Tectonic-Shift: A Composite Storage Fabric for Large-Scale ML Training

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Stanford University, Meta

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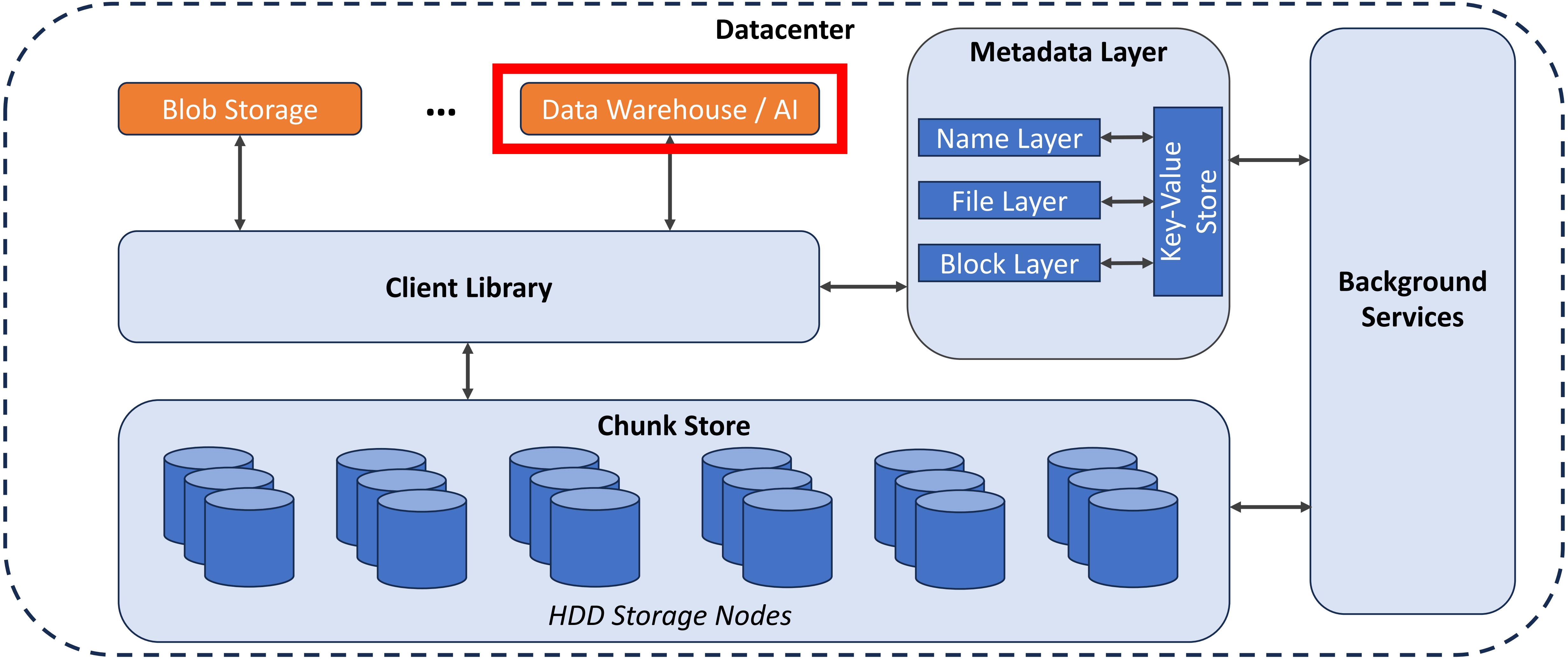
Stanford MAST

Tectonic Filesystem: Meta's storage foundation

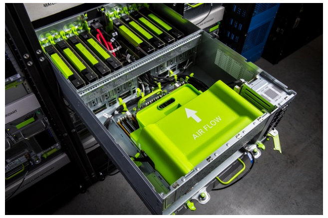


S. Pan, et al., *Facebook's Tectonic Filesystem: Efficiency from Exascale, FAST'21*

ML infrastructure scaling trends

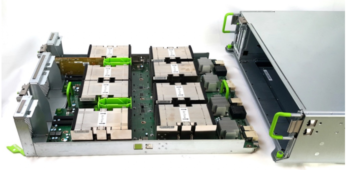
Training larger and more complex models (e.g., LLMs, DLRMs) requires…

