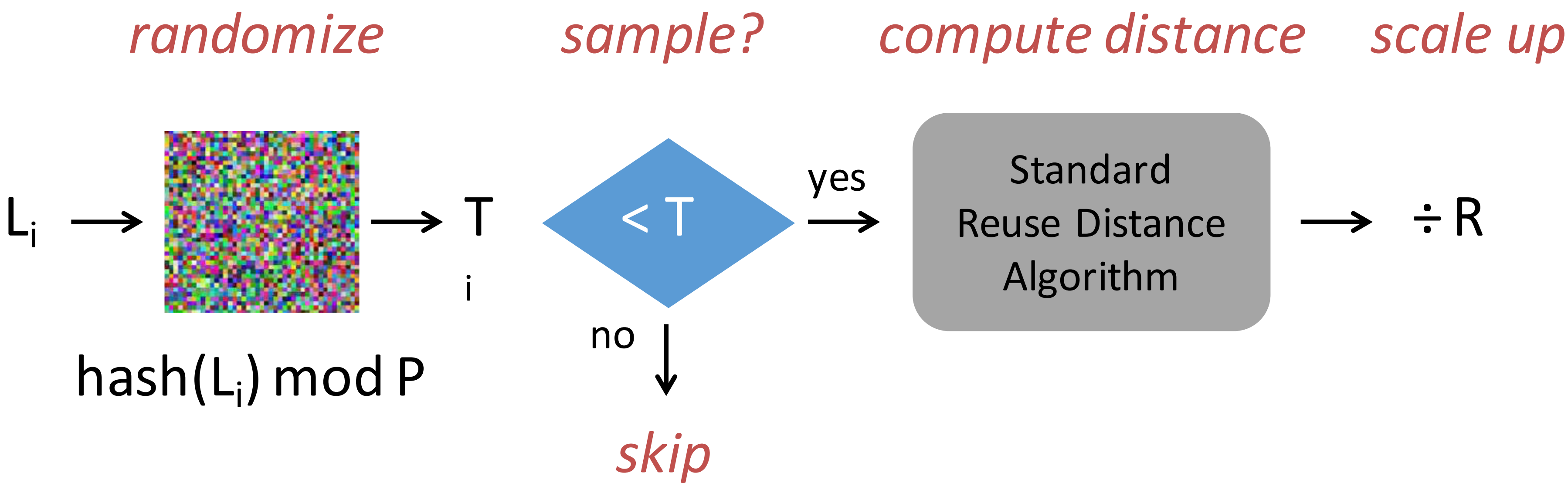




sampling rate R = T / P

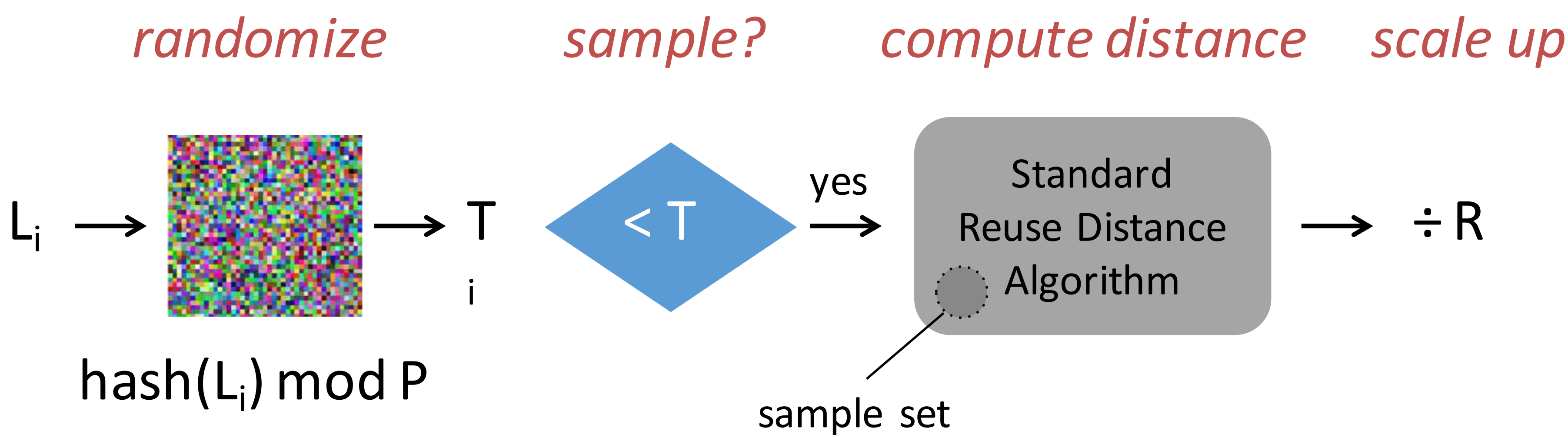
subset inclusion property
maintained as R is lowered

