Design Tradeoffs for Data Deduplication Performance in Backup Workloads

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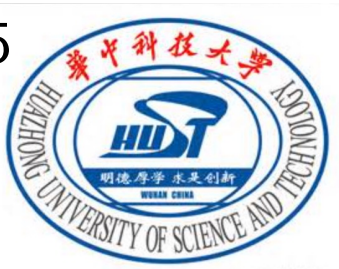
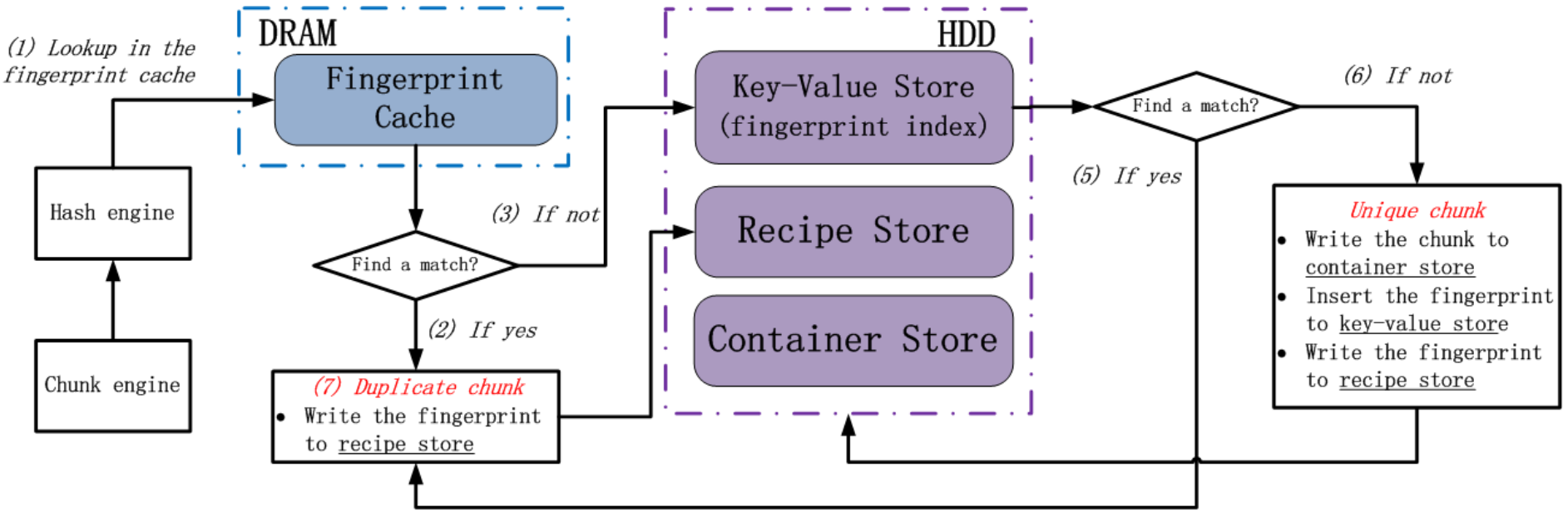


Background

- In big data era,
  - we had 4.4 ZB of data in 2013, and expectedly to grow by 10-fold in 2020 [IDC'2014];
  - data redundancy widely exists in real-world applications.
- Data deduplication is a scalable compression technology
  - non-overlapping chunking
  - no byte-by-byte comparison (fingerprinting)
- A significantly lower computation overhead than traditional compression technologies
  - faster due to coarse-grained compression
  - higher compression ratio since it looks for duplicate chunks in a larger scope. (The entire system VS. a limited compression window)

An Overview of a Typical Deduplication System



Motivations

- Challenges to design an efficient deduplication system
  - Chunking
  - Indexing
  - Defragmenting
  - Restoring
  - Garbage collecting
  - ...
- We have a huge number of papers, solutions, and design choices
  - Which one is better?
  - Better in what?
    - ★ *backup performance, restore performance, deduplication ratio, or memory footprint?*
  - How about their interplays?

The Parameter Space

- In this paper, we mainly explore
  - fingerprint indexing,
  - rewriting algorithm (in-line defragmenting),
  - restore algorithm (cache replacement),
  - and their interplays.

Parameter Space		**Descriptions**
Indexing	Key-value mapping	*Mapping fingerprints to their prefetching units*
	Fingerprint cache	*In-memory fingerprint cache*
	Sampling	*Selecting representative fingerprints*
	Segmenting	*Splitting the unit of logical locality*
	Segment selection	*Selecting segments to be prefetched*
	Segment prefetching	*Exploiting segment-level locality*
Defragmenting (rewriting)		*Reducing fragmentation*
Restoring		*Designing restore cache/algorithm*

Table: The major parameters we discuss.

Indexing Bottleneck

- A deduplication system requires a huge key-value store to identify duplicates
- An in-memory key-value store is not cost-efficient:
  - Amazon.com: a 1 TB HDD costs $60, and an 8 GB DRAM costs $80
  - suppose 4KB-sized chunks and 32-byte-sized key-value pair
  - indexing 1 TB unique date requires an 8 GB-sized key-value store
- An HDD-based key-value store easily becomes the performance bottleneck, compared to the fast CDC chunking (400 MB/s and 102,400 chunks per sec under commercial CPUs)
- Modern fingerprint indexes exploit workload characteristics (*locality*) of backup systems to prefetch and cache fingerprints
- Hence, a fingerprint index consists of two major components:
  - key-value store
  - fingerprint prefetching/caching module