Scale-Up Infrastructure



Big Sur

2016



Big Basin

2017

Big Basin v2

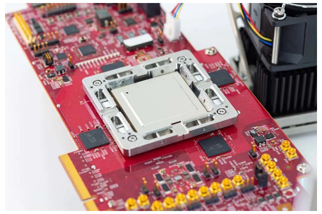
2018

Zion / ZionEX

2019-2021

Grand Teton

2022



MTIA

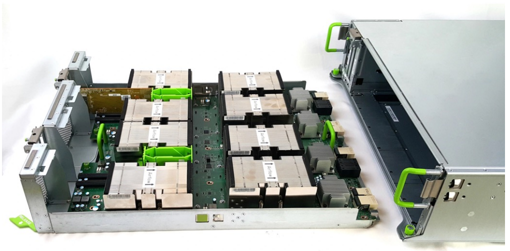
2023+

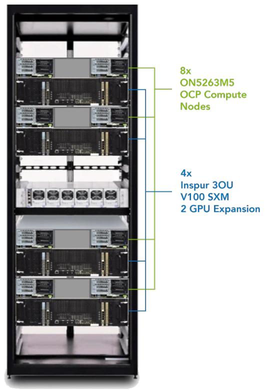
CPUs → **GPUs / ASICs**

ML infrastructure scaling trends

Training larger and more complex models (e.g., LLMs, DLRMs) requires…

Scale-Out Infrastructure





Node-Scale

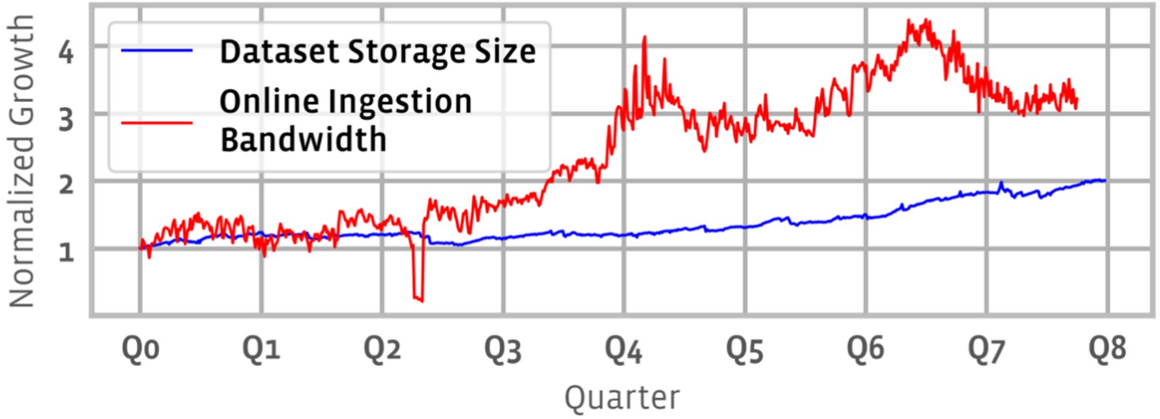
Rack-Scale

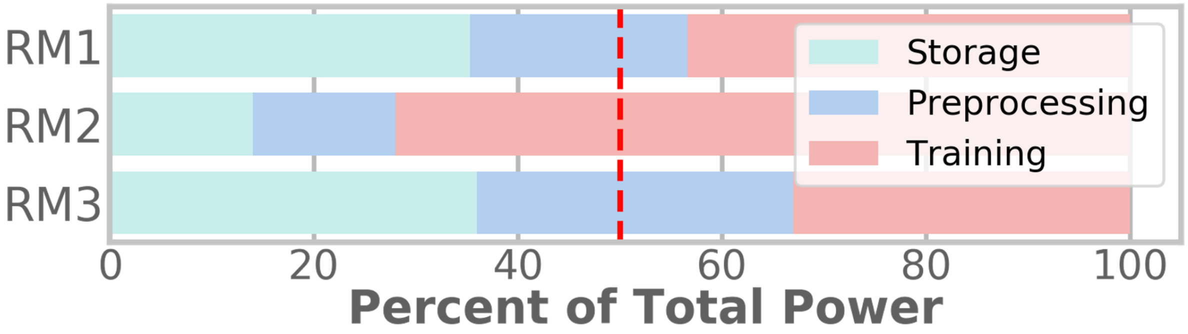
Warehouse-Scale

Single-Node Trainers → **Datacenter-Scale Training Clusters**

ML infrastructure needs IOPS scaling

Result: A *massive* growth in IOPS demand for ML training datasets





How do we scale Tectonic to meet exploding IOPS demands?

M. Zhao, et al., Understanding Data Storage and Ingestion for Large-Scale Deep Recommendation Model Training, ISCA'22

Hardware design space exploration

Need to provision storage fabric with *both* sufficient **storage** and **IOPS** capacity

Hardware design space exploration

Option 1: Scale Tectonic's HDD Chunk Store

	Storage Power	IOPS Power	Storage & IOPS Power
HDD Cluster	1.00	9.92	9.92

