A large scale analysis of hundreds of in-memory cache clusters at Twitter

Juncheng Yang, Yao Yue, Rashmi Vinayak

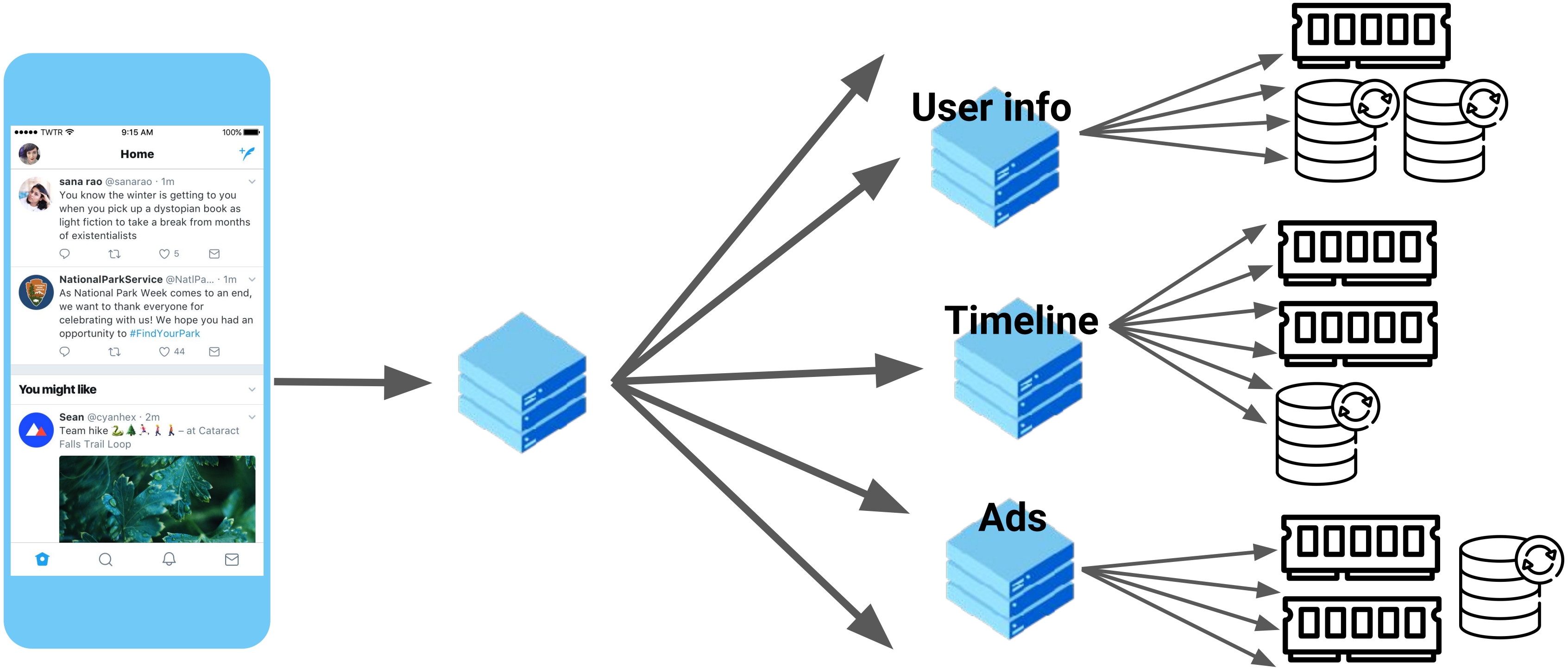
Carnegie Mellon University Twitter Carnegie Mellon University

Carnegie Mellon University
School of Computer Science

Background

In-memory caching is ubiquitous in the modern web services

To reduce latency, increase throughput, reduce backend load



How are in-memory caches used?

Do existing assumptions still hold?

