

# DeepSketch: A New Machine Learning-Based Reference Search Technique for Post-Deduplication Delta Compression

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**USENIX FAST 2022**

*\*J. Park and J. Kim are co-primary authors.*

# Executive Summary

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- **Motivation**
  - ❑ **Data reduction:** Effective at **reducing the management cost** of a data center by reducing the amount of data physically written to storage devices
  - ❑ **Post-deduplication delta compression:** **Maximizes the data-reduction ratio** by applying **delta compression** along with deduplication and lossless compression
- **Problem:** Existing post-deduplication delta-compression techniques provide **significantly low data-reduction ratios** compared to the optimal.
  - ❑ Due to the **limited accuracy of reference search** for delta compression
  - ❑ **Cannot identify a good reference block** for many incoming data blocks
- **Key Idea:** DeepSketch, a new **machine learning-based** reference search technique that uses the **learning-to-hash** method
  - ❑ Generates a given data block's **signature (sketch)** using a deep neural network
  - ❑ The higher the **delta-compression benefit** of two data blocks, the more similar the **signatures** of the two blocks to each other
- **Evaluation Results:** DeepSketch reduces the amount of physically-written data
  - ❑ Up to **33%** (**21%** on average) compared to a state-of-the-art baseline

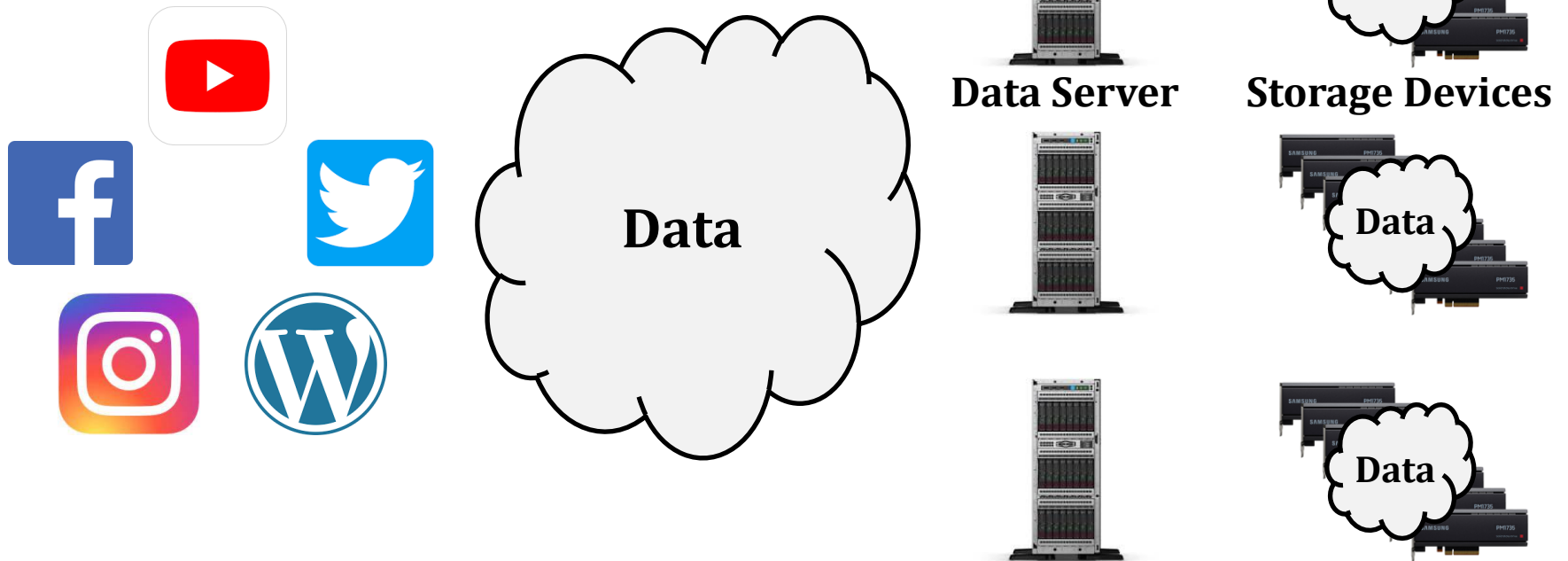
# Talk Outline

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- Data Reduction in Storage Systems
- DeepSketch: A New Machine Learning-based Reference Search Technique
- Evaluation Results

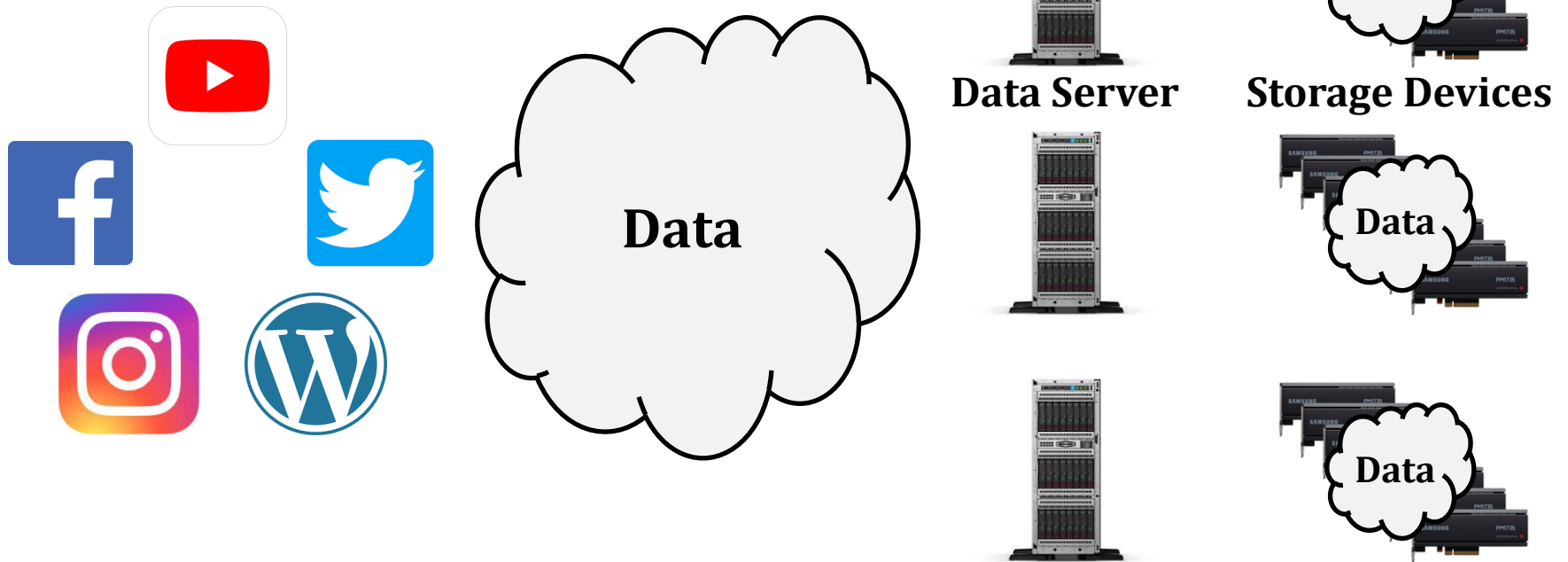
# Big Data Era

- Unprecedented amounts of data processed in modern computing systems
  - e.g., Facebook generates 4 petabytes of new data every day