IOPS-Bound

Provision enough HDDs to meet IOPS demand

Hardware design space exploration

Option 2: Place ML datasets in flash

IOPS-Bound

	Storage Power	IOPS Power	Storage & IOPS Power
HDD Cluster	1.00	9.92	9.92
Flash Cluster	6.53	1.88	6.53

Storage-Bound

Provision enough SSDs to store datasets

Hardware design space exploration

Option 3: Composite storage

IOPS-Bound → HDD Cluster

Storage-Bound → Flash Cluster

	Storage Power	**IOPS Power**	**Storage & IOPS Power**
HDD Cluster	1.00	9.92	9.92
Flash Cluster	6.53	1.88	6.53
HDD + Flash Cluster	1.00	1.88	**2.69**

HDDs: Storage Efficient

Provision enough HDDs to store datasets

Hardware design space exploration

Option 3: Composite storage

	Storage Power	IOPS Power	Storage & IOPS Power
HDD Cluster	1.00	9.92	9.92
Flash Cluster	6.53	1.88	6.53
HDD + Flash Cluster	1.00	1.88	**2.69**

IOPS-Bound → HDD Cluster

Storage-Bound → Flash Cluster

Flash: IOPS Efficient

Provision SSDs to serve IOPS

Hardware design space exploration

Option 3: Composite storage

	Storage Power	IOPS Power	Storage & IOPS Power
HDD Cluster	1.00	9.92	9.92
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IOPS-Bound → HDD Cluster