Cache use cases

Write-heavy workloads

Object size distribution and evolution

Time-to-live (TTL) and working set

In-memory caches at Twitter

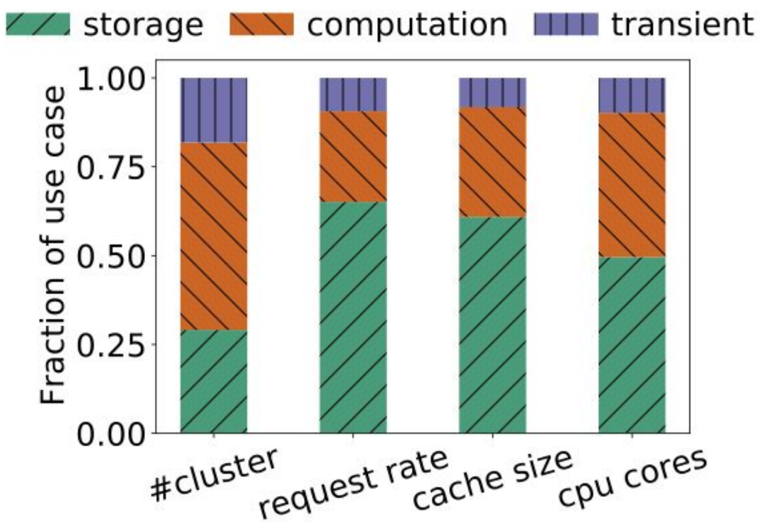
- Single tenant, single layer
  - Container-based deployment
- Large scale deployment
  - 100s cache clusters
  - 1s billion QPS
  - 100s TB DRAM
  - 100,000s CPU cores

Trace collection and open source

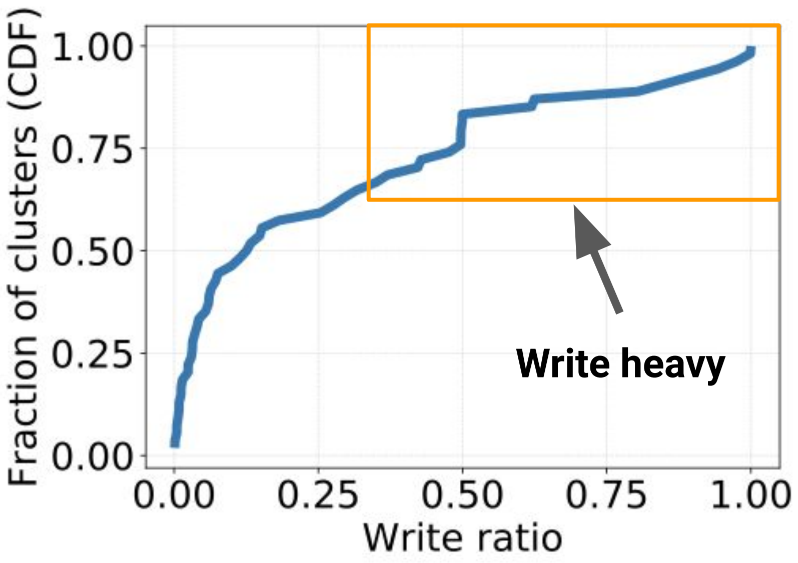
- Week-long **unsampled** traces from one instance of **each** Twemcache cluster
    - 700 billion requests, 80 TB in size
    - Focus on 54 representative clusters
- Traces are open source
    - https://github.com/twitter/cache-trace
    - https://github.com/Thesys-lab/cacheWorkloadAnalysisOSDI20

Cache use cases

- Caching for storage
  - Most common and use most resources
- Caching for computation
  - Increasingly popular
  - Machine learning, stream processing
- Transient data with no backing store
  - Rate limiters
  - Negative caches



Write-heavy workloads

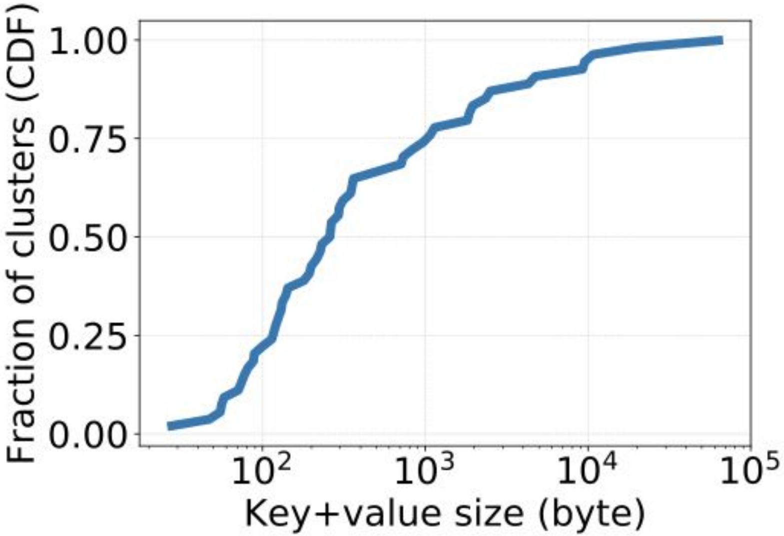


35% of clusters are write-heavy (more than 30% writes)