Basic SHARDS

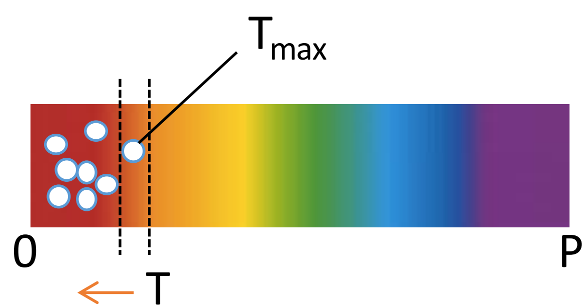


Each sample statistically represents 1 / R blocks
Scale up reuse distances by same factor

SHARDS in Constant Space



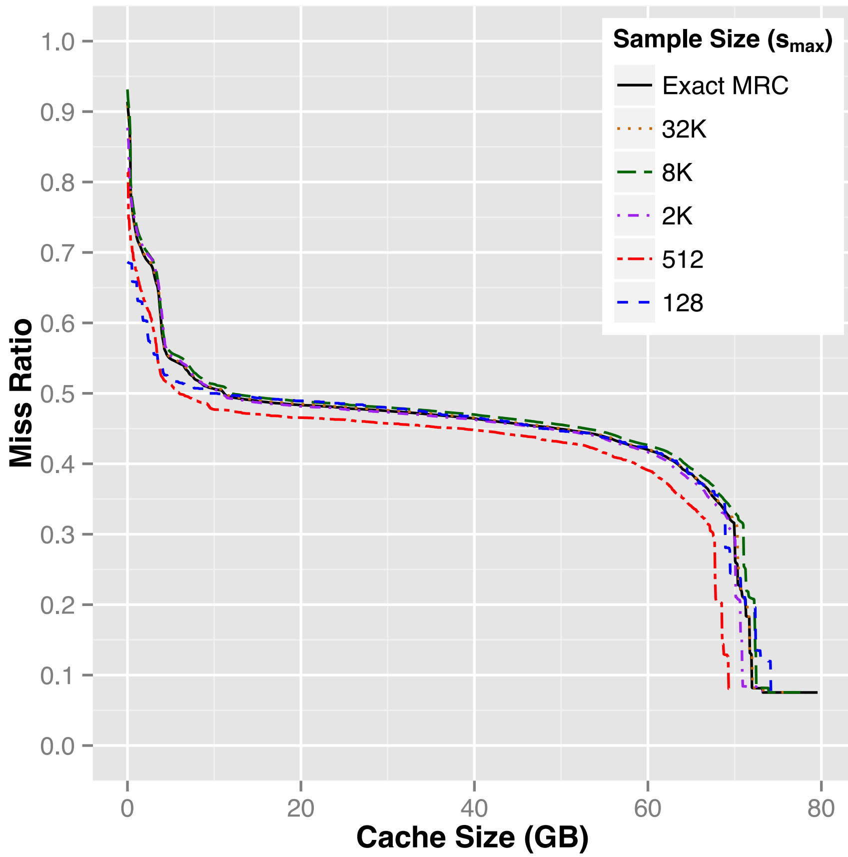
evict samples to bound set size



lower threshold $T = T_{max}$

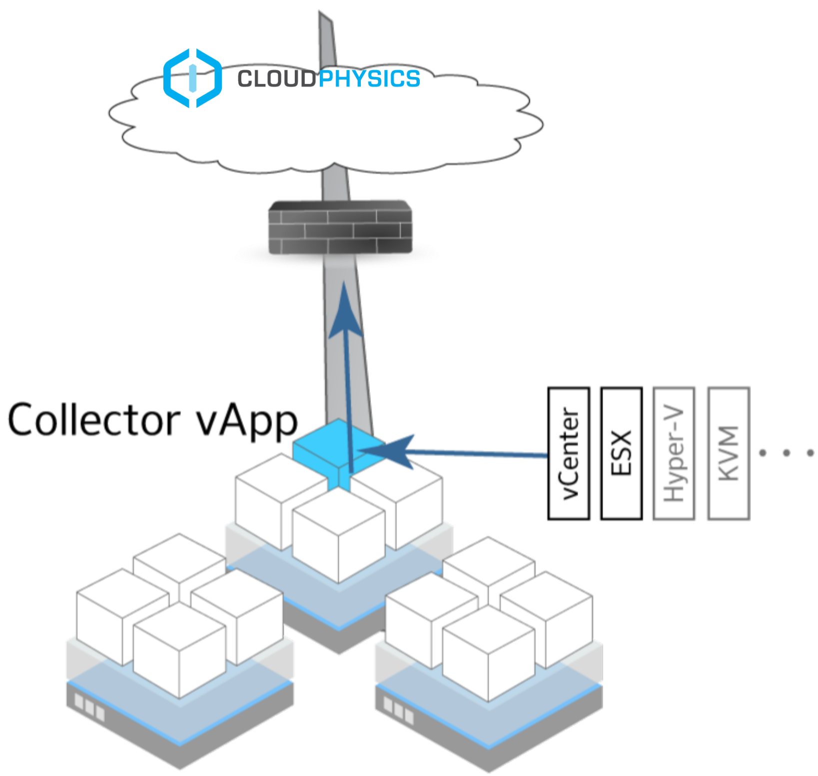