The Fingerprint Index Taxonomy

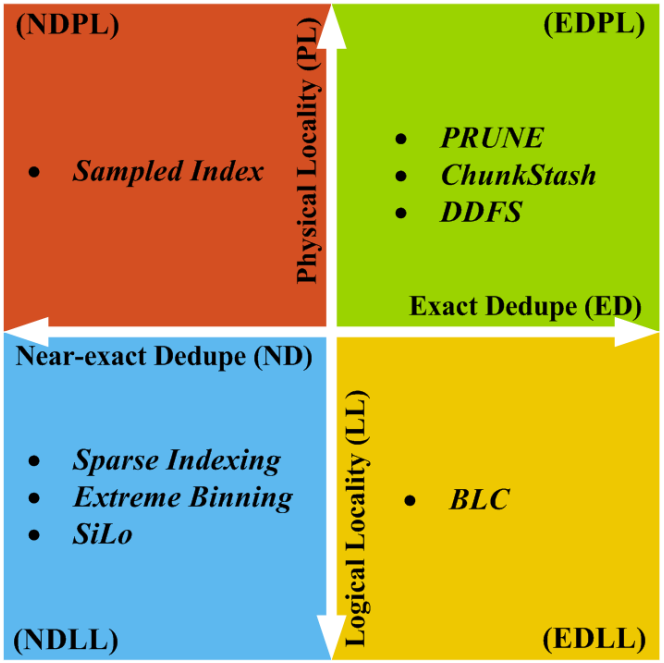


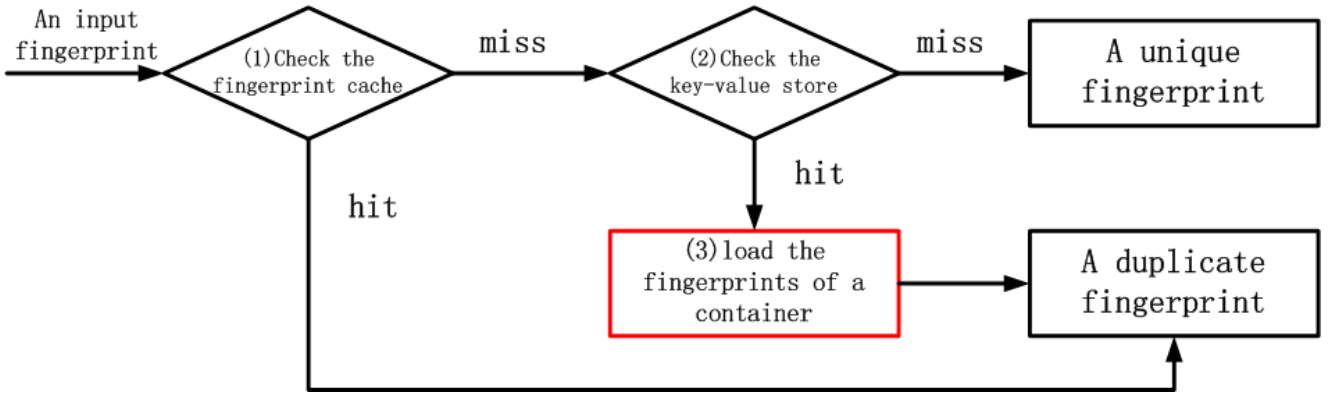
Figure: Categories of existing work.

- Classification according to the use of key-value store
  - Exact Deduplication (ED): fully indexing stored fingerprints
  - Near-exact Deduplication (ND): partially indexing stored fingerprints
- Classification according to the prefetching policy
  - Logical Locality (LL): the chunk sequence before deduplication
  - Physical Locality (PL): the physical layout of stored chunks

Exact vs. Near-exact Deduplication

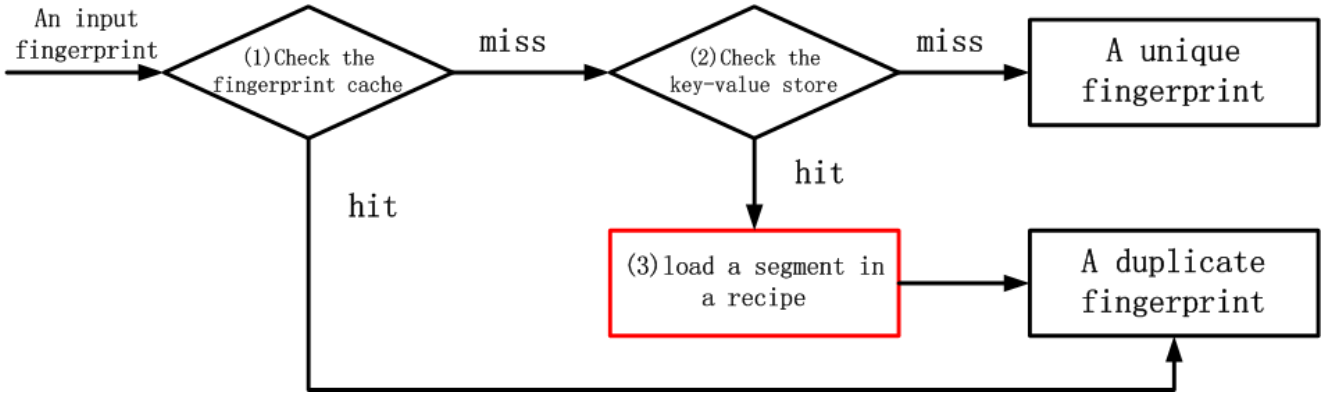
- Exact Deduplication (ED) indexes all stored fingerprints
  - a huge key-value store on disks
  - fingerprint prefetching/caching to improve *backup throughput*
- Near-exact Deduplication (ND) indexes only sampled (representative) fingerprints
  - a small key-value store in DRAM
  - fingerprint prefetching/caching to improve *deduplication ratio*
- ND trades deduplication ratio for higher backup/restore performance and lower memory footprint
  - Does a lower memory footprint indicate a lower financial cost?
  - To avoid an increase of the storage cost, ND needs to achieve 97% of the deduplication ratio of ED.

Exploiting Physical Locality



- The key-value store maps a fingerprint to its physical location, i.e., a container.
- Weakness: the prefetching efficiency decreases over time due to the fragmentation problem.
  - Older containers have many useless fingerprints for new backups.
- For Near-exact Deduplication, how to select (sample) representative fingerprints in each container?
  - Selects the fingerprints that $mod\ R = 0$ in a container, or
  - Selects the first fingerprint every R fingerprints in a container.

Exploiting Logical Locality



- The key-value store maps a fingerprint to its logical location, i.e., a segment in a recipe.
- The segment serves as the prefetching unit
- Advantage: no fragmentation problem
- Weakness: extremely high update overhead to the key-value store
  - Even duplicate fingerprints have new logical locations (in new recipes and new segments).
  - **Optimization**: only update sampled duplicate fingerprints.
- How to segmenting and sampling?