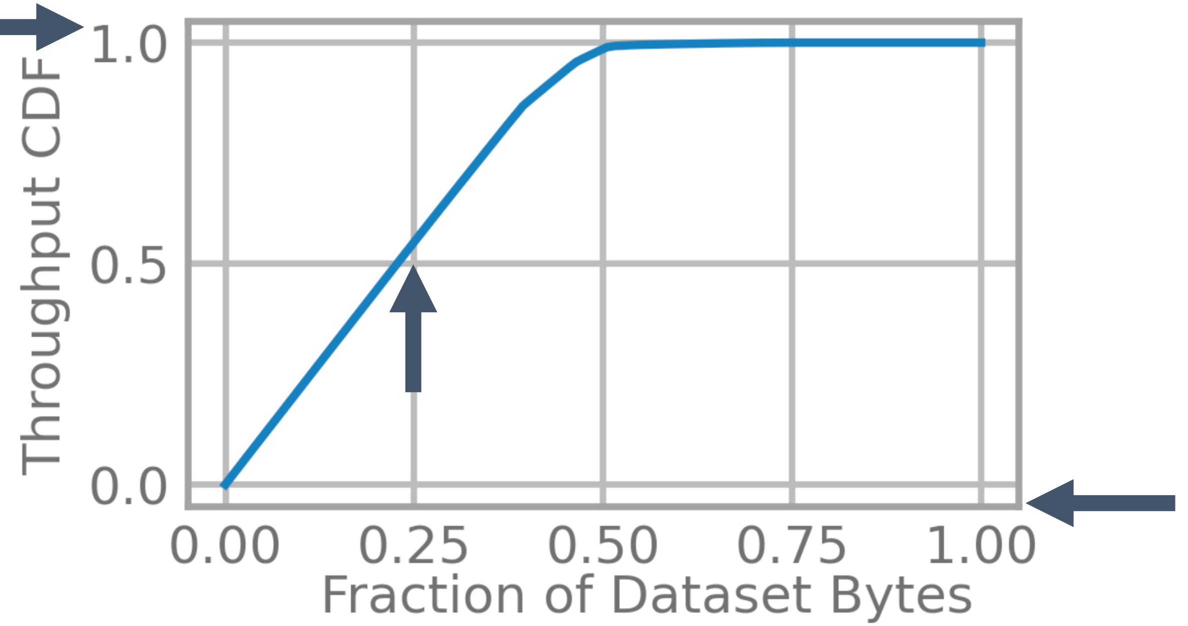
Storage-Bound → Flash Cluster

Composite Storage
Provision HDDs for storage, flash for IOPS not covered by HDDs

Software design space exploration

Goal: *Build a flash tier that **absorbs read IOPS** without storing the entire dataset.*

...contribute to y% total storage IOPS

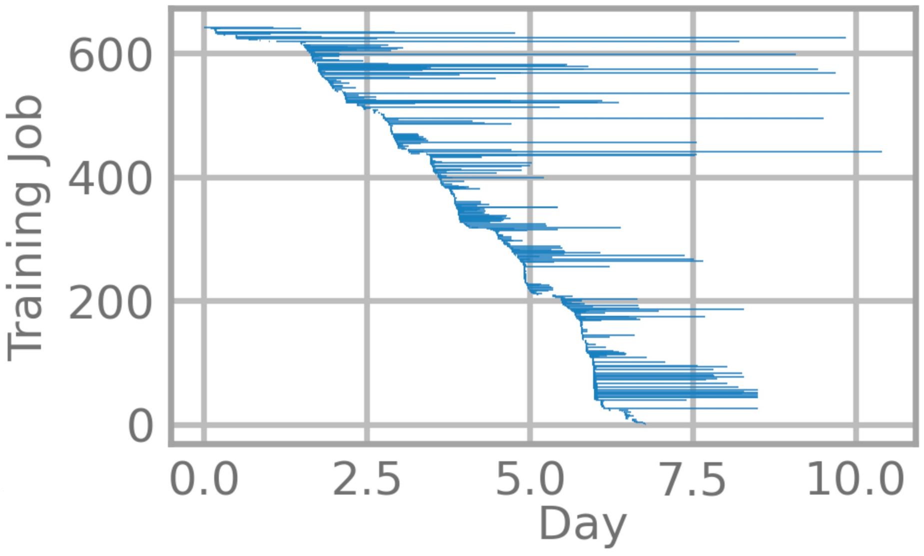


x% of stored bytes

Challenge: While our ML workloads exhibit skewed popularity, *current caches are ineffective at capturing their data reuse*.

Why current caches will not work

- ML jobs present challenging cache patterns
  - Scans: Large O(10-100PB), long-running single-epoch reads
  - Churn: data reuse *across* massive, asynchronous multi-tenant jobs
- *General-purpose LRU caches thrash*
- *ML caches focus on data reuse within multi-epoch jobs and single-tenant environments*




```
>>> dataset = tf.data.Dataset.range(5)
>>> dataset = dataset.map(lambda x: x**2)
>>> dataset = dataset.cache()
>>> # The first time reading through the data will generate the data using
>>> # `range` and `map`.
>>> list(dataset.as_numpy_iterator())
[0, 1, 4, 9, 16]
>>> # Subsequent iterations read from the cache.
>>> list(dataset.as_numpy_iterator())
[0, 1, 4, 9, 16]
```