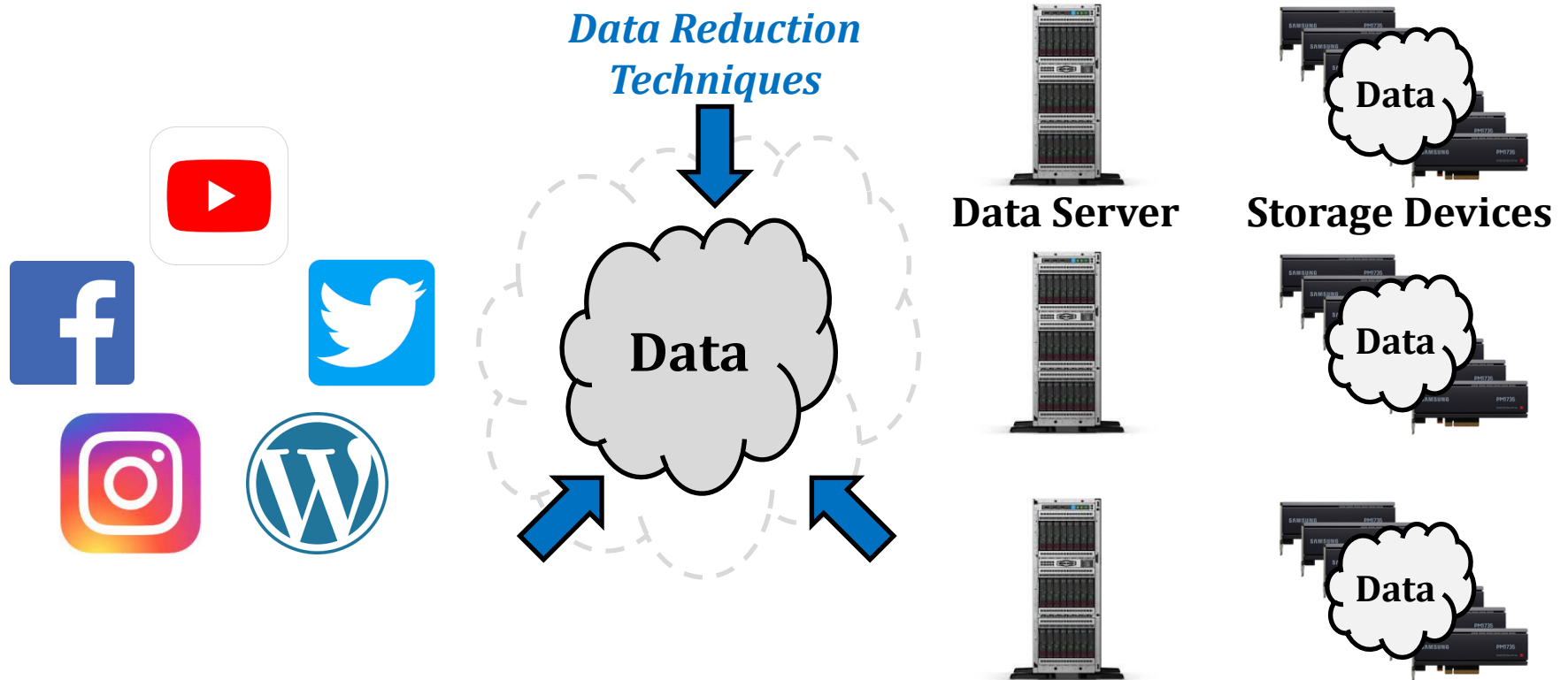
# Data Reduction in Storage Systems

- Effective at reducing the management cost of a data center



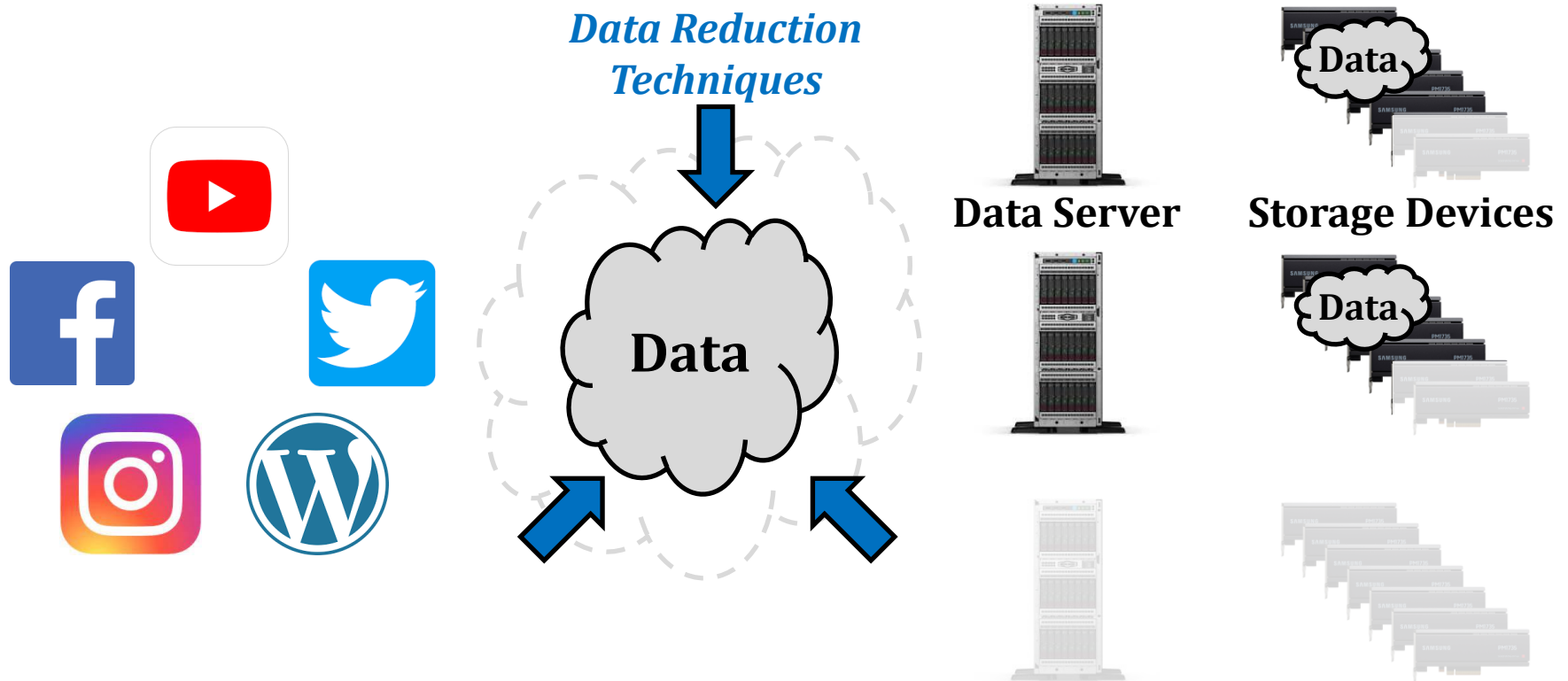
# Data Reduction in Storage Systems

- Effective at reducing the management cost of a data center
  - By reducing the amount of written data to storage devices



# Data Reduction in Storage Systems

- Effective at reducing the management cost of a data center
  - By reducing the amount of written data to storage devices
  - Enabling the system to deal with the same amount of data with fewer and/or smaller storage devices



# Post-deduplication Delta Compression

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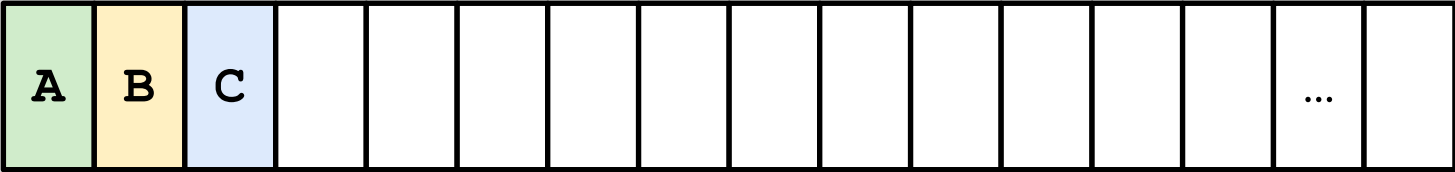
- Combines three different data-reduction approaches
  - To maximize the data-reduction ratio ( $= \frac{\textit{Original Data Size}}{\textit{Reduced Data Size}}$ )
  - Deduplication → Delta compression → Lossless compression
  - Can achieve more than 2x data reduction over a simple combination of deduplication and lossless compression



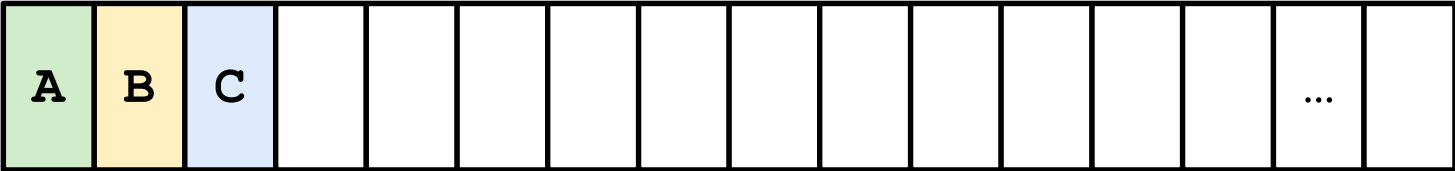
# Overview of Post-Deduplication Delta Compression

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## File System



## Data Reduction Module



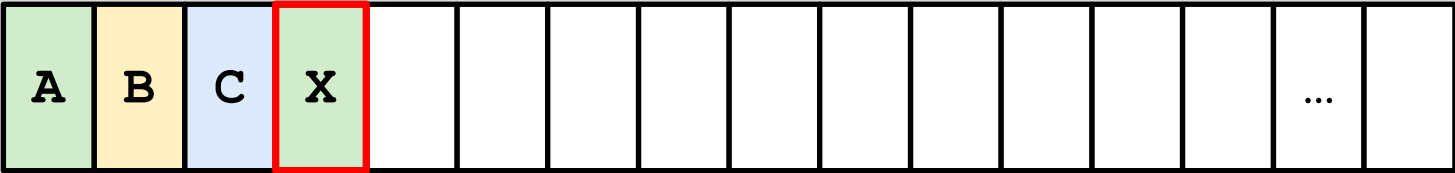
## Storage Device

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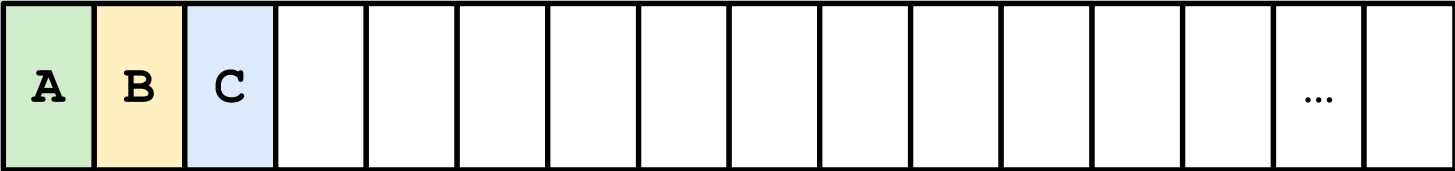
# Step 1: Deduplication