reduces rate $R = T / P$

Example SHARDS MRCs



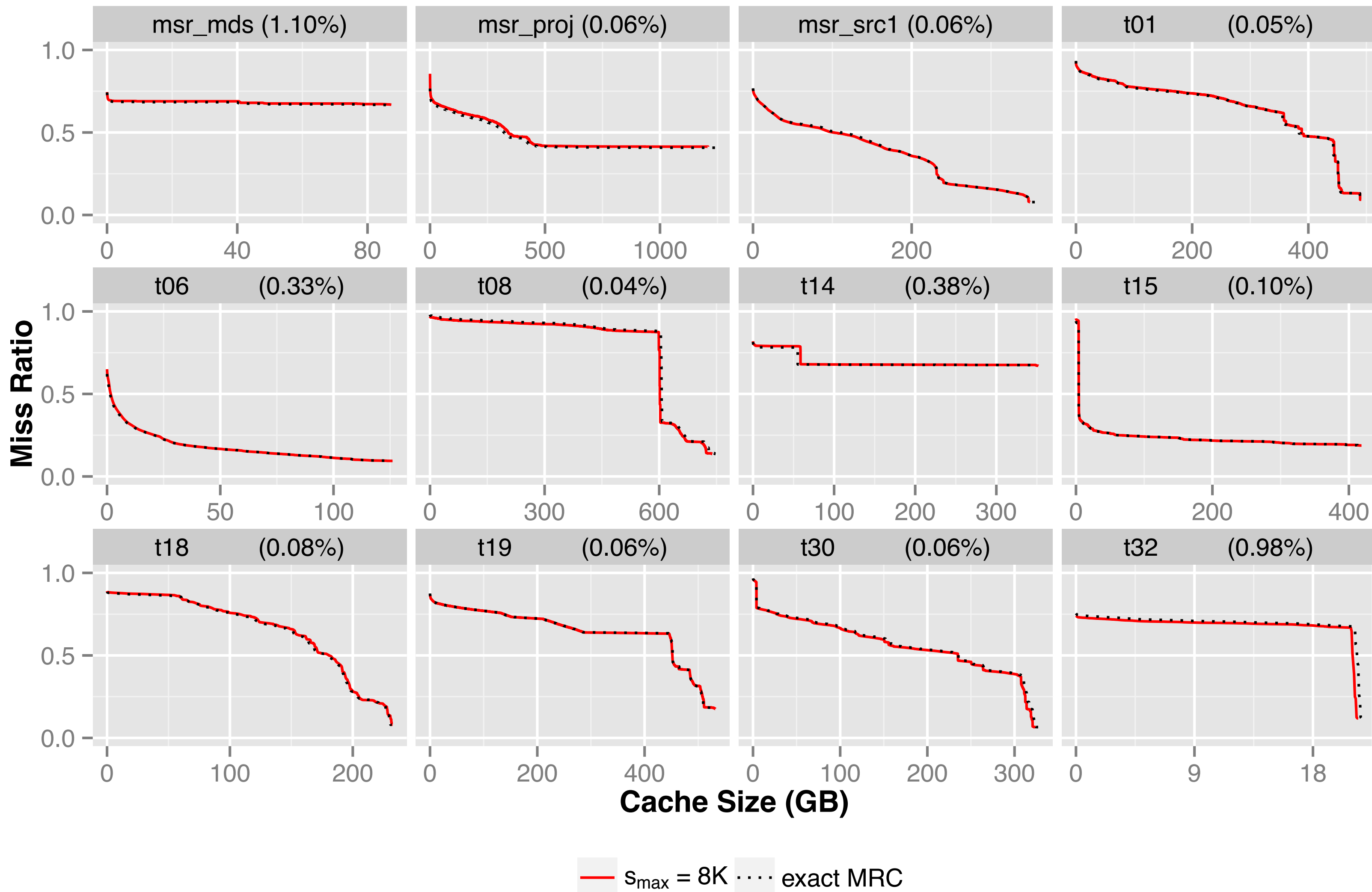
- Block I/O trace *t04*
  - Production VM disk
  - 69.5M refs, 5.2M unique
- Sample size s_{max}
  - Vary from 128 to 32K
  - $s_{max} \geq$ 2K very accurate
- Small constant footprint
- SHARDS_{adj} adjustment