Implication for future research:

- **Optimization needed for write-heavy workloads**
  - Challenges: scalability, tail latency

Object size



Object sizes are small

- 24% cluster mean object size < 100 bytes
- Median 230 bytes

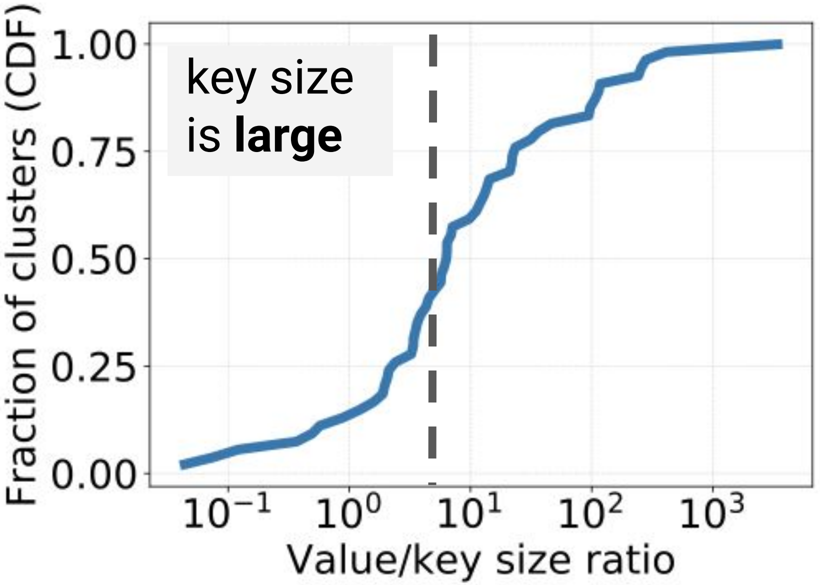
Metadata size is large

- Memcached uses 56 bytes per-obj metadata
- Research systems often add more metadata
- -> Reduce effective cache size

Implication for future research:

- **Minimizing object metadata to increase effective cache size**

Object size



Value/key size ratio can be small

- 15% cluster value size <= key size
- 50% cluster value size <= 5 x key size

Small value/key size ratio

- Name spaces are part of keys
  - `Ns1:ns2:obj` or `obj/ns1/ns2`

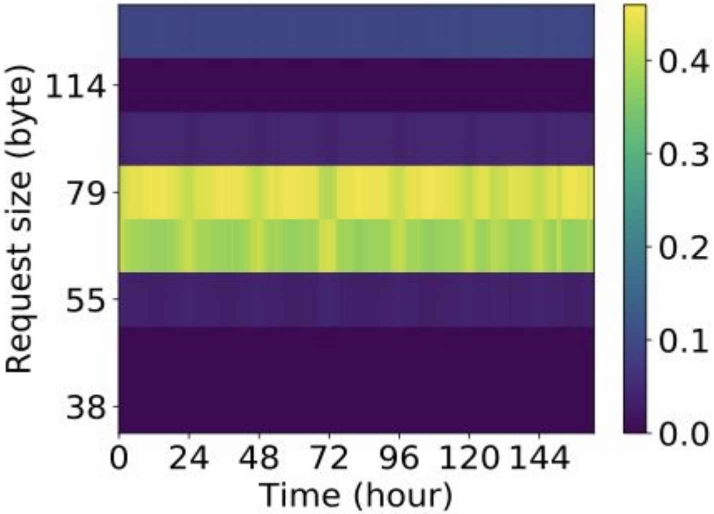
Implication for future research:

- **A robust and lightweight key compression algorithm can increase effective cache size**