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## File System



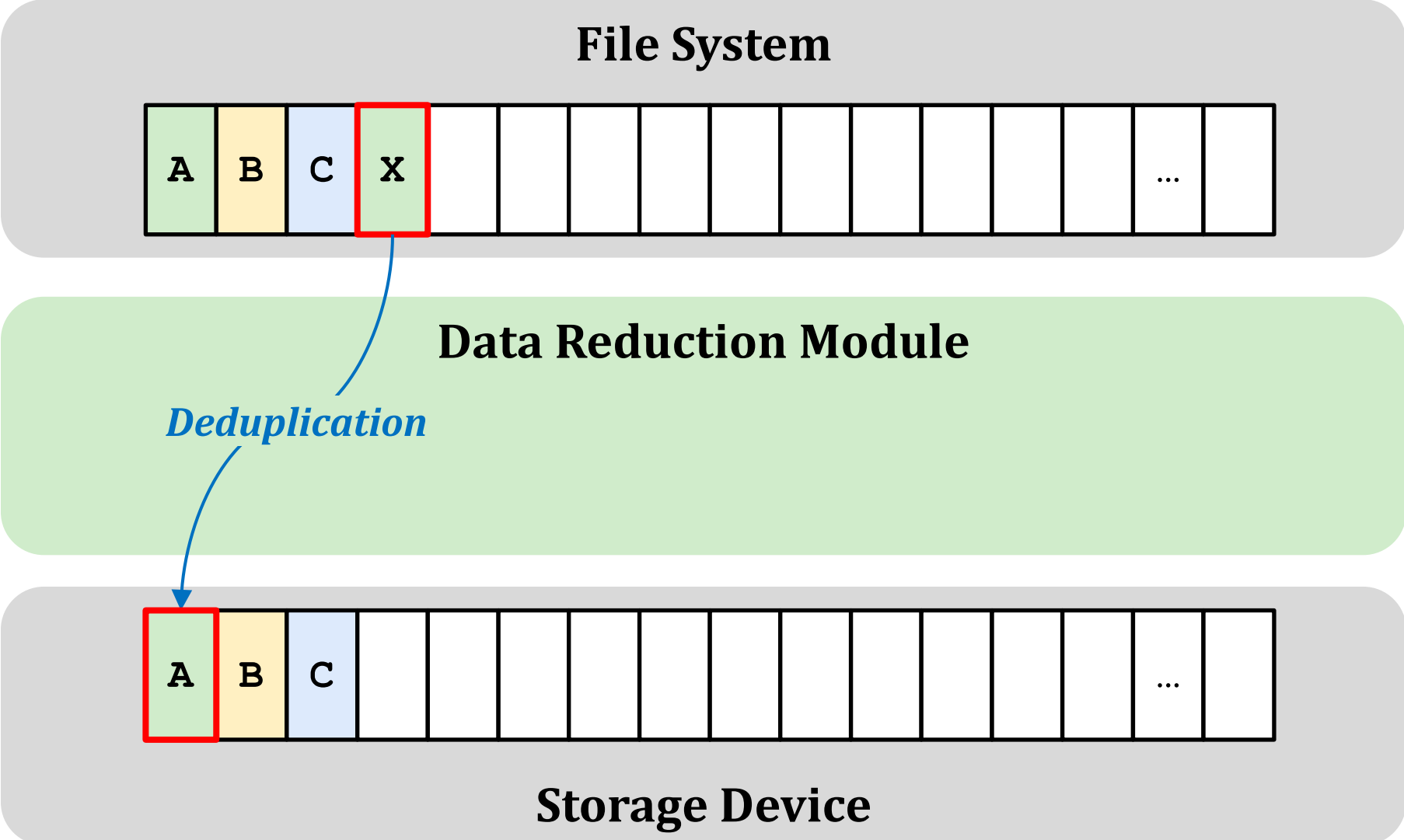
## Data Reduction Module



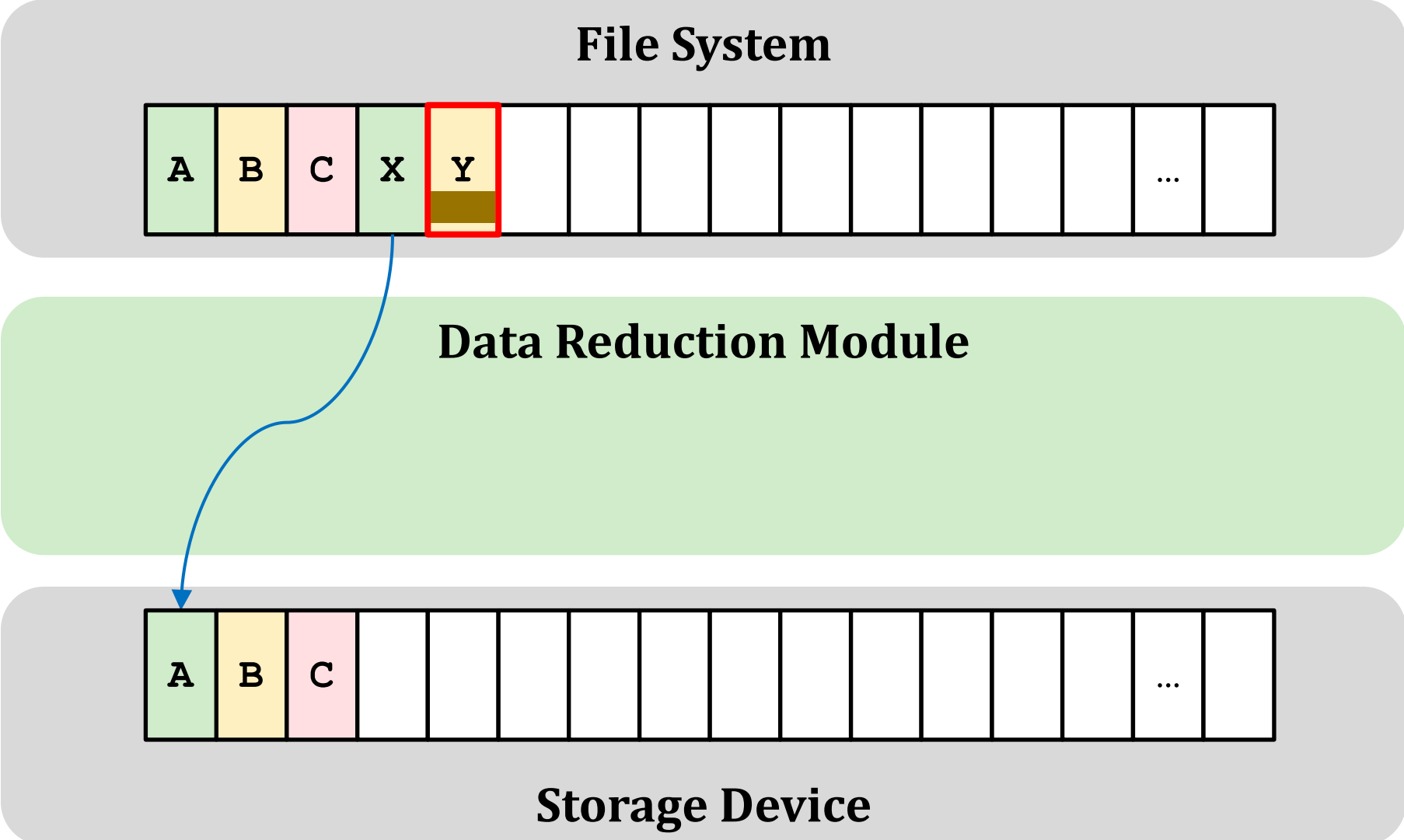
## Storage Device

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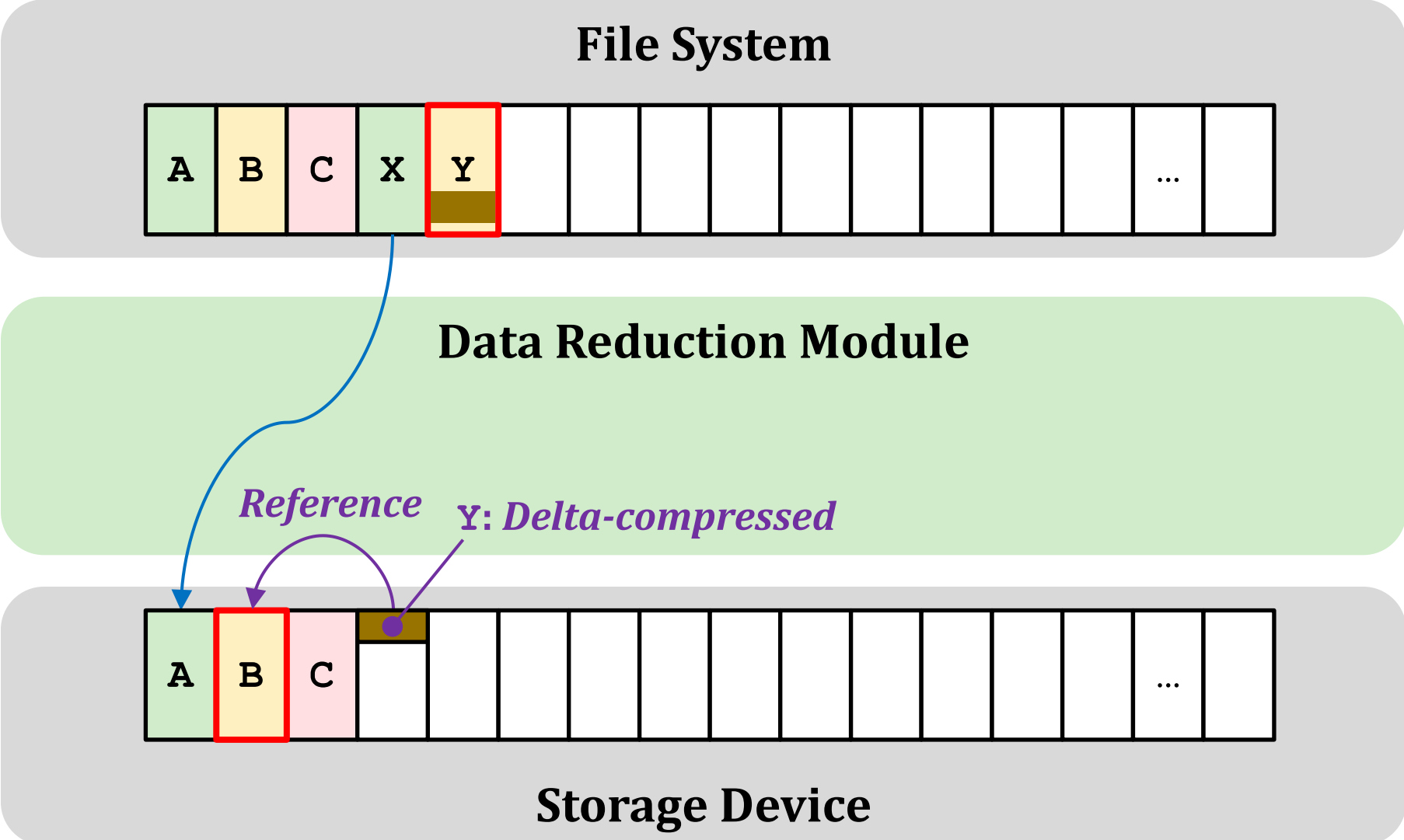
# Step 1: Deduplication