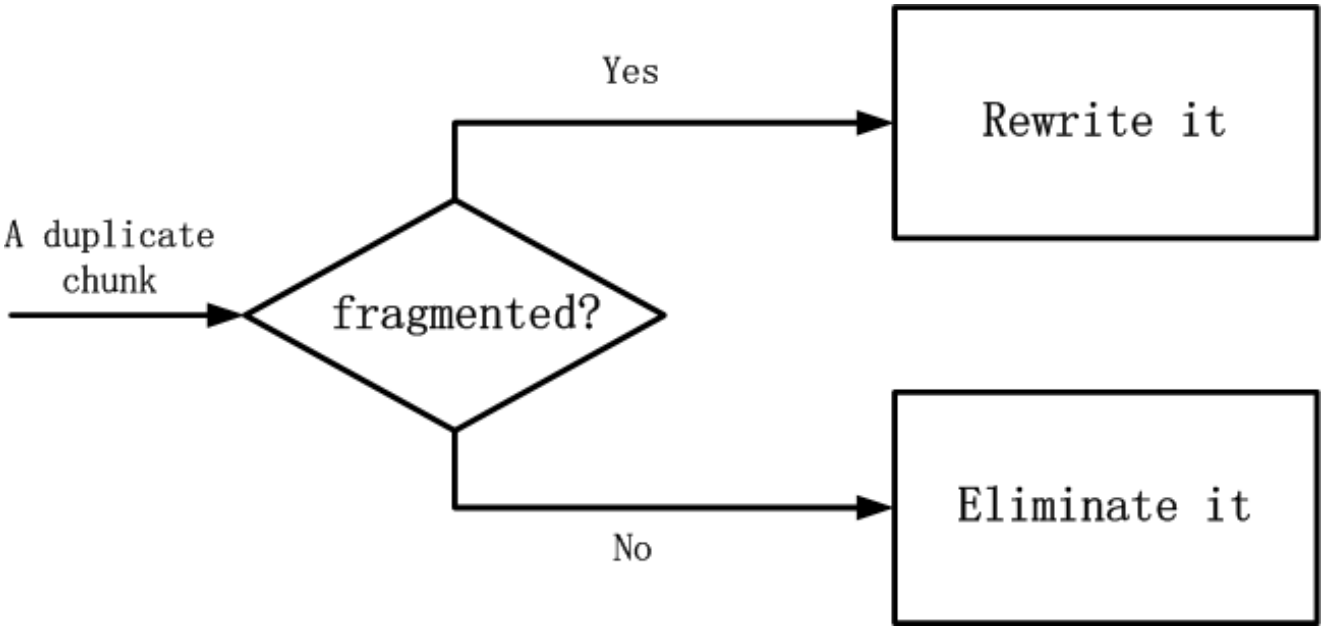
Design Choices for Exploiting Logical Locality

	BLC	Extreme Binning	Sparse Indexing	SiLo
Exact deduplication	Yes	No	No	No
Segmenting method	FSS	FDS	CDS	FSS & FDS
Sampling method	N/A	Minimum	Random	Minimum
Segment selection	Base	Top-*all*	Top-*k*	Top-1
Segment prefetching	Yes	No	No	Yes
Key-value mapping relationship	1:1	1:1	Varied	1:1

Table: Existing work exploiting logical locality.

- Segmenting: Fixed-Sized Segmenting (FSS), File-Defined Segmenting (FDS), and Content-Defined Segmenting (CDS)
- Sampling: Uniform, Random, and Minimum.
- Segment selection: *Base*, *Top-k*, and *Mix*.
- Segment prefetching: exploiting segment-level locality.
- Key-value mapping: each representative fingerprint can refer to a varied number of logical locations.

Defragmenting and Rewriting Algorithm

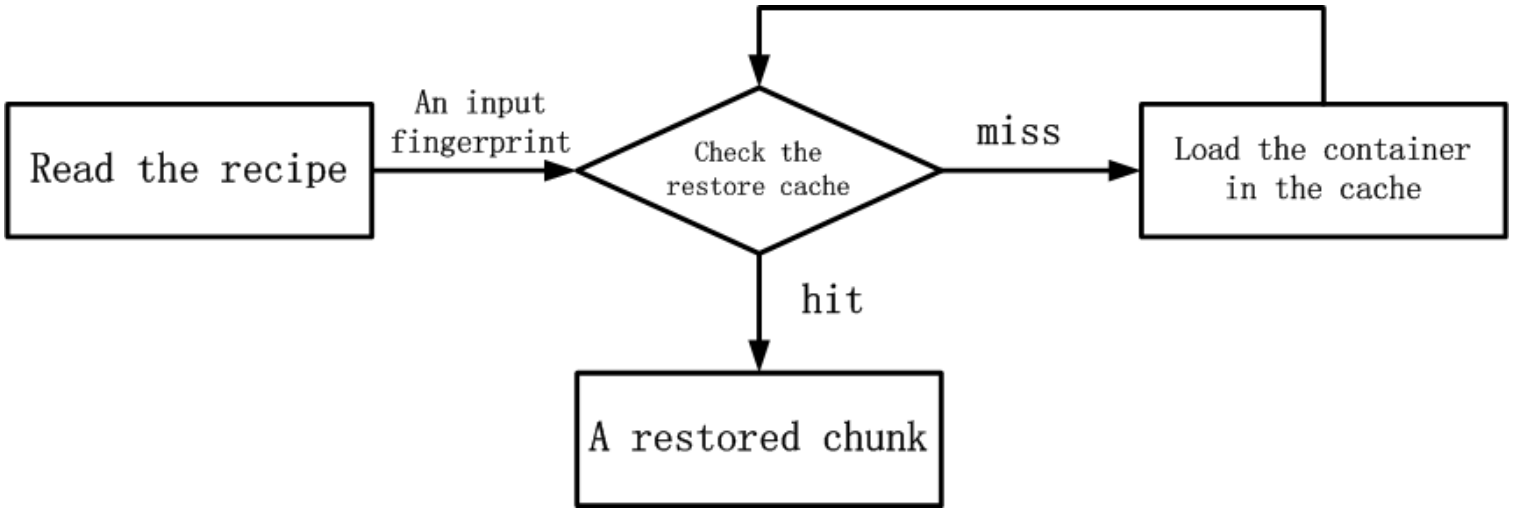


- The rewriting algorithm is an emerging dimension to reduce fragmentation.
- What is the fragmentation?
  - The deviation between the logical locality and physical locality.
- The fragmentation hurts the restore (read) performance, and the backup performance of the fingerprint index exploiting physical locality.