Experimental Evaluation

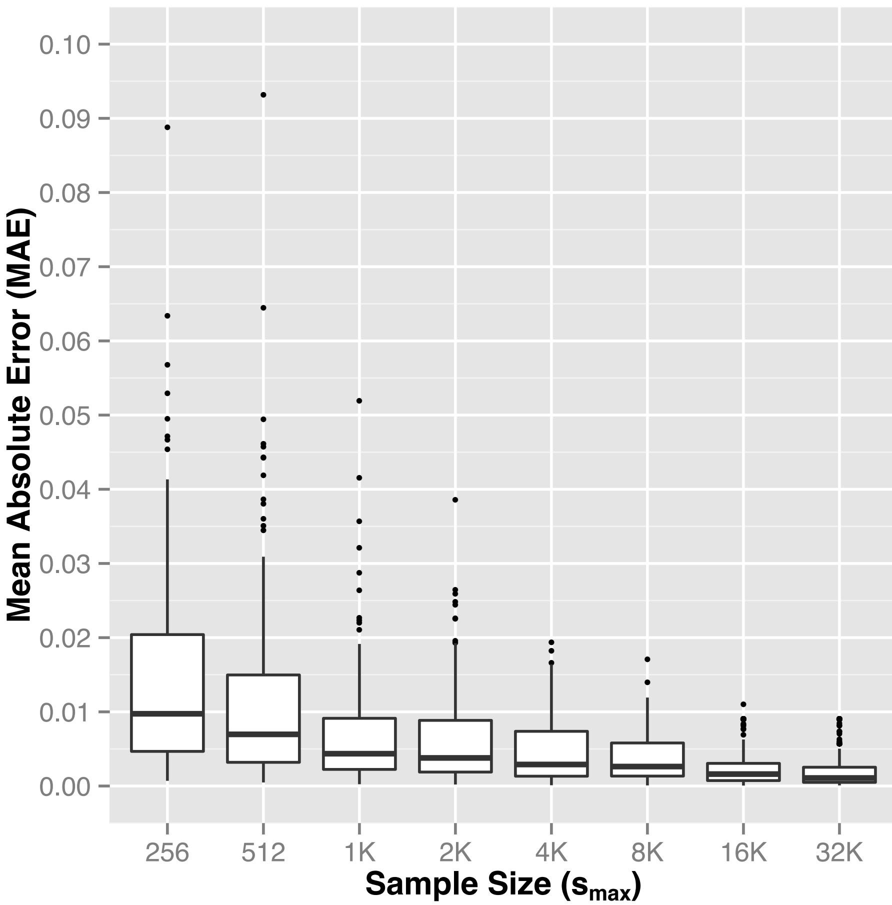


- Data collection
  - SaaS caching analytics
  - Remotely stream VMware vscsiStats
- 124 trace files
  - 106 week-long traces CloudPhysics customers
  - 12 MSR and 6 FIU traces SNIA IOTTA
- LRU, 16 KB block size

Exact MRCs vs. SHARDS

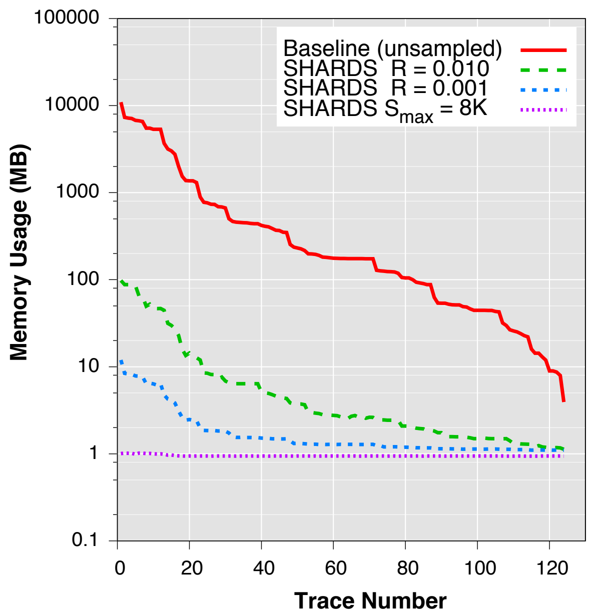


Error Analysis



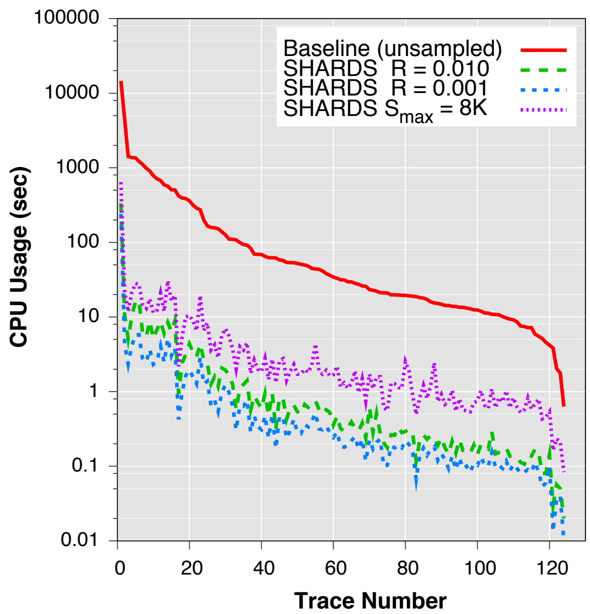
- Mean Absolute Error (MAE)
  - |exact – approx|
  - Average over all cache sizes
- Full set of 124 traces
- Error $\propto 1 / \sqrt{s_{max}}$
- MAE for s_{max} = 8K ___
  - 0.0027 median
  - 0.0171 worst-case