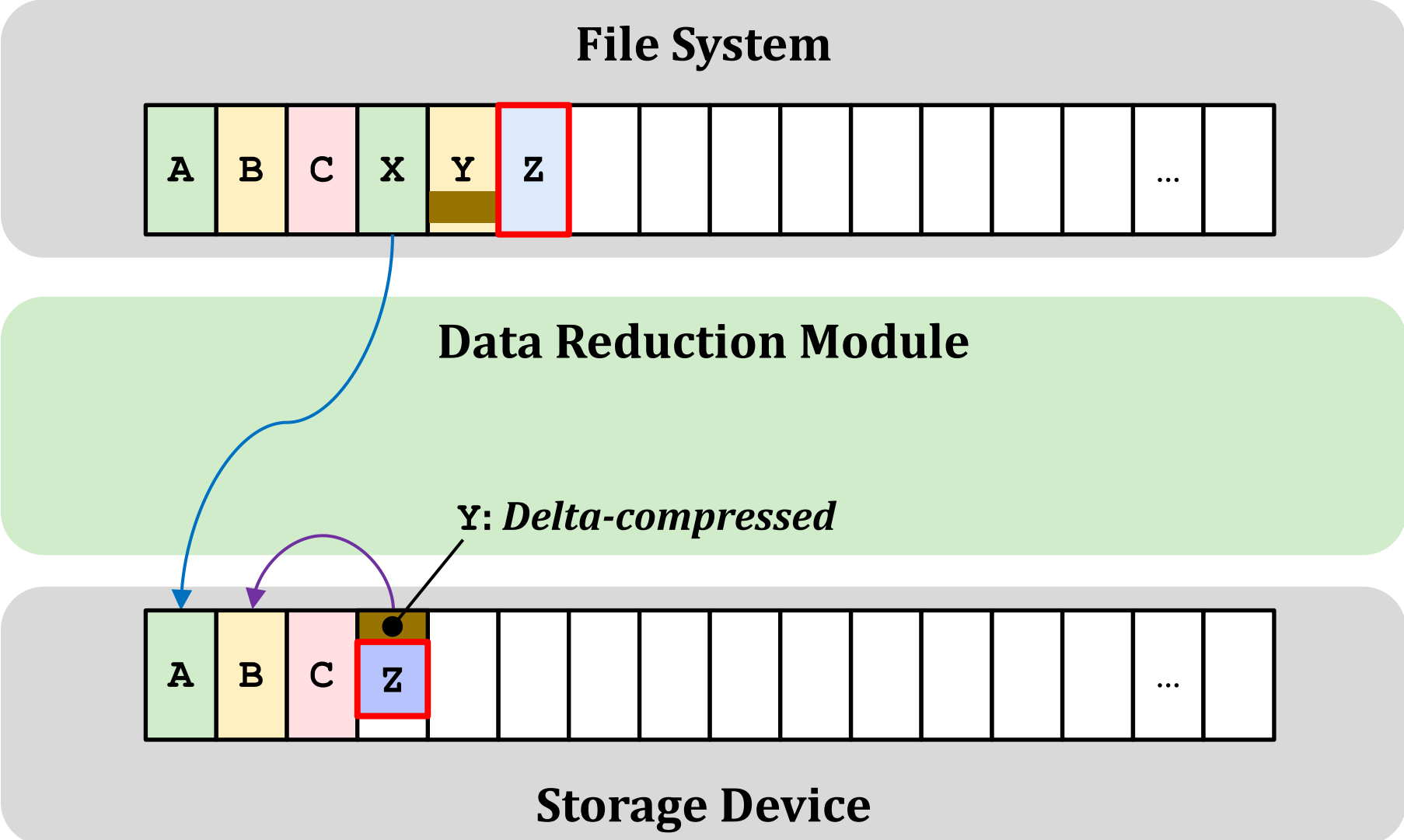
# Step 2: Delta Compression



# Step 2: Delta Compression



# Step 3: Lossless Compression



# Key Challenge: Reference Search

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- How to find a good reference block for an incoming data block across a wide range of stored data at low cost
- Scanning all stored data blocks: Prohibitive performance overhead
- Reference search in deduplication
  - Uses a strong hash function (e.g., SHA1 or MD5) to generate a data block's fingerprint
  - Enables quick reference search by comparing only fingerprints
- Reference search in delta compression
  - Difficult to use a strong hash function that generates significantly different hash values for non-identical yet similar data blocks

# State-of-the-Art: Data Sketching

- Generates a data signature (called **sketch**) of each data block
  - **Sketch**: More **approximate** signature than fingerprint
  - Goal: two similar data blocks have similar sketches

**Block 1**

U	S	E	N	I	X	F	A	S	T	2	0	2	2
---	---	---	---	---	---	---	---	---	---	---	---	---	---

**Block 2**

U	S	E	N	I	X	F	A	S	T	2	0	2	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---

*Feature*<sub>1</sub> =  $H_1(\text{SENI}) = 0x73$

*Feature*<sub>2</sub> =  $H_2(\text{FAST}) = 0x32$

*Feature*<sub>3</sub> =  $H_3(\text{USEN}) = 0xF1$

*Feature*<sub>4</sub> =  $H_4(\text{S202}) = 0xCC$

*Feature*<sub>1</sub> =  $H_1(\text{SENI}) > H_1(2020)$

*Feature*<sub>2</sub> =  $H_2(\text{FAST}) > H_2(2020)$

*Feature*<sub>3</sub> =  $H_3(\text{USEN}) > H_3(2020)$

*Feature*<sub>4</sub> =  $H_4(\text{S202}) > H_4(2020)$

*Super Feature*

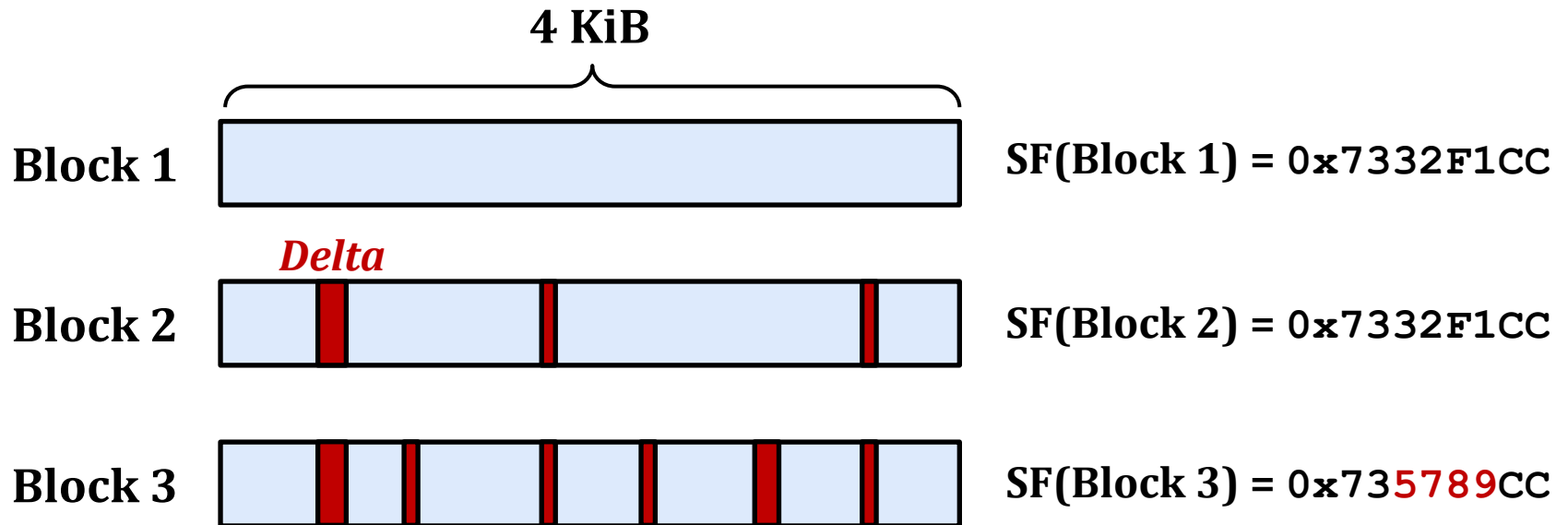
**SF(Block 1) = 0x7332F1CC**

**SF(Block 2) = 0x7332F1CC**



# Limitations of Existing Techniques

- Provide **significantly lower data-reduction ratios** than the optimal
  - Due to **limited accuracy** in reference search for delta compression
- In a general-PC-usage workload, an SF-based approach
  - Provides only **60% of the data-reduction ratio** of **brute-force search**
  - **High false-negative ratio**: Fails to find any reference data block for **36%** of the incoming data blocks that can benefit from delta compression