Existing Rewriting Algorithms

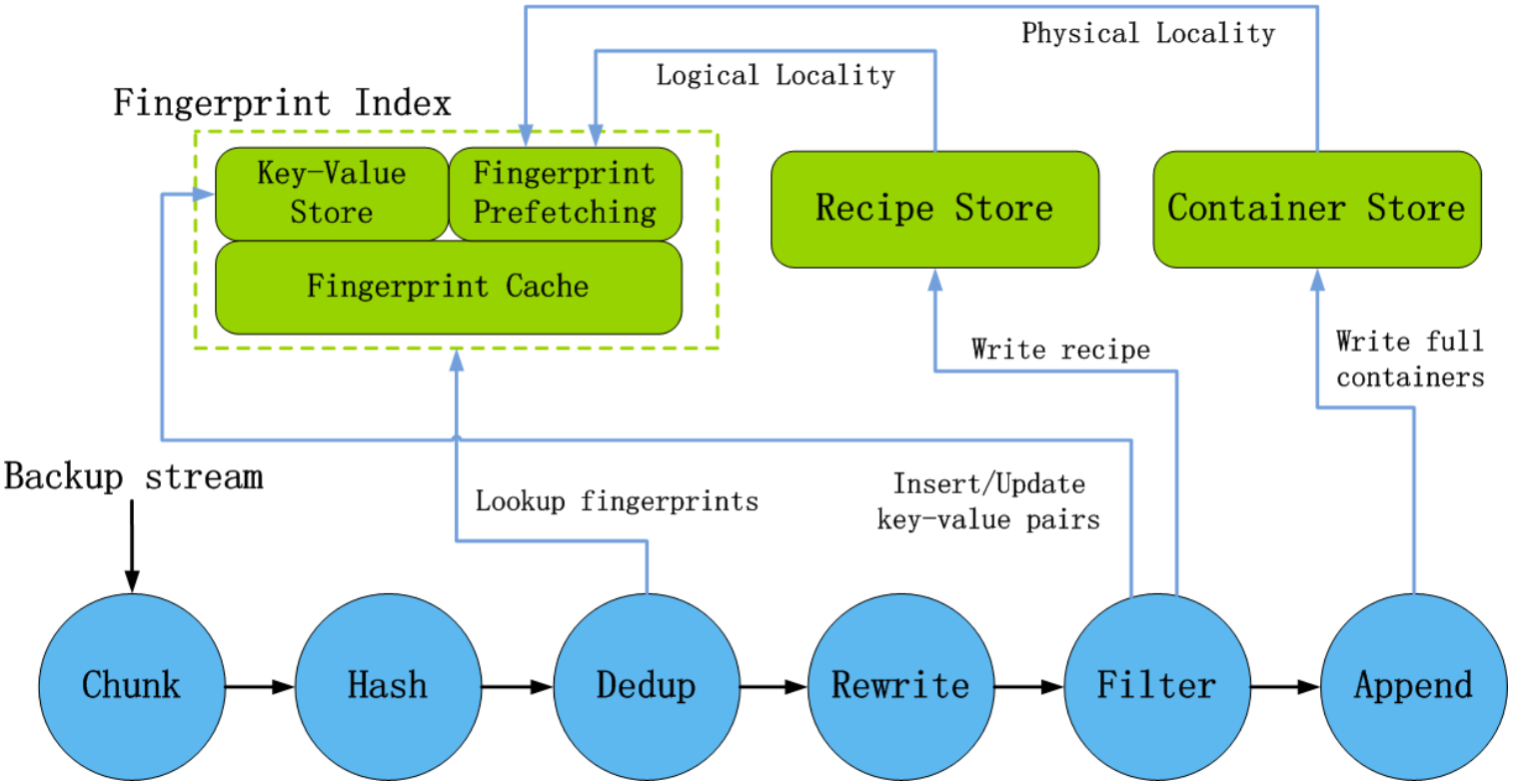
- Buffer-based algorithm
  - CFL-based Selective Deduplication [Nam'2012]
  - Context-Based Rewriting [Kaczmarczyk'2012]
  - Capping [Lillibridge'2013]
- History-aware algorithm
  - History-Aware Rewriting [Fu'2014]
- How about their interplays with the state-of-the-art fingerprint indexes?
  - How does the rewriting algorithm improve the fingerprint index exploiting physical locality?
  - How do the different prefetching schemes affect the efficiency of the rewriting algorithm?

The Restore Algorithm



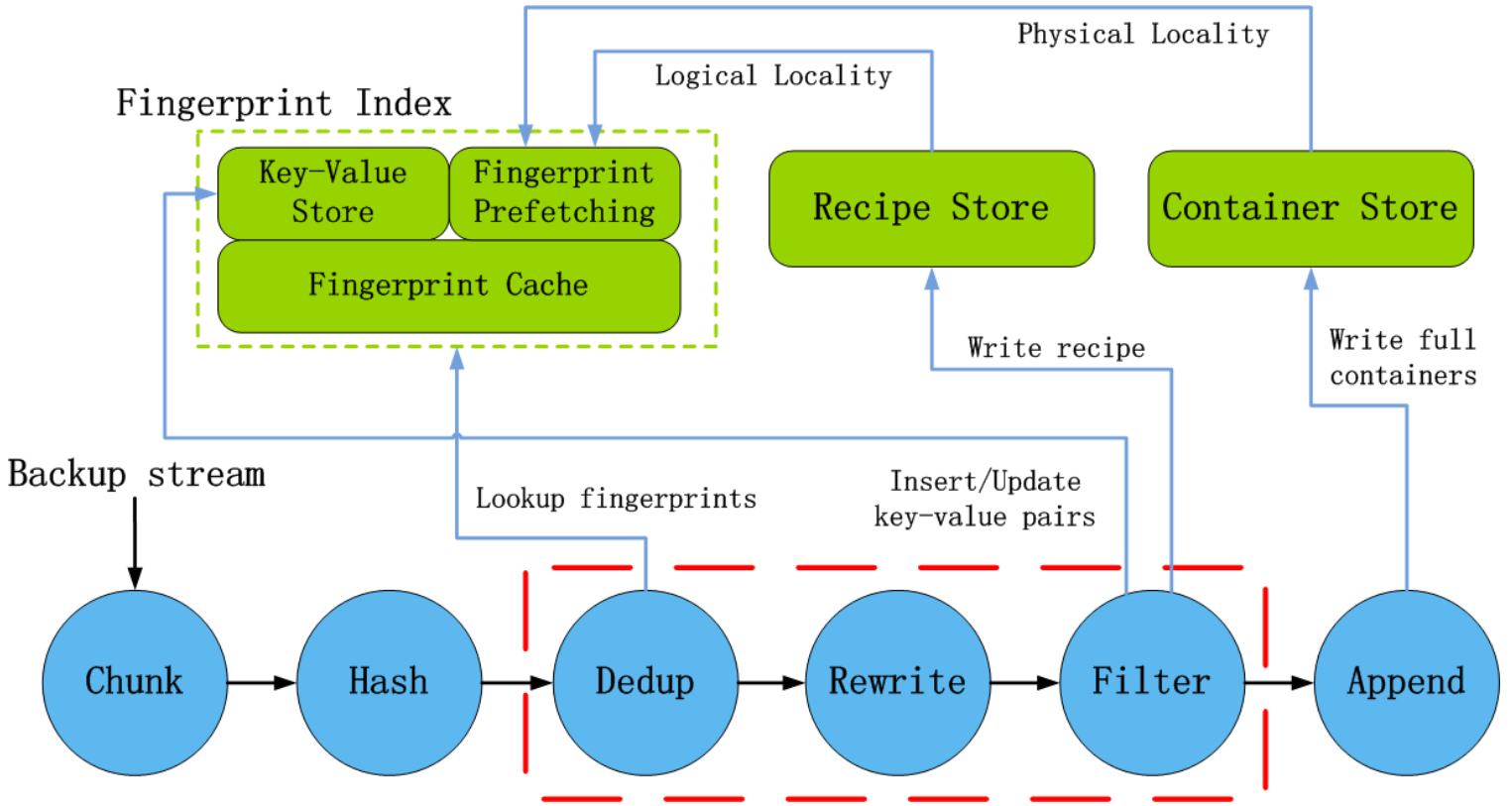
- While the rewriting algorithm determines the chunk layout, the restore algorithm improves restore performance under limited memory.
  - How to write, and then how to read.
- Existing restore algorithms:
  - traditional LRU cache
  - Belady's optimal replacement cache
  - rolling forward assembly area [Lillibridge'2013]
- How about their interplays with the rewriting algorithm?

The DeFrame Architecture



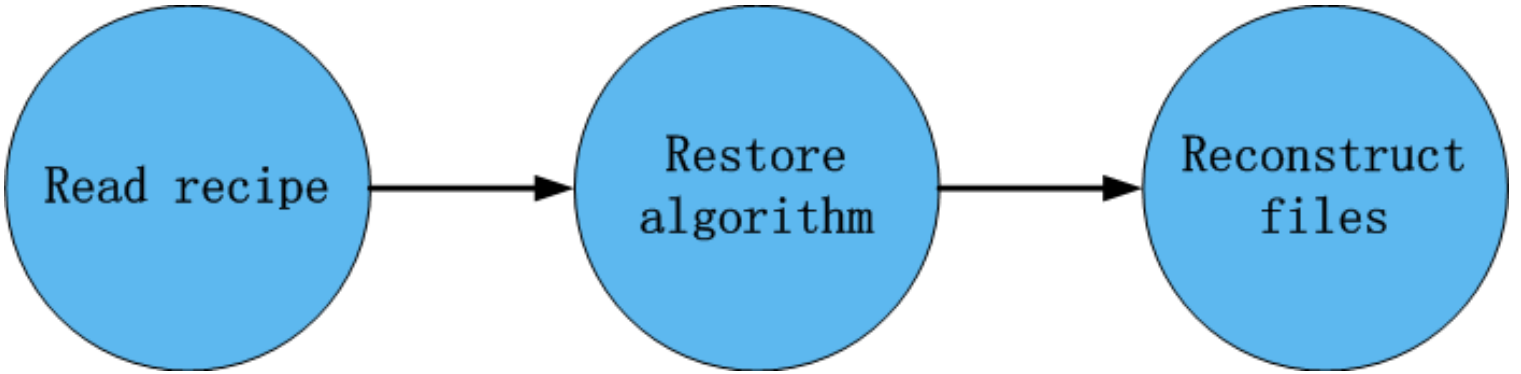
- *Fingerprint index*: duplicate identification
  - key-value store
  - fingerprint prefetching/caching
- *Container store*: container management (physical locality)
- *Recipe store*: recipe management (logical locality)

The Backup Pipeline



- *Dedup phase* identifies duplicate/unique chunks
- *Rewrite phase* identifies fragmented duplicate chunks
- *Filter phase* determines whether write a chunk
- Advantage: we can implement a new rewriting algorithm without the need to modify the fingerprint index, and vice versa.

The Restore Pipeline



- *Read recipe phase* reads the recipe and output fingerprints
- *Restore algorithm phase* receives fingerprints and fetch chunks from the container store
- *Reconstruct file phase* receives the chunks and reconstruct files

Garbage Collection

- Users can set a retention time for the backups.
- All expired backups will be deleted automatically by DeFrame.
- How to reclaim the invalid chunks becomes a major challenge.
  - We develop History-Aware Rewriting algorithm to aggregate valid chunks into fewer containers
  - We develop Container-Marker Algorithm to reclaim invalid containers.
- More details can be found in our ATC'14 paper.

Experimental Setups

Dataset name	Kernel	VMDK	RDB
Total size	104 GB	1.89 TB	1.12 TB
# of versions	258	127	212
Deduplication ratio	45.28	27.36	39.1
Avg. chunk size	5.29 KB	5.25 KB	4.5 KB
Self-reference	$< 1\%$	15-20%	0
Fragmentation	Severe	Moderate	Severe

Table: The characteristics of our datasets.

- *Kernel*: downloaded from `kernel.org`
- *VMDK*: 127 consecutive snapshots of a virtual machine disk image
- *RDB*: 212 consecutive snapshots of a Redis database

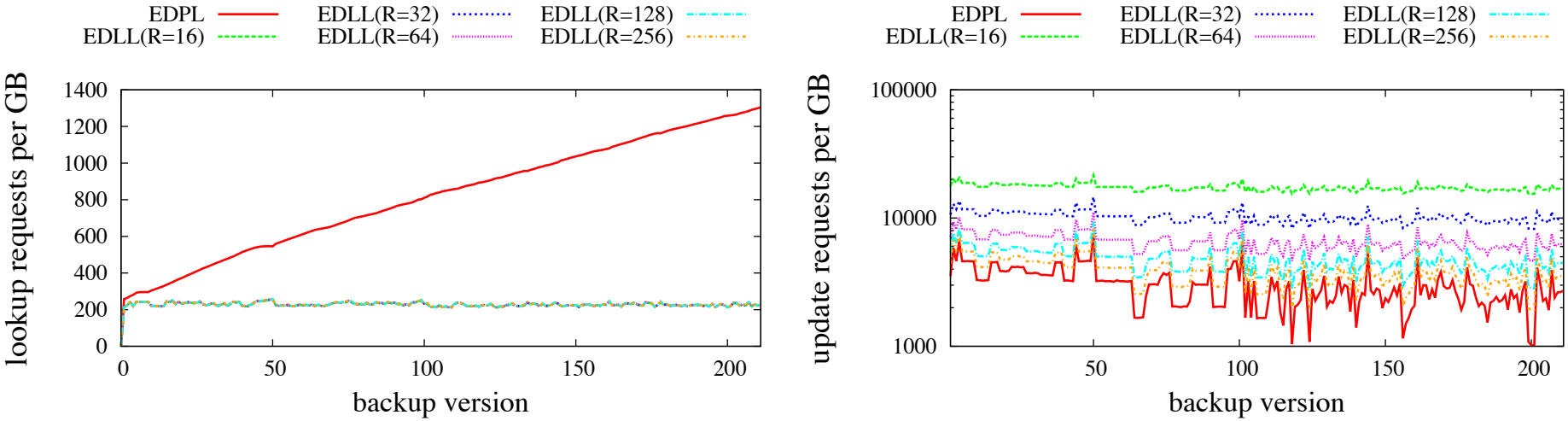
Metrics and Our Goal

Quantitative Metrics

- *Deduplication ratio*: the original backup data size divided by the size of stored data.
- *Memory footprint*: the runtime DRAM consumption.
- *Storage cost*: the total cost of HDDs and DRAM for stored chunks and the fingerprint index.
- *Lookup/update request per GB*: the number of lookup/update requests to the key-value store to deduplicate 1 GB of data.
- *Restore speed*: 1 divided by mean containers read per MB of restored data.