D. G. Murray, et al., tf.data: A Machine Learning Data Processing Framework, VLDB vol. 14

Why current caches will not work

- ML jobs present challenging cache patterns
  - Scans: Large O(10-100PB), long-running single-epoch reads
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- *General-purpose LRU caches thrash*
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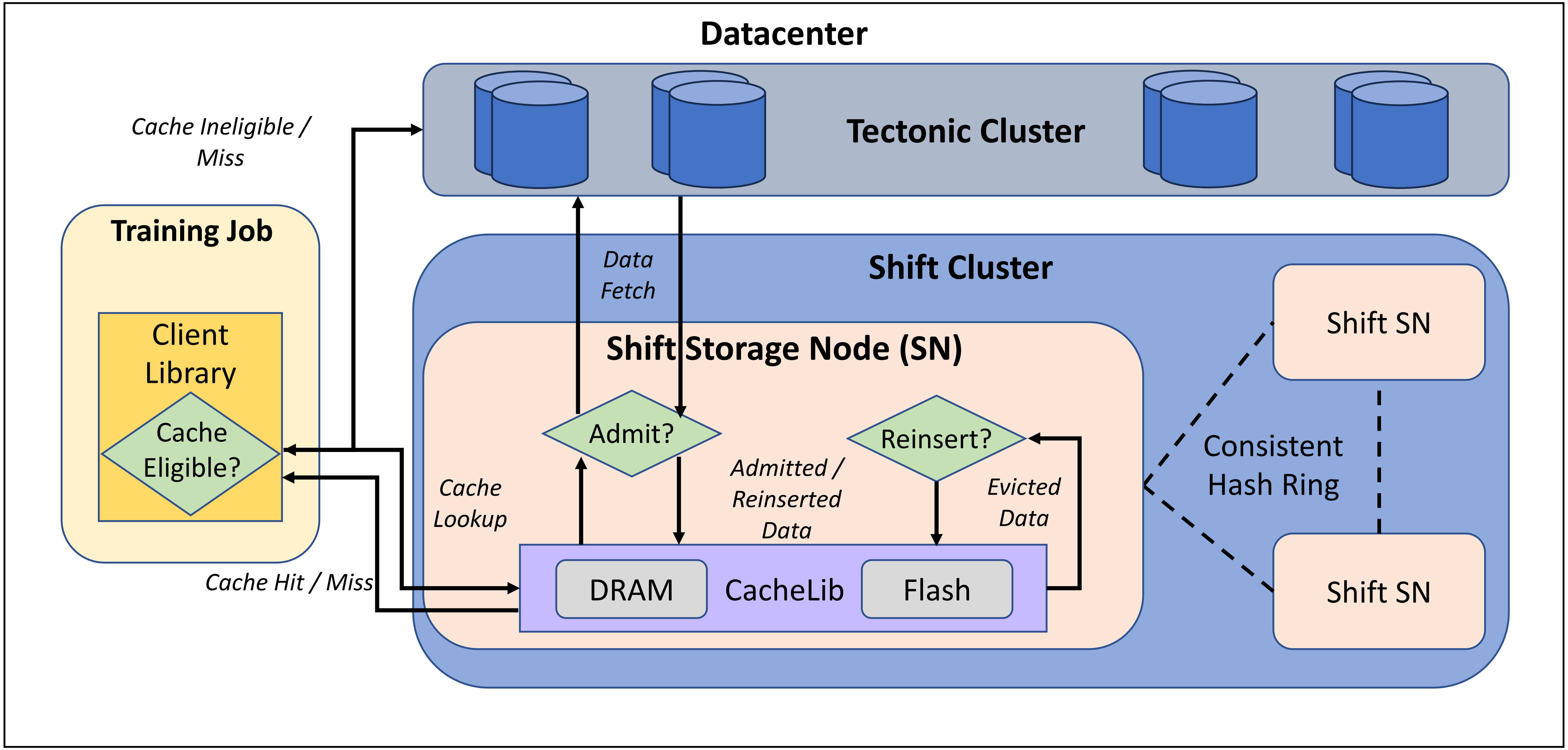
Need for a flash storage tier designed for industrial ML workloads.