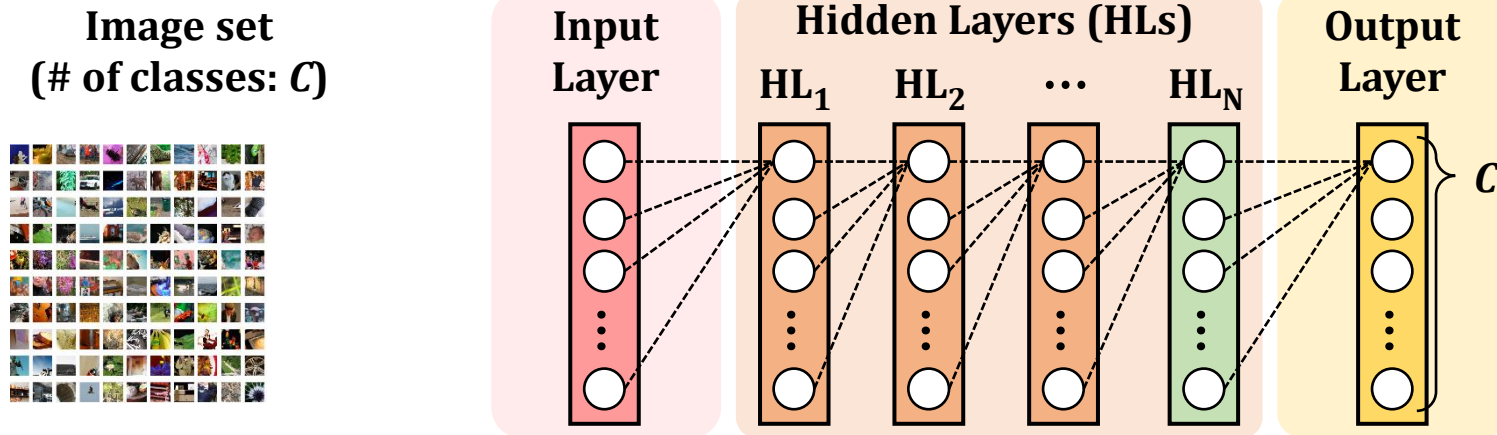
# Talk Outline

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- Data Reduction in Storage Systems
- DeepSketch: A New Machine Learning-based Reference Search Technique
- Evaluation Results

# DeepSketch: Key Idea

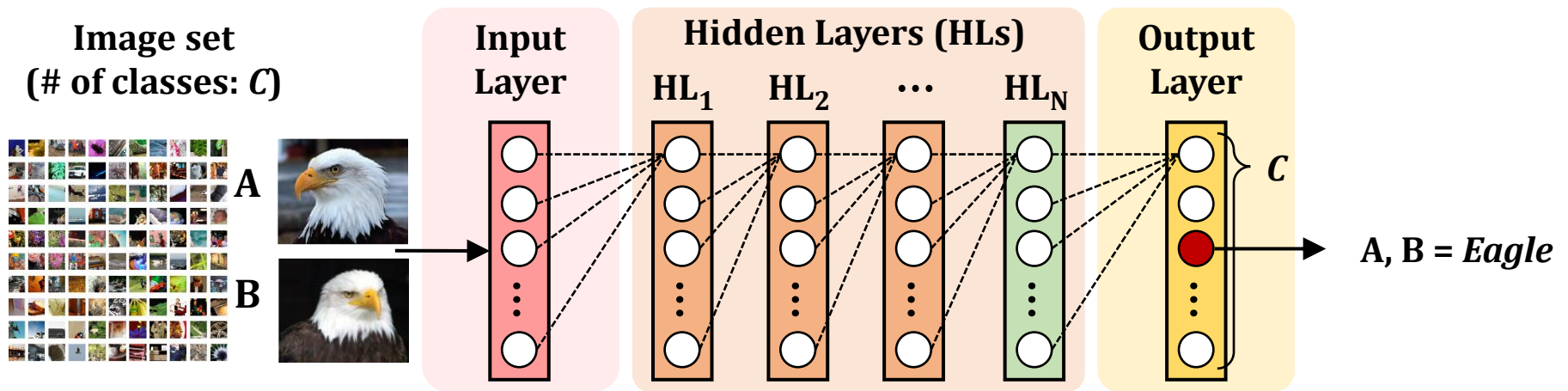
- Use the **learning-to-hash method** for sketch generation
  - A promising machine learning (ML)-based approach for the **nearest-neighbor search problem**



<Learning-to-hash for content-based image retrieval>

# DeepSketch: Key Idea

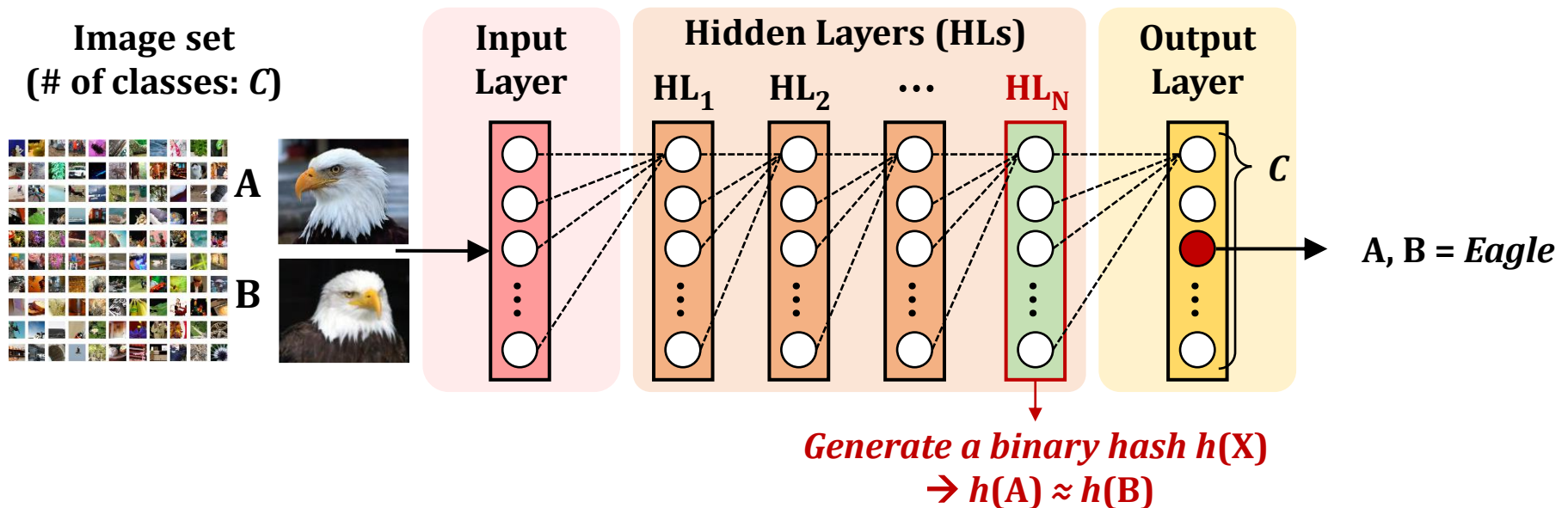
- Use the **learning-to-hash method** for sketch generation
  - A promising machine learning (ML)-based approach for the **nearest-neighbor search problem**



<Learning-to-hash for content-based image retrieval>

# DeepSketch: Key Idea

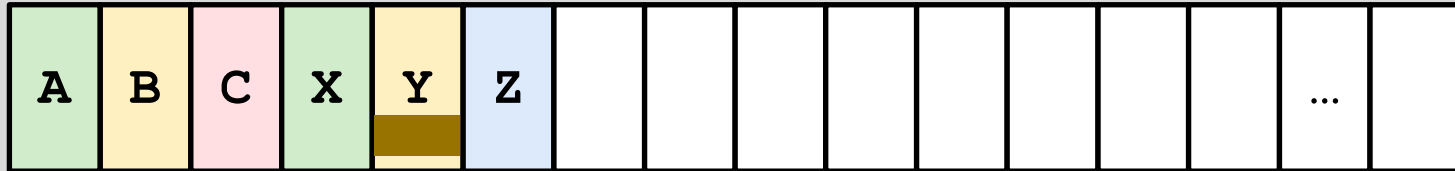
- Use the **learning-to-hash method** for sketch generation
  - A promising machine learning (ML)-based approach for the **nearest-neighbor search problem**



<Learning-to-hash for content-based image retrieval>

# DeepSketch: Overview

## File System



## Data Reduction Module

Fingerprint (FP)  
Generator  
(e.g., SHA-1)

### FP Store

Data	FP
A	0x32
B	0x47
...	...

Super Feature-  
based  
Sketch (SK)  
Generator

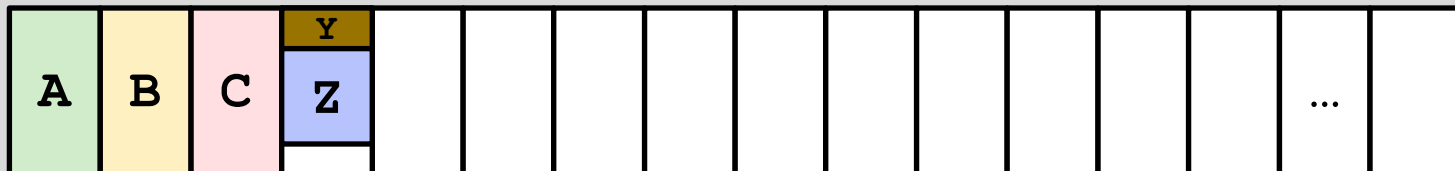
### SK Store

Data	SK
A	0x73
B	0xF9
...	...

### Ref. Table

Data	Ref.	T
X	A	0
Y	B	1
...	...	...

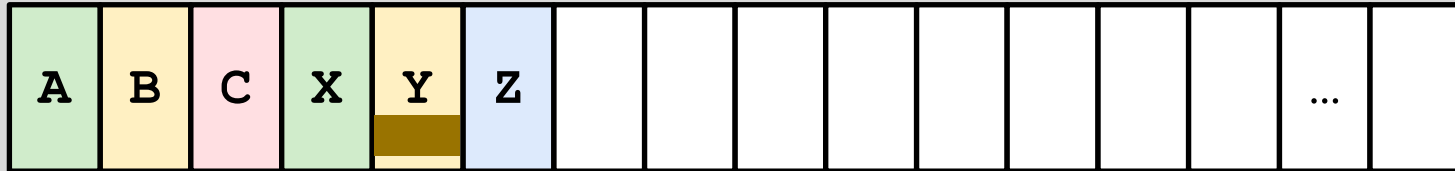
T: Ref. type  
(0: dedup., 1: delta-comp.)