Memory Footprint



- Full set of 124 traces
- Sequential PARDA
- Basic SHARDS
  - Modified PARDA
  - Memory ≈ R × baseline for larger traces
- Fixed-size SHARDS
  - New space-efficient code
  - Constant 1 MB footprint

Processing Time



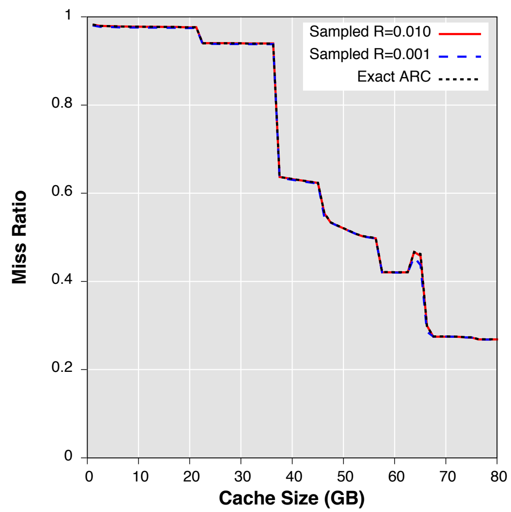
- Full set of 124 traces
- Sequential PARDA
- Basic SHARDS
  - Modified PARDA
  - R=0.001 speedup 41–1029×
- Fixed-size SHARDS
  - New space-efficient code
  - Overhead for evictions
  - S_{max}= 8K speedup 6–204×

Generalizing to Non-LRU Policies

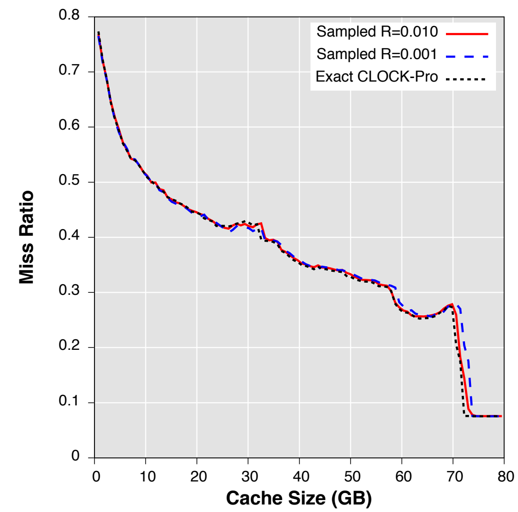
- Many sophisticated replacement policies
  - ARC, LIRS, CAR, CLOCK-Pro, …
  - Adaptive, frequency and recency
  - No known single-pass MRC methods!
- Solution: efficient scaled-down simulation
  - Filter using spatially hashed sampling
  - Scale down simulated cache size by sampling rate
  - Run full simulation at each cache size
- Surprisingly accurate results

Scaled-Down Simulation Examples

ARC — MSR-Web Trace



CLOCK-Pro — Trace *t04*



Conclusions

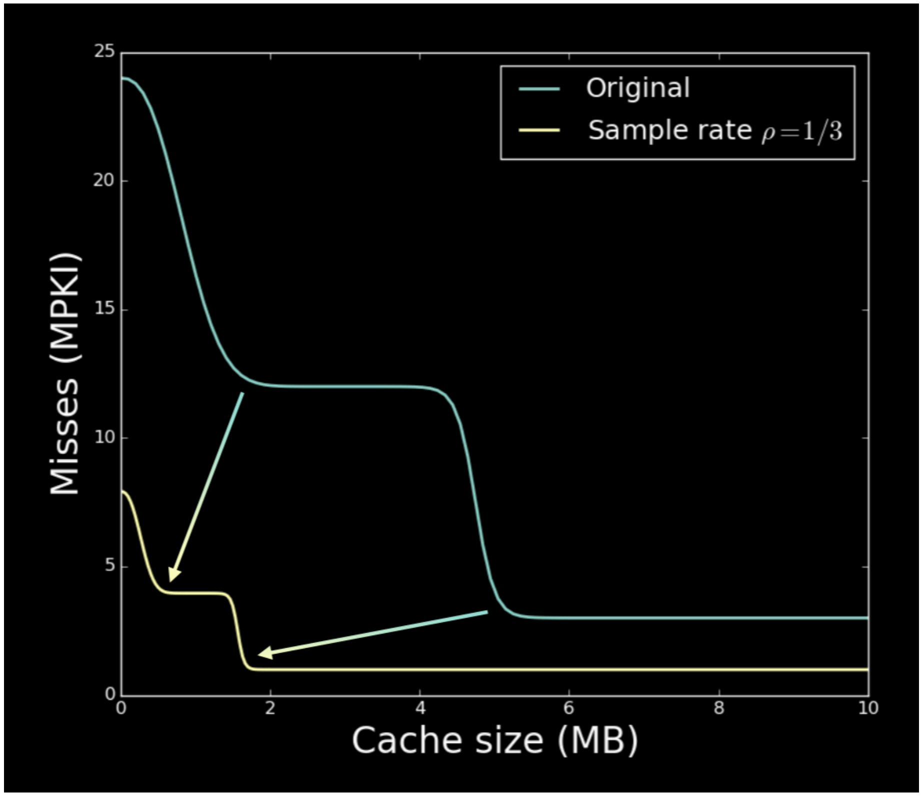
- New SHARDS algorithm
  - Approximate MRC in O(1) space, O(N) time
  - Excellent accuracy in 1 MB footprint
- Practical online MRCs
  - Even for memory-constrained drivers, firmware
  - So lightweight, can run multiple instances
- Scaled-down simulation of non-LRU policies