Dynamic size distribution

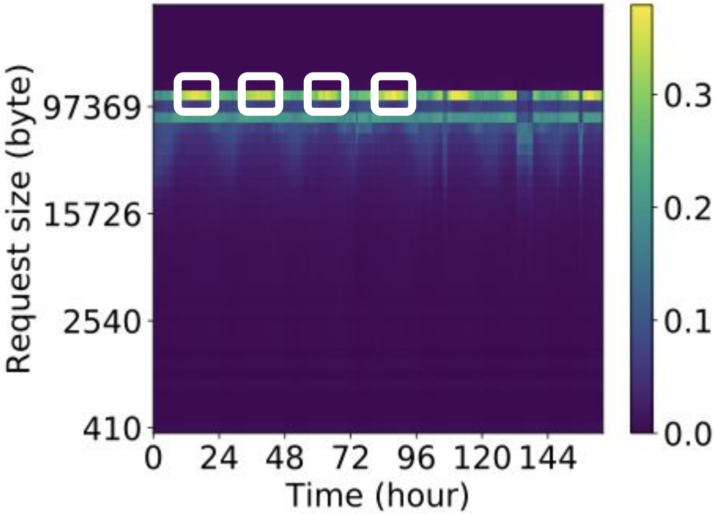
Size distribution can be static

Bright color: more requests are for objects of that size in the time window



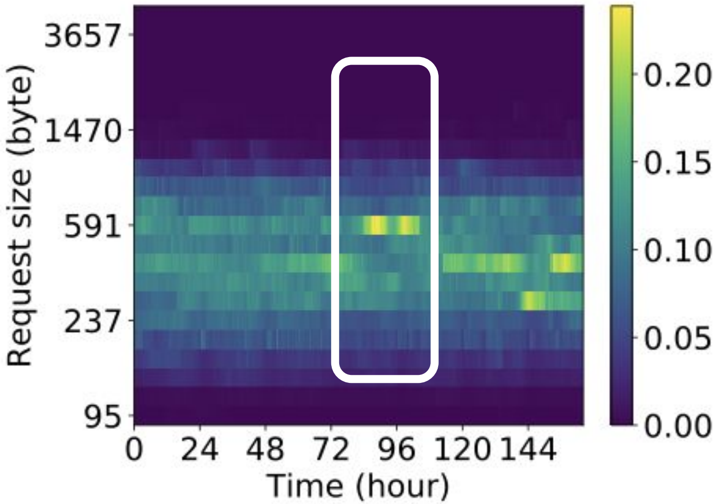
Most of the time, it is not static

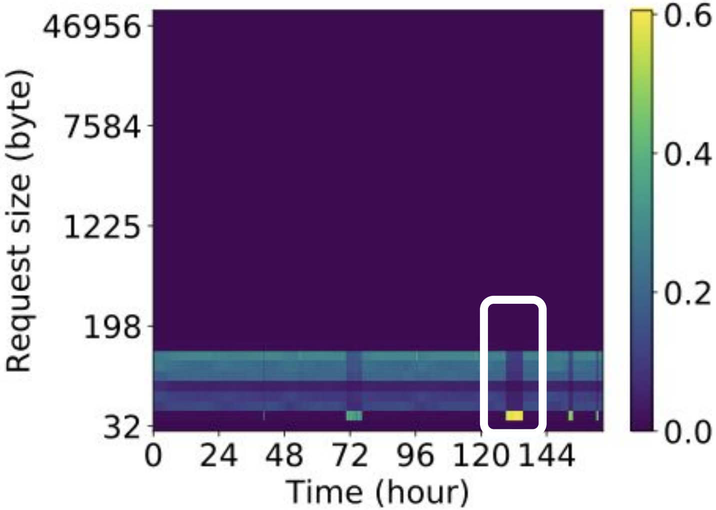
The workload below shows a diurnal patterns



Size distribution over time

Sudden changes are not rare





Implication for future research:

- **Size distribution changes pose challenges to memory management**
- **Innovations needed on better memory management techniques**