## Storage Device

# DeepSketch: Overview

## File System



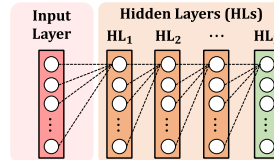
## Data Reduction Module

Fingerprint (FP)  
Generator  
(e.g., SHA-1)

### FP Store

Data	FP
A	0x32
B	0x47
...	...

### DNN-based SK generator



### SK Store

Data	SK
A	0x73
B	0xF9
...	...

### Ref. Table

Data	Ref.	T
X	A	0
Y	B	1
...	...	...

T: Ref. type  
(0: dedup., 1: delta-comp.)



## Storage Device

# DeepSketch: Challenges

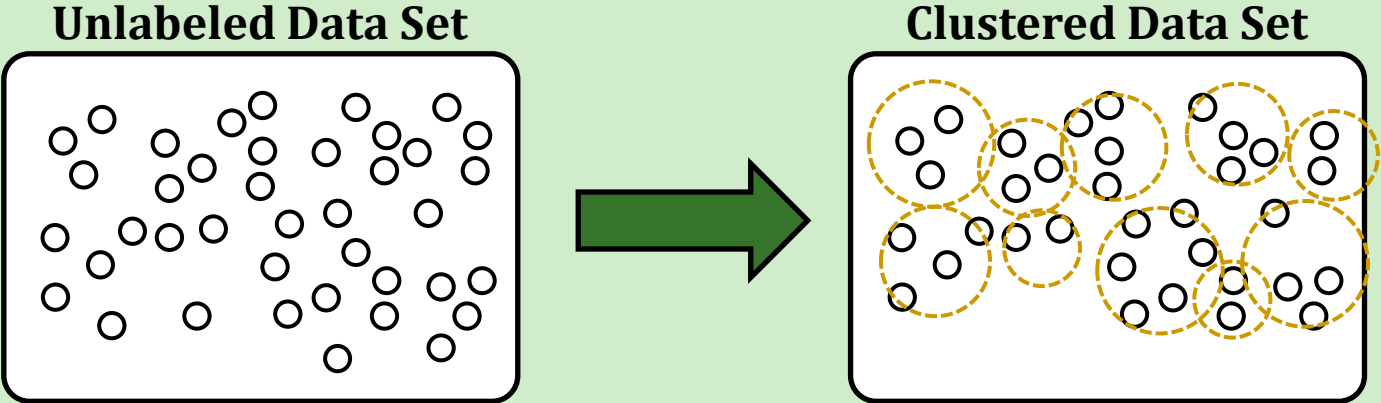
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- Lack of semantic information
  - Most prior learning-to-hash approaches deal with **specific data types** (e.g., image sets with **well-defined classes**)
  - DeepSketch needs to process **general binary data**
  
- Extremely high dimensional space
  - Possible bit patterns:  $2^{4,096 \times 8}$  for a data block size of 4 KiB
  - Difficult to collect large enough data to train the DNN with high inference accuracy

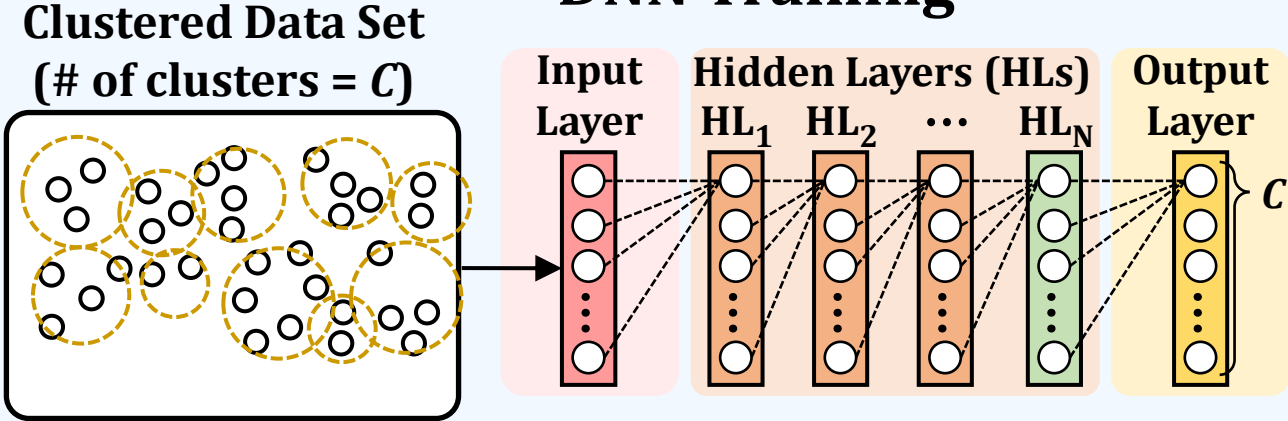


# Training the DNN of DeepSketch

## Clustering

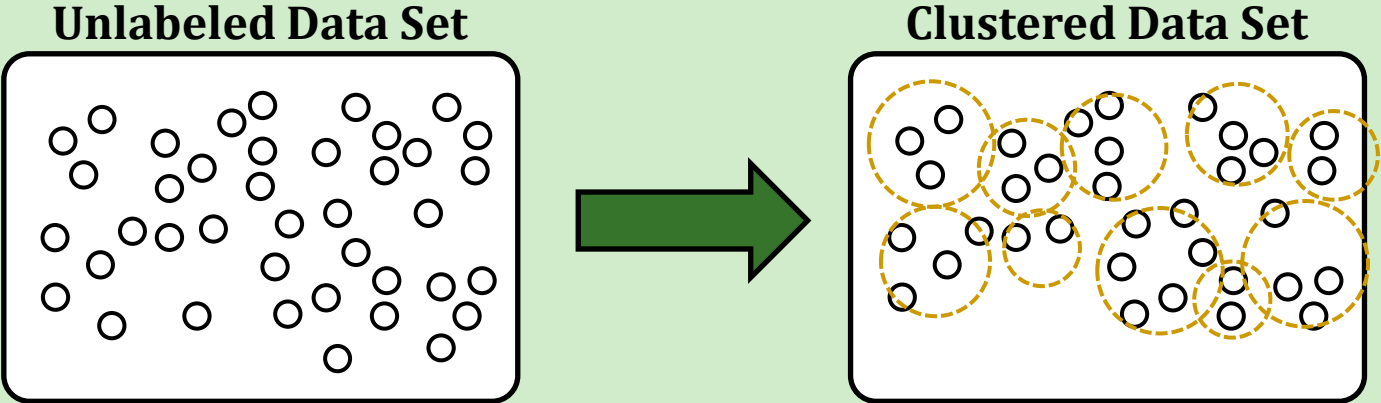


## DNN Training

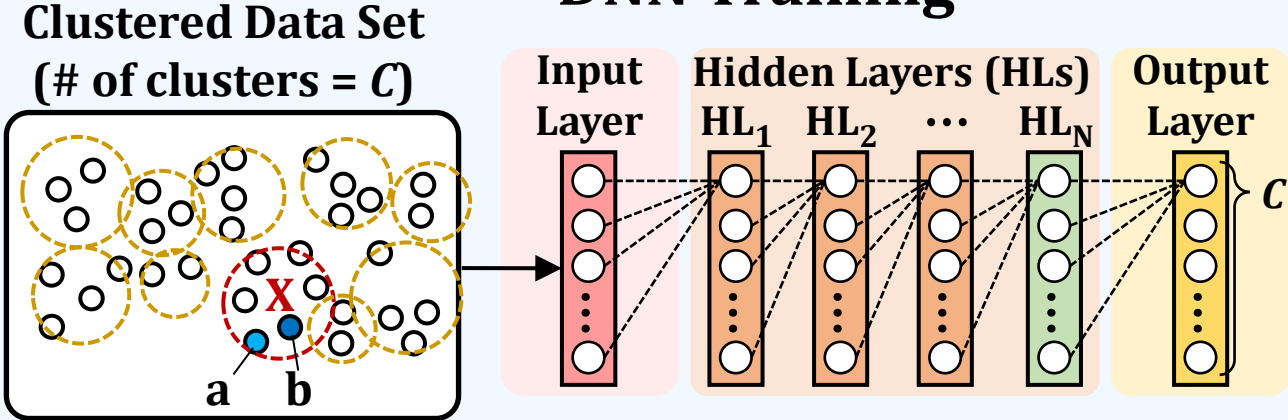


# Training the DNN of DeepSketch

## Clustering



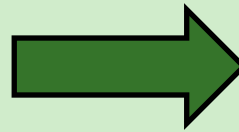
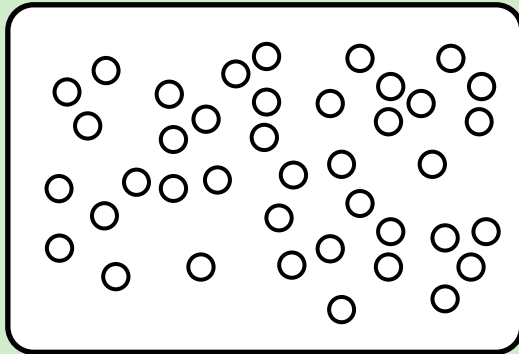
## DNN Training



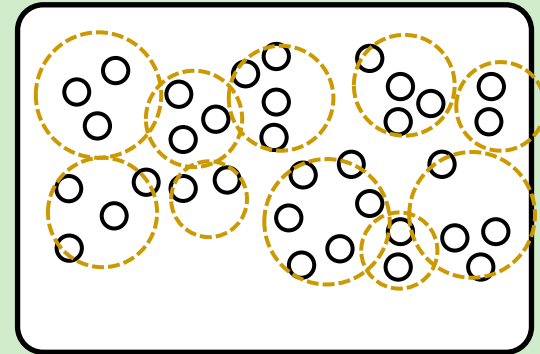
# Training the DNN of DeepSketch

## Clustering

Unlabeled Data Set

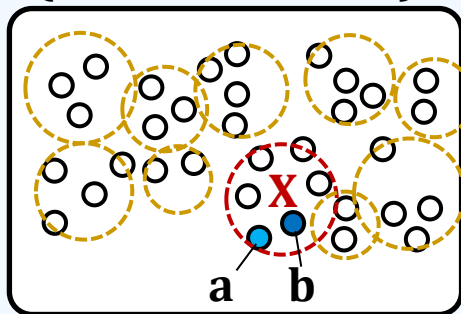


Clustered Data Set



## DNN Training

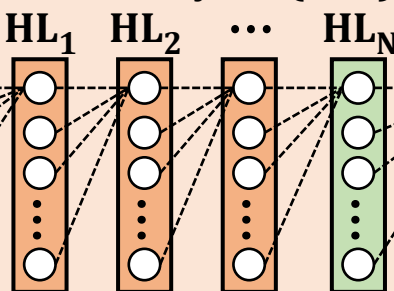
Clustered Data Set  
(# of clusters =  $C$ )