Shift: A transparent, application-aware flash tier

A disaggregated flash storage tier that is…

- Transparent to end users
  - Exposes *Tectonic* API and semantics used across Meta
- Application-aware
  - Maximizes IOPS absorption using application metadata
- Simple
  - Builds upon *Tectonic*'s Metadata Layer and CacheLib
- Scalable and Fault Tolerant
  - Decentralized, DHT-based architecture

Tectonic-Shift: Meta's ML storage fabric

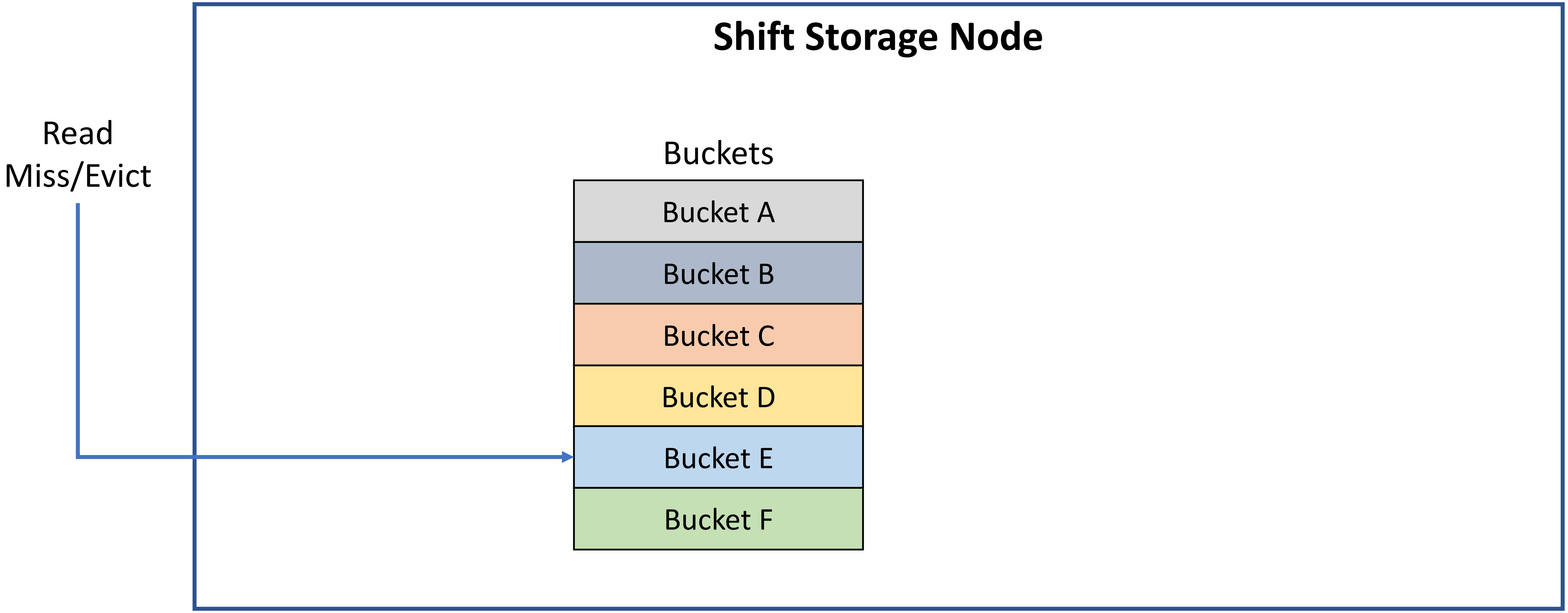


Absorbing IOPS with intelligent *Shift* policies

Each *Shift* Storage Node implements cache policies *on top of CacheLib* to **maximize absorbed IOPS:**