Talus

A simple way to remove cliffs in cache performance

Key Idea

- Random spatial sampling results in a smilar MRC scaled by the sampling rate.



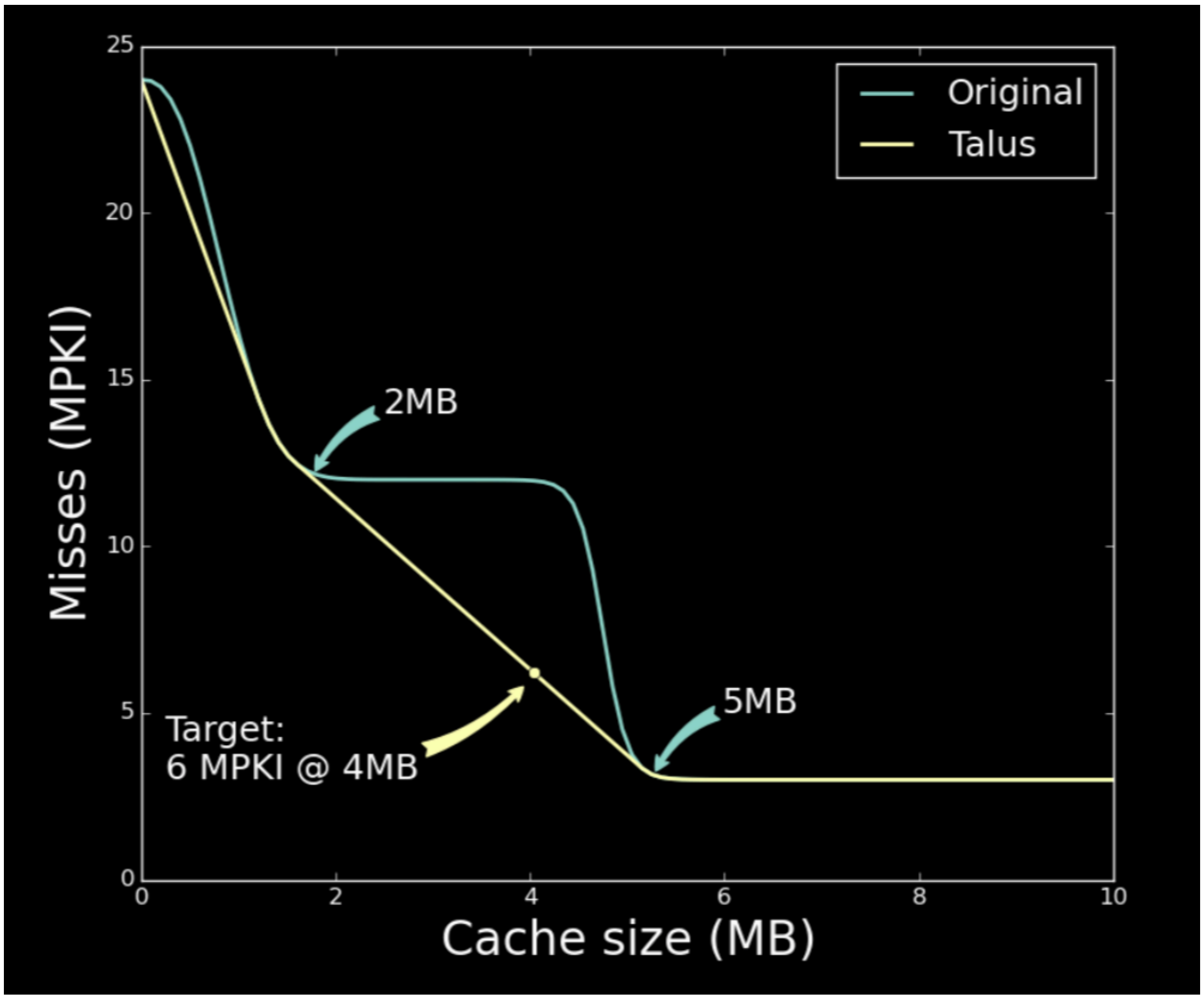
Shards and Talus

- One way to think about SHARDS is that it simulates N size cache using N/r size cache with sampling rate of r.

- If we use N/r size cache with sampling rate of r’ where r’ < r, than the effective cache size increases. If r’ > r than the effective cache size decreases.