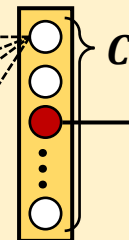
Input Layer



Hidden Layers (HLs)



Output Layer

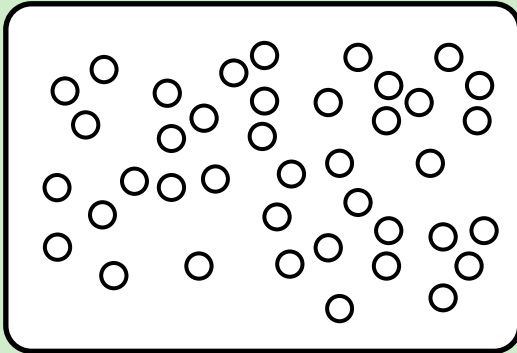


$a, b \in X$

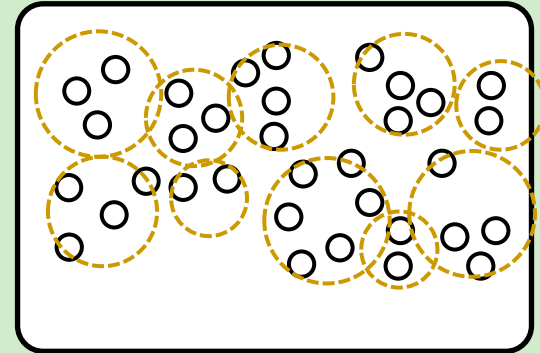
# Training the DNN of DeepSketch

## Clustering

Unlabeled Data Set

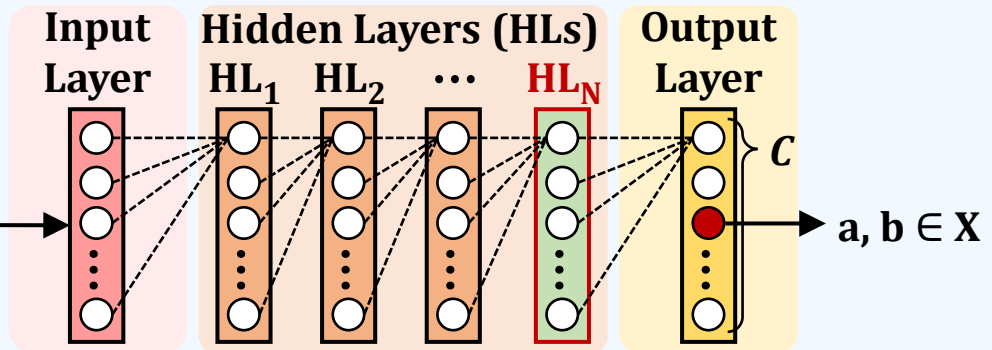
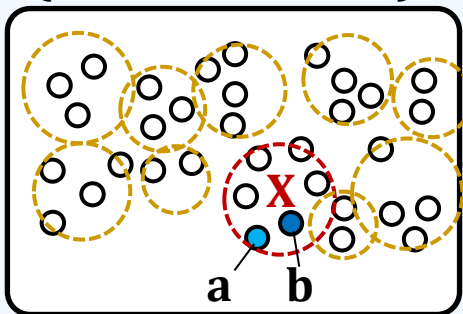


Clustered Data Set



## DNN Training

Clustered Data Set  
(# of clusters =  $C$ )



*Generate sketches*  $\rightarrow SK(a) \approx SK(b)$

# Data Clustering for DeepSketch

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- Existing clustering algorithms are **unsuitable** for DeepSketch
  - K-means clustering: **No information** of appropriate **initial parameter values** (e.g., # of cluster  $k$ ) in DeepSketch
  - Hierarchical clustering: Huge **computation and memory overheads** for large data sets
- Dynamic k-means clustering (DK-Clustering)
  - A version of k-means clustering that **dynamically refines** the value for  $k$  while clustering a data set
  - Key idea: **Two-step** clustering that iterates
    - **Step 1:** Coarse-grained clustering to **roughly group data blocks at low cost** and **remove low-impact data blocks**
    - **Step 2:** Fine-grained clustering to find **the best mean block and outliers** of each group

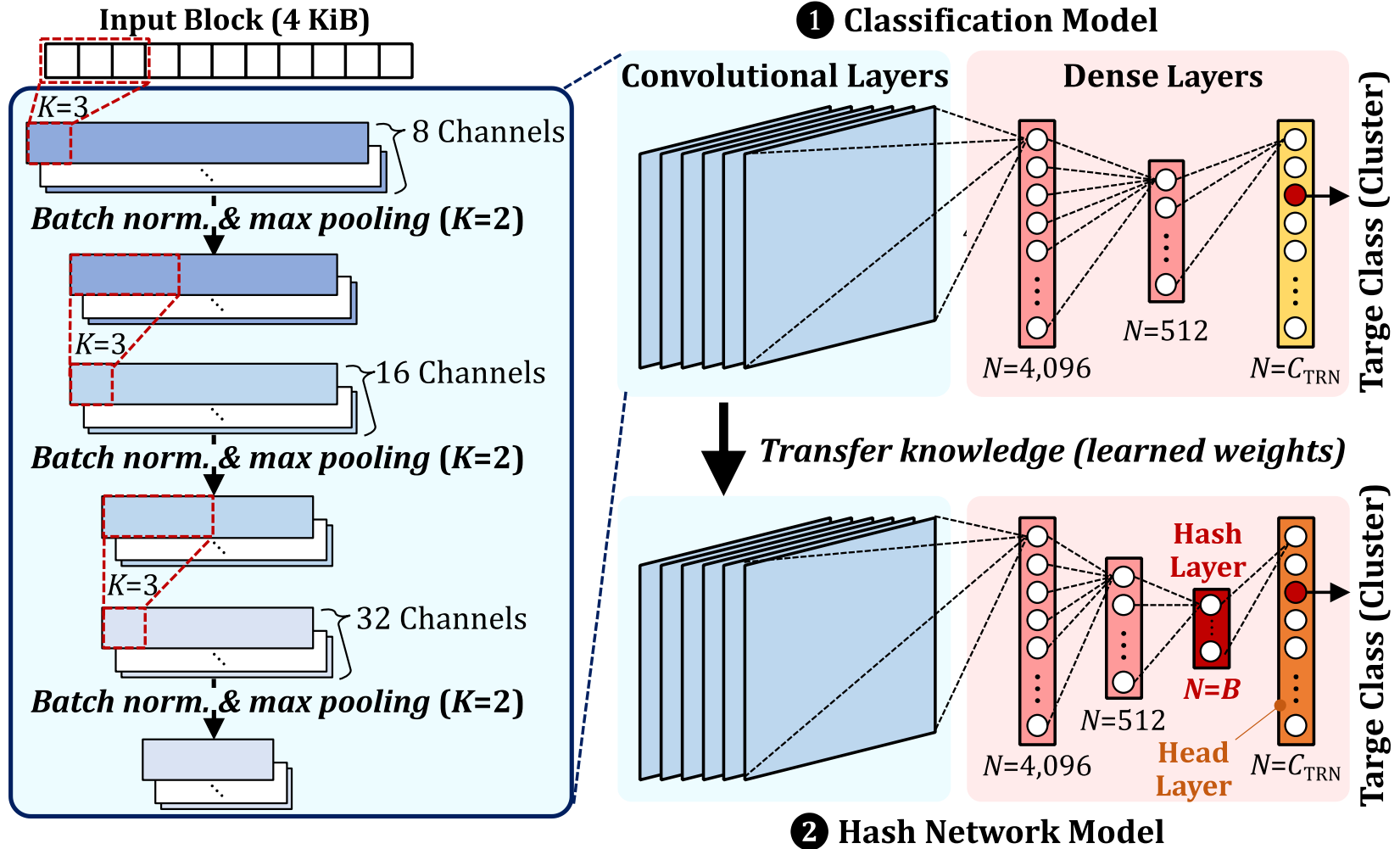
# Post-Processing for Training Data Set

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- **Non-uniform distribution** of data blocks across the clusters
  - e.g., the **largest 10%** clusters contain **47.93% of the total data blocks**.
  - Can make DNN training significantly biased towards specific data patterns
  
- **Resize** every cluster to have **the same number of data blocks**
  - If # of data blocks  $> T \rightarrow$  **Randomly select  $T$  data blocks**
  - If # of data blocks  $< T \rightarrow$  **Add randomly-modified data blocks** (shifting random part of data blocks)

# DNN Training

- Two-step transfer learning from GreedyHash [Su+, NeurIPS'18]