- It is practically impossible to find a solution that performs the best in all metrics.
- We aim to find a solution with the following properties:
  - sustained, high backup performance as the top priority.
  - reasonable tradeoffs in the remaining metrics.

EDPL vs. EDLL



(a) Lookup overhead

(b) Update overhead

Figure: Comparisons between EDPL and EDLL in terms of lookup and update overheads. $R = 256$ indicates a sampling ratio of 256:1. Results come from RDB.

- EDPL suffers from the ever-increasing lookup overhead.
- For EDLL, the sampling optimization is efficient.

NDPL vs. NDLL

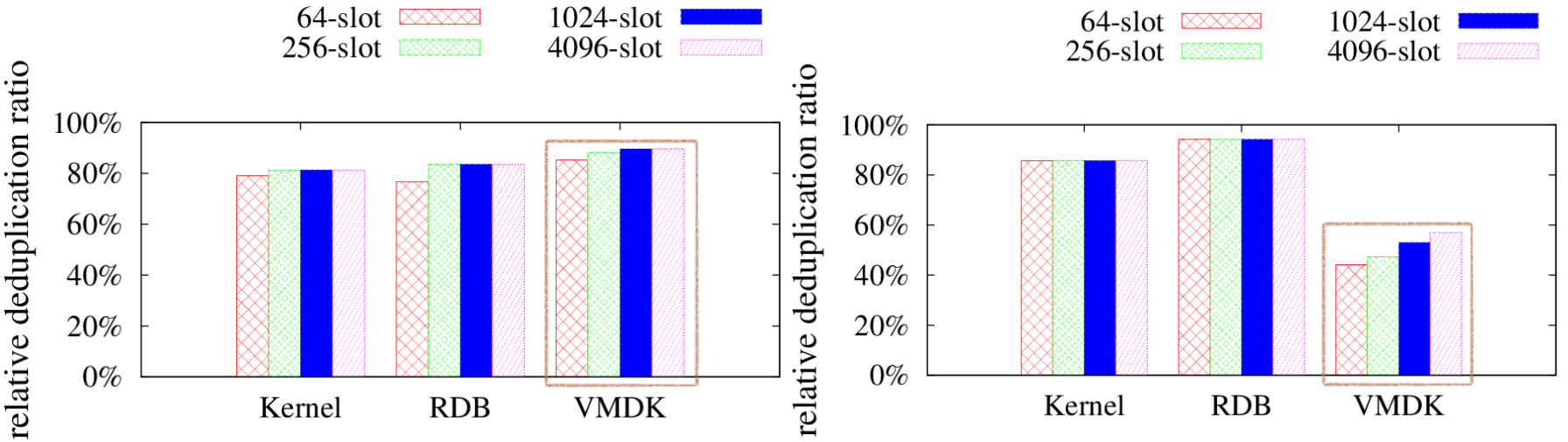


Figure: Comparing NDPL and NDLL under different cache sizes. The Y-axis shows the relative deduplication ratio to exact deduplication.

- NDLL performs better in Kernel and RDB, but worse in VMDK than NDPL.

The Interplays Between Fingerprint Index and Rewriting Algorithm

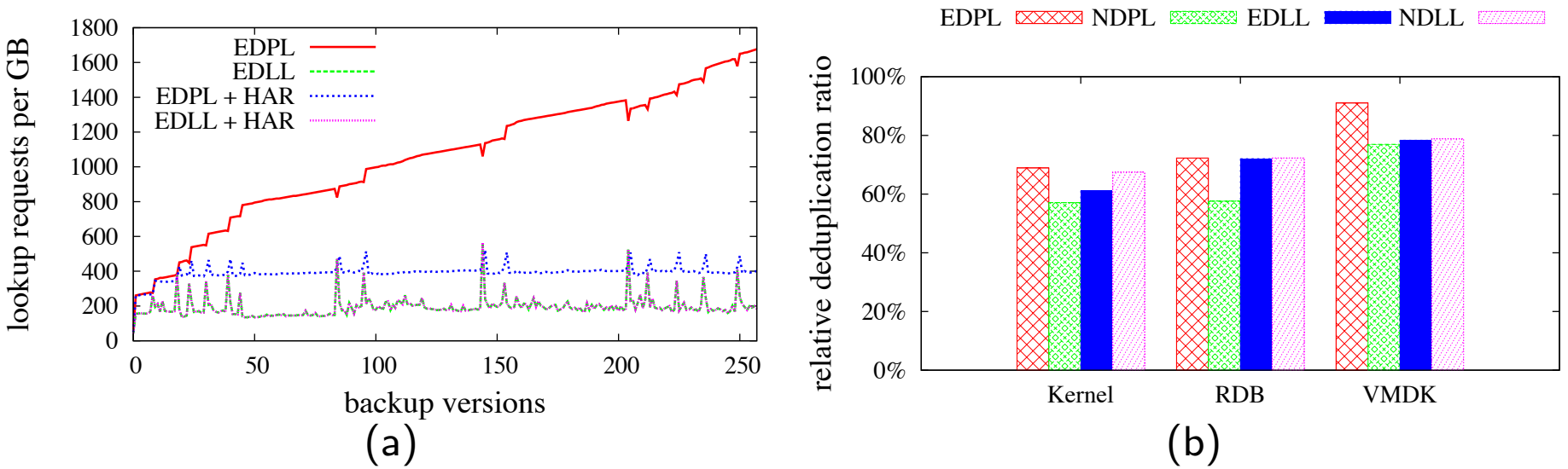


Figure: **(a)** How does HAR improve EDPL in terms of lookup overhead in Kernel? **(b)** How does fingerprint index affect HAR? The Y-axis shows the relative deduplication ratio to that of exact deduplication without rewriting.

- Exact Deduplication exploiting Physical Locality (EDPL) has the best interplays with the rewriting algorithm (HAR).

The Interplays Between Rewriting and Restore Algorithm

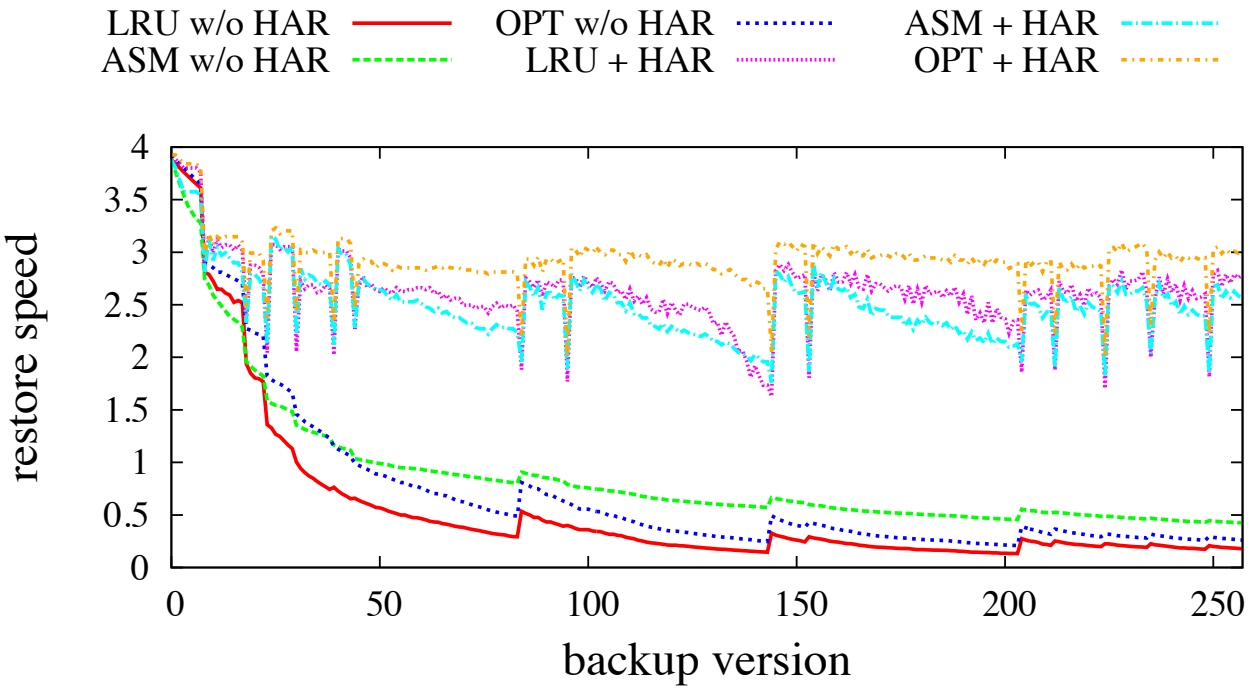


Figure: EDPL is used as the fingerprint index

- When HAR is used, the optimal cache is better; otherwise, the rolling forward assembly area is better.

Conclusions

- We propose a taxonomy to understand the parameter space of data deduplication.
- We design and implement a framework to evaluate the parameter space.
- We present our experimental results, and draw the following recommendations.

Subspace	Recommended parameter settings	Advantages
EDLL	content-defined segmenting random sampling	lowest storage cost sustained backup performance
NDPL	uniform sampling	lowest memory footprint simplest logical frame
NDLL	content-defined segmenting similarity detection & segment prefetching	lowest memory footprint high deduplication ratio
EDPL	an efficient rewriting algorithm	sustained high restore performance good interplays with the rewriting algorithm

Table: How to choose a reasonable solution according to required tradeoff.

Thank You!

Q & A

DeFrame is released at *www.github.com/fomy/destor*

Exploiting Similarity for NDLL

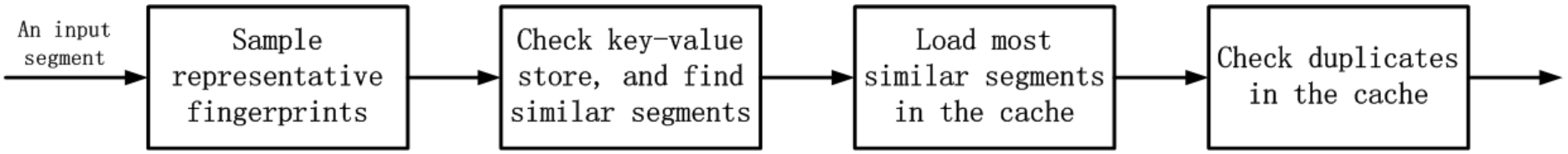


Figure: This figure shows the workflow of the Top-k similarity detection.

- **Observations**: NDLL works better than NDPL in datasets where self-references are rare, but worse in datasets where self-references are common.
  - Self-references are duplicates in a single file (backup).
- We could exploit similarity to improve deduplication ratio.
- **Advantage**: higher deduplication ratio than the Base procedure.
- **Weakness**: more complicated procedure and an additional buffer, compared to the *Base* procedure.

The efficiency of similarity detection

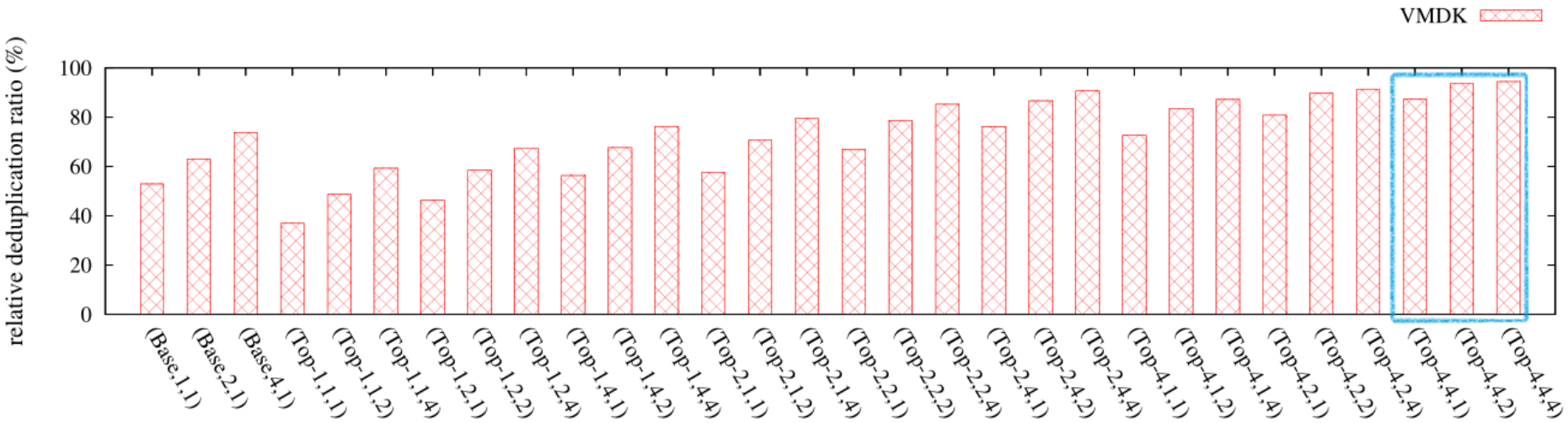


Figure: Impacts of the segment selection (s), segment prefetching (p), and mapping relationship (v) on deduplication ratio.

- On the X-axis, we have parameters in the format (s, p, v).
  - s could be Base and Top-k (k varies from 1 to 4).
  - p varies from 1 to 4.
  - v varies from 1 to 4.
- They finally achieve 90% of the deduplication ratio of exact deduplication.

The efficiency of similarity detection

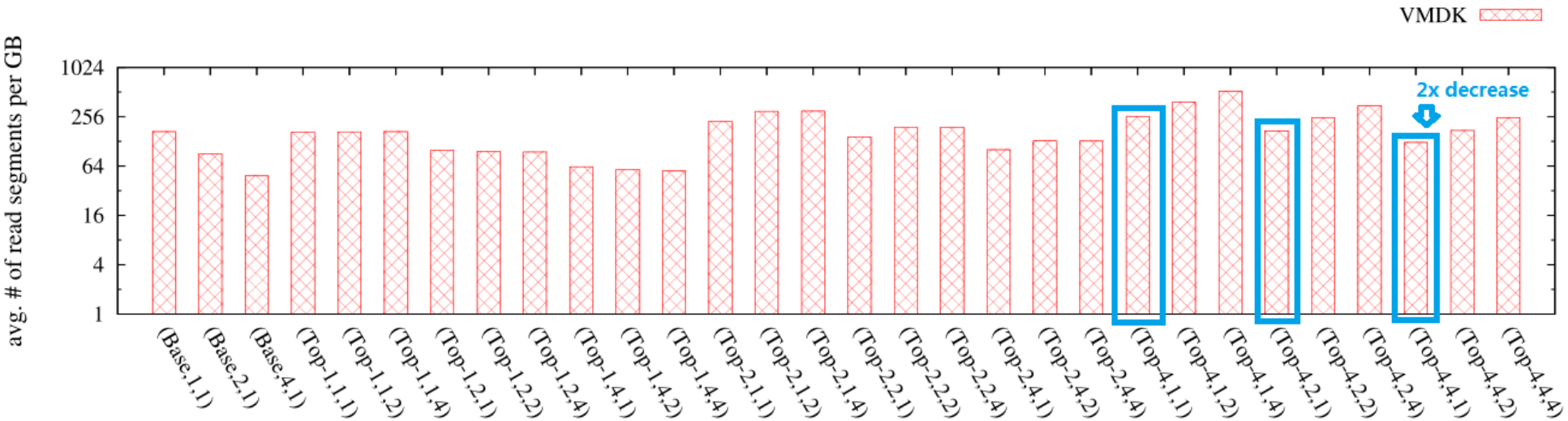


Figure: Impacts of the segment selection (s), segment prefetching (p), and mapping relationship (v) on segments read.

- The segment prefetching is complementary with Top-k.

Storage cost

Dataset	*Fraction*	*EDPL/EDLL*	*NDPL-64*	*NDPL-128*	*NDPL-256*	*NDLL-64*	*NDLL-128*	*NDLL-256*
Kernel	DRAM	1.33%	0.83%	0.49%	0.31%	0.66%	0.34%	0.16%
	HDD	57.34%	65.01%	70.56%	77.58%	59.03%	59.83%	60.23%
	Total	58.67%	65.84%	71.04%	77.89%	59.69%	60.17%	60.39%
RDB	DRAM	1.40%	0.83%	0.48%	0.31%	0.70%	0.35%	0.17%
	HDD	55.15%	61.25%	66.08%	73.58%	55.27%	55.34%	55.65%
	Total	56.55%	62.07%	66.56%	73.89%	55.97%	55.69%	55.82%
VMDK	DRAM	1.41%	0.82%	0.45%	0.27%	0.71%	0.35%	0.18%
	HDD	54.86%	60.32%	63.16%	67.10%	59.79%	62.92%	71.24%
	Total	56.27%	61.14%	63.61%	67.36%	60.49%	63.27%	71.42%

Table: The storage costs relative to the baseline which indexes all fingerprints in DRAM. NDPL-128 is NDPL of a 128:1 uniform sampling ratio.

- Via exploiting locality, the storage cost reduces by about 40%.
- Near-exact deduplication reduces the memory footprint, however it generally increases the total storage cost.

Choosing Sampling Method in NDPL

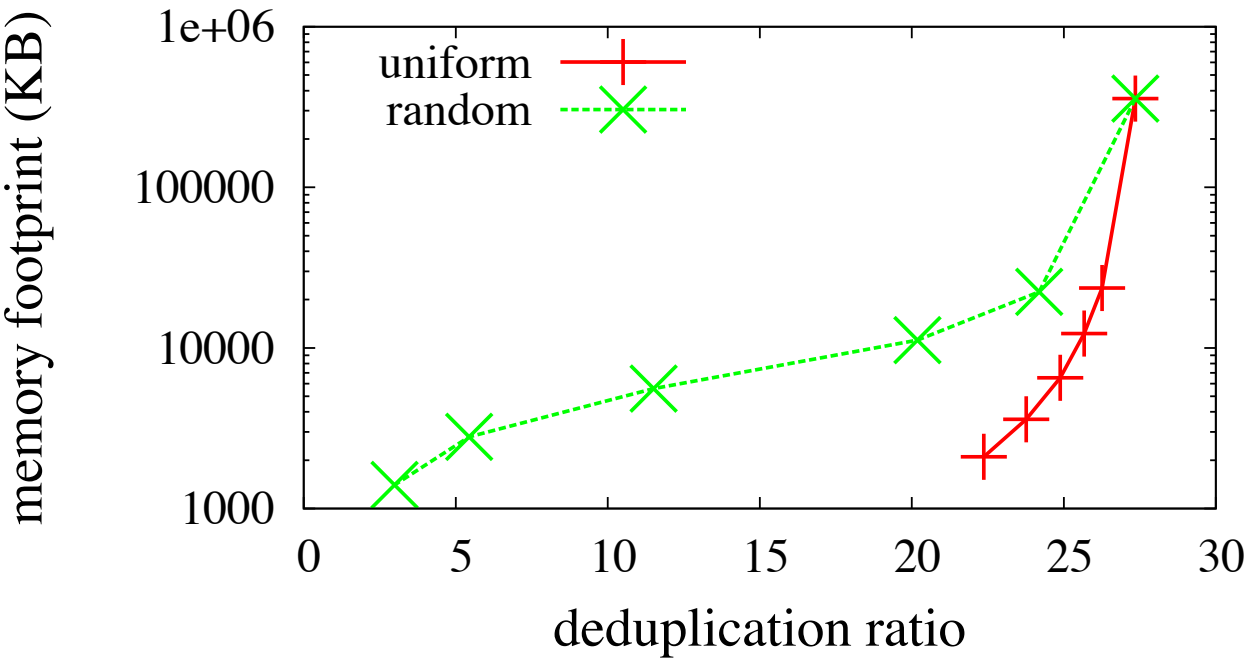


Figure: Impacts of varying sampling method on NDPL. Points in each line are of different sampling ratios, which are 256, 128, 64, 32, 16, and 1 from left to right.

- The uniform sampling achieves significantly better deduplication ratio than the random sampling.