- If a knee in the MRC curve does not fit the cache size, we can fit it by increasing the effective cache size.

Talus

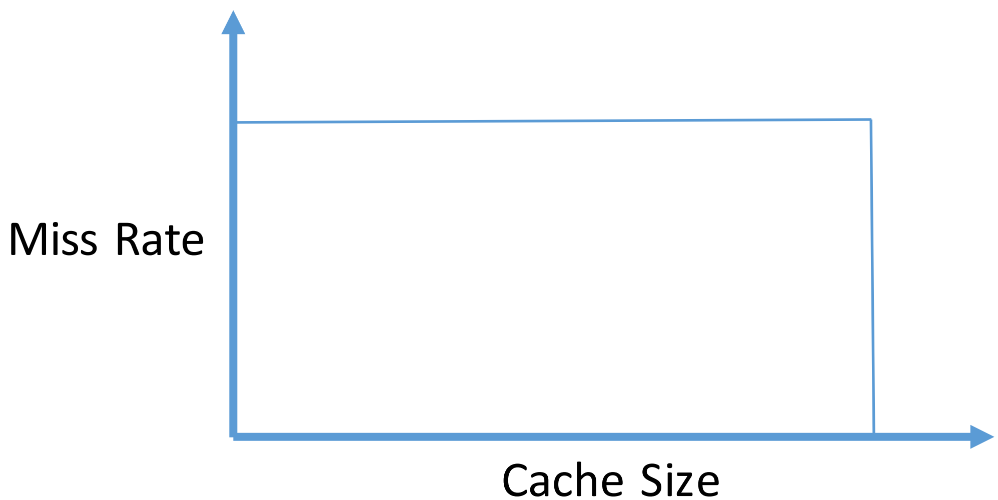


Original
Talus
2MB
5MB
Target:
6 MPKI @ 4MB
Misses (MPKI)
Cache size (MB)
0
5
10
15
20
25
0
2
4
6
8
10

Talus Property

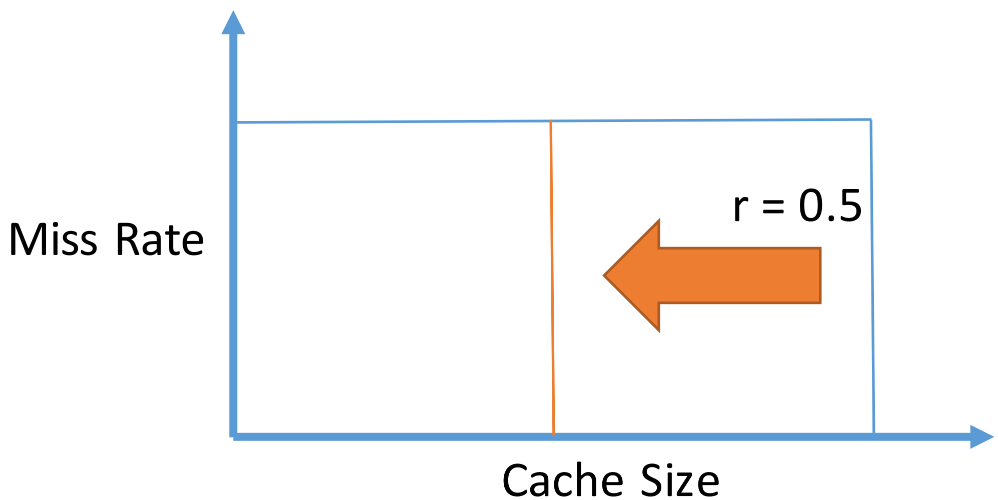
- Can make ANY MRC curve to follow the convex hull of the original MRC.
- With SHARDS, the overhead is fairly small.
- All resulting MRC is convex.

Talus insight.



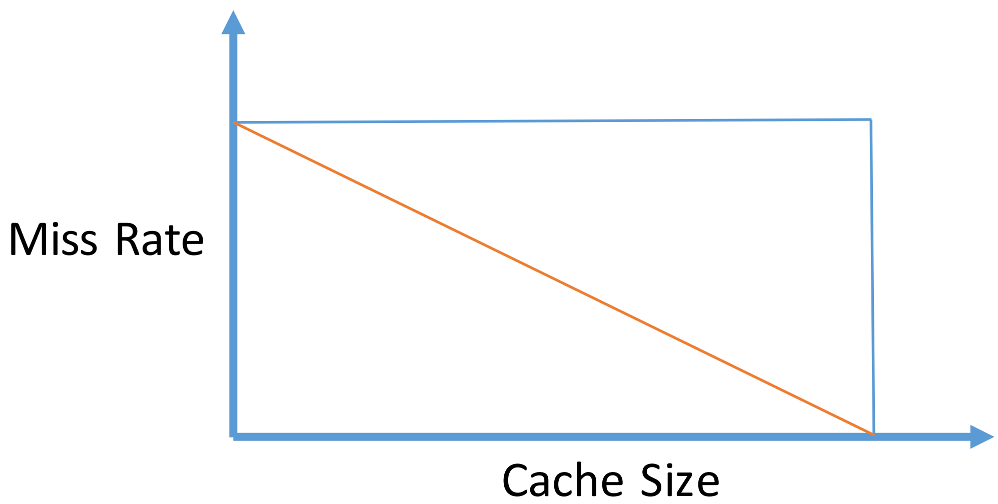
- 0 hits until the the cache size is big enough to fit the entire workload.

Talus insight.



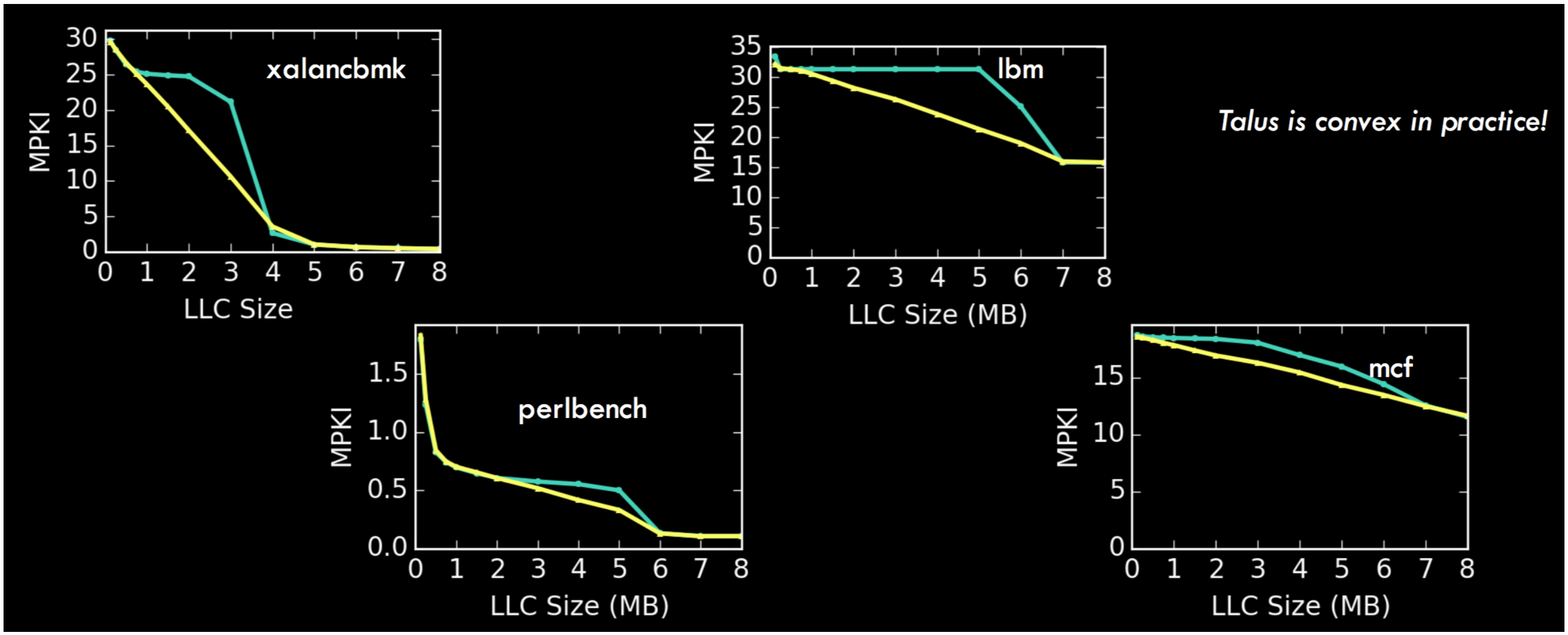
- 0 hits until the the cache size is big enough to fit the entire workload.
- We can reduce the miss rate by 50% by feeding only the 50% of the addresses to the cache.

Talus insight.



- 0 hits until the the cache size is big enough to fit the entire workload.
- We can reduce the miss rate by 50% by feeding only the 50% of the addresses to the cache.
- By repeating the experiment for all cache sizes, we can verify that it form the convex hull of the MRC.

Talus results



SHARDS + Talus

- Use 1MB for the MRC prediction for stack algorithms like LRU.
- Use 32MB for the MRC prediction for other caching algorithms.
  - With 32 SHARDS.
- Calculate Convex hull.
- Apply Talus.
- Less than 0.01% overhead.

Benefits of SHARDS + Talus

- Removes the cliffs.
- Resulting MRC is convex – partitioning problem is now greedy.
- Very low cost.
  - SHARDS capacity also serves actual cache request.
- Seems to work with any caching algorithm.
- Convex hull is fairly stable over time.

Conclusion

- Online generation of multiple MRCs for very large caches is possible.
  - Using fixed memory cost.
  - Low CPU cost.
  - Using different parameters.
- MRC driven QoS.
  - Control average latency via miss rate control
- Larger effective cache size via Talus.
  - Comes for almost free with SHARDS.

Q & A

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Thank you!