# Talk Outline

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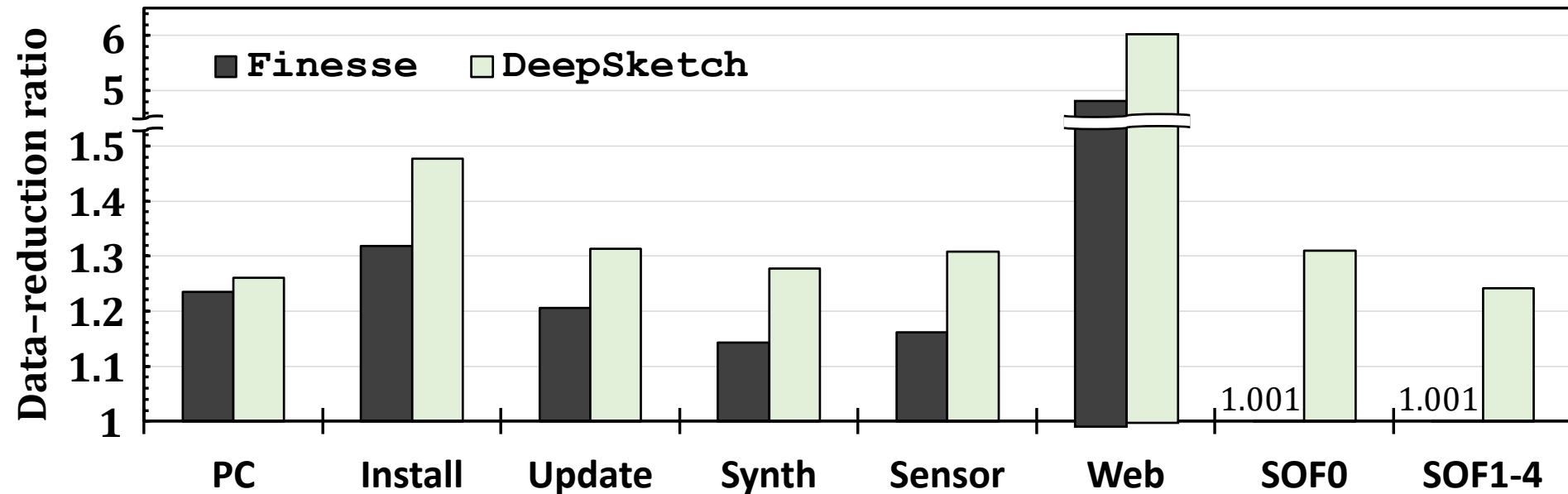


# Evaluation Methodology

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- Compared data-reduction techniques
  - **Dedup+Comp**: Deduplication → Lossless compression (LZ4)
  - **Finesse** [Zhang+, FAST'19]
    - High-performance super-feature-based reference search
    - Deduplication → Delta compression (XDelta) → LZ4
- Workloads
  - Six workloads collected from real systems w/ written data
    - PC, Install, Update, Synth, Sensor, Web
    - 10% of each trace: Training data set
    - Remaining 90%: Data-reduction & performance evaluation
  - Five workloads collected while storing Stack Overflow databases (SOF)
    - **Not used for training**
    - To see the generality of DeepSketch

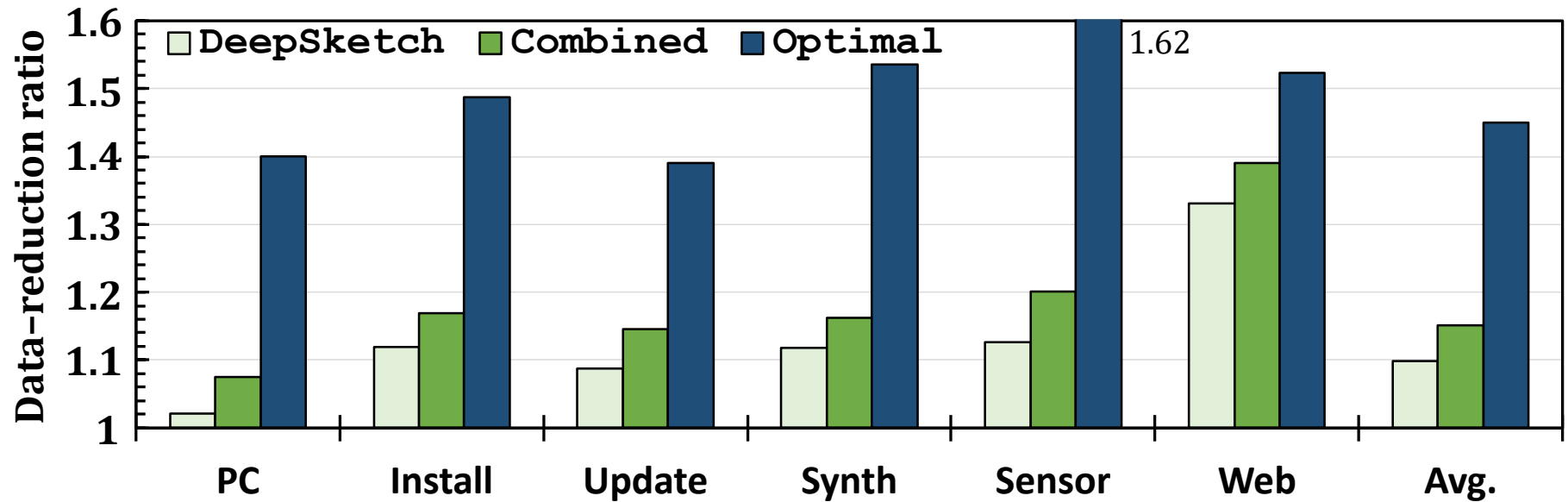
# Overall Data-Reduction Benefits



Large data-reduction improvement:  
Up to 33% (21% on average)

Effective for **unseen** workloads (SOFs)  
that **cannot benefit from the state-of-the-art**

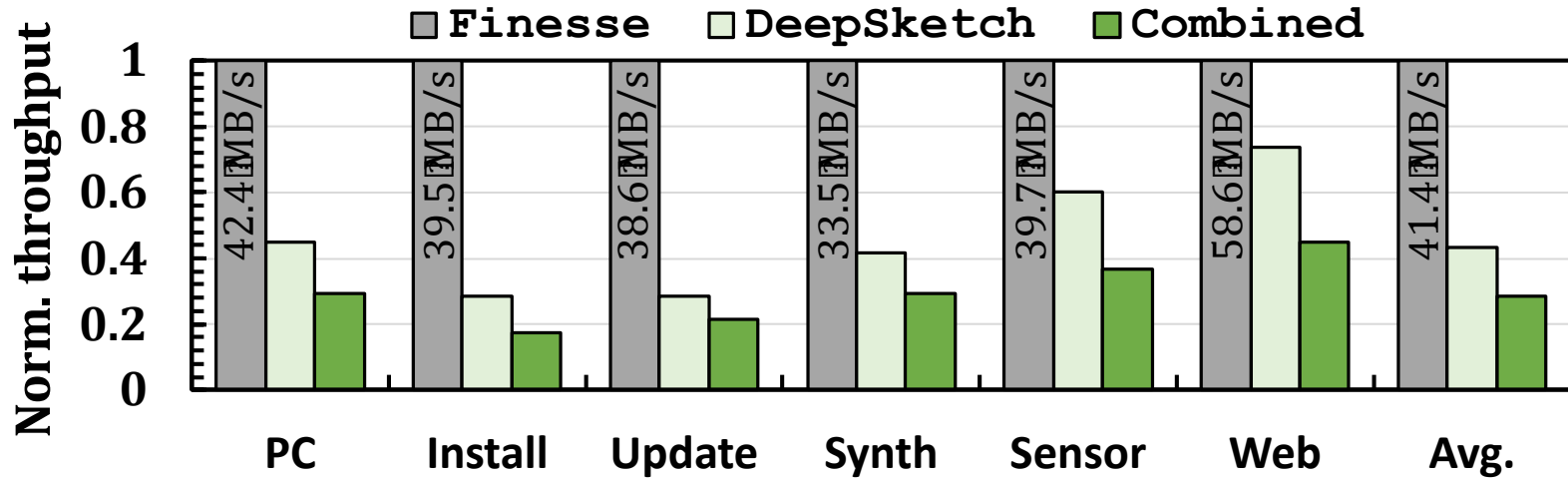
# Combined w/ Existing SF-Based Technique



Higher benefits over stand-alone techniques:  
DeepSketch and Finesse can complement each other

Call for future work: Significant room for improvement

# Performance Overhead



Call for future work: **Non-trivial performance overheads** due to **approximate nearest-neighbor search** (details in the full paper)

# Other Analyses in the Paper

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- Empirical Study on Super Feature-Based Reference Search
- Hyper-Parameter Exploration for DeepSketch's DNN
- Performance and Space Overheads
- Reference Search Patterns of DeepSketch and Finesse
- Impact of Training Data Set

# Executive Summary

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- **Problem:** Existing post-deduplication delta-compression techniques provide significantly low data-reduction ratios compared to the optimal.
  - Due to the limited accuracy of reference search for delta compression
  - Cannot identify a good reference block for many incoming data blocks
- **Key Idea:** DeepSketch, a new machine learning-based reference search technique that uses the learning-to-hash method
  - Generates a given data block's signature (sketch) using a deep neural network
  - The higher the delta-compression benefit of two data blocks, the more similar the signatures of the two blocks to each other
- **Evaluation Results:** DeepSketch reduces the amount of physically-written data
  - Up to 33% (21% on average) compared to a state-of-the-art baseline

We hope that our key ideas inspire many valuable studies going forward

# DeepSketch: A New Machine Learning-Based Reference Search Technique for Post-Deduplication Delta Compression

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Institute of Science & Technology

**USENIX FAST 2022**

*\*J. Park and J. Kim are co-primary authors.*

# DeepSketch: Application Scenarios

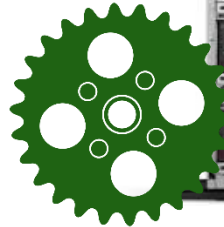
## Data Servers



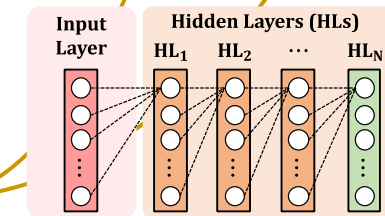
1) *Collect data for DNN training (preferably from data servers storing similar data types)*



2) *DNN Training (with powerful machines)*



3) *Update or build a new one*



**Trained DNN**

**New Server**