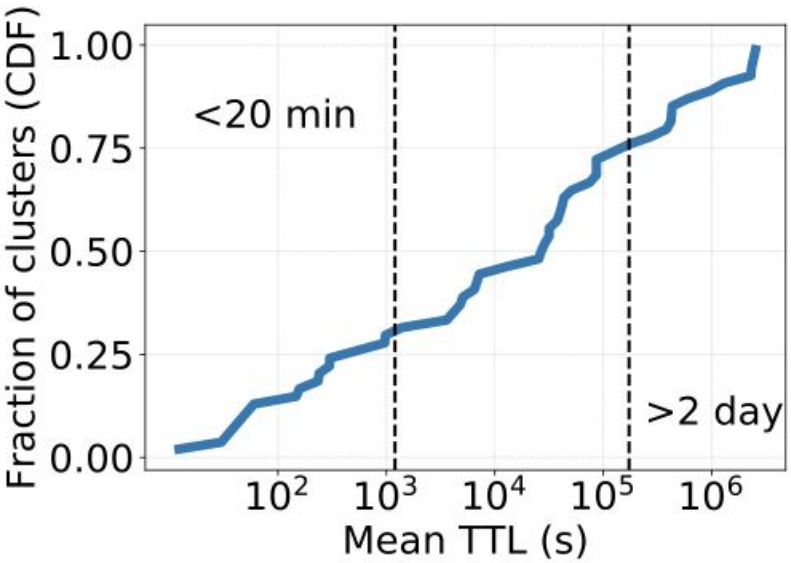
Time-to-live (TTL)

- How long an object can be used for serving requests
- Set during object writes
- Expired objects cannot be served

TTL use cases and usages

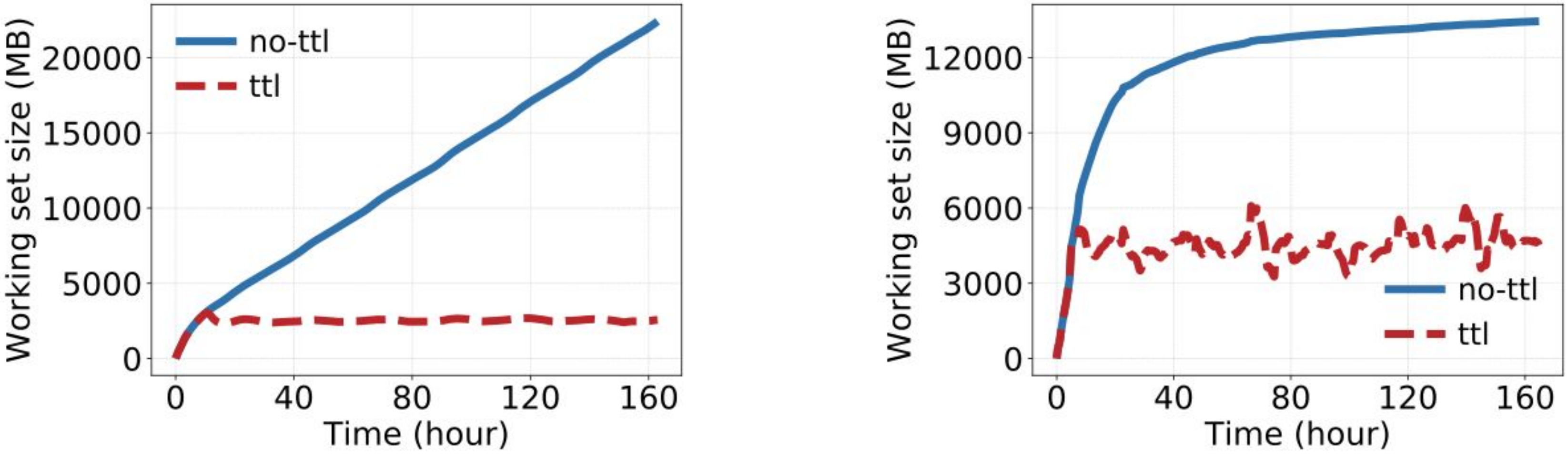
- Bounding inconsistency
  - Cache updates are best-effort
- Periodic refresh
  - Caches for computation store computation based on dynamic features
- Implicit deletion
  - Rate limiter
  - GDPR compliant

TTLs are usually short



Short TTLs lead to bounded working set sizes

There is no need for a huge cache size if expired objects can be removed in time.



Implication for future research:

- **Efficient proactive expiration techniques are more important than evictions**
- **Innovation needed on efficient TTL expiration**

More in the paper

Production statistics

- Small miss ratio and small variations
- Request spikes are not always caused by hot keys

Object popularity

- Mostly Zipfian with large parameter alpha
- Small deviations

Eviction algorithms

- Highly workload dependent
- Four types of results
- FIFO achieves similar miss ratios as LRU

Summary

- Key observations and implications
  - Non-trivial fraction of write-heavy workloads
  - Small objects -> expensive metadata
  - Dynamic object size distribution
  - Short TTLs -> proactive expiration > eviction
- Traces open sourced for the community

Traces are available at
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Contact: juncheny@cs.cmu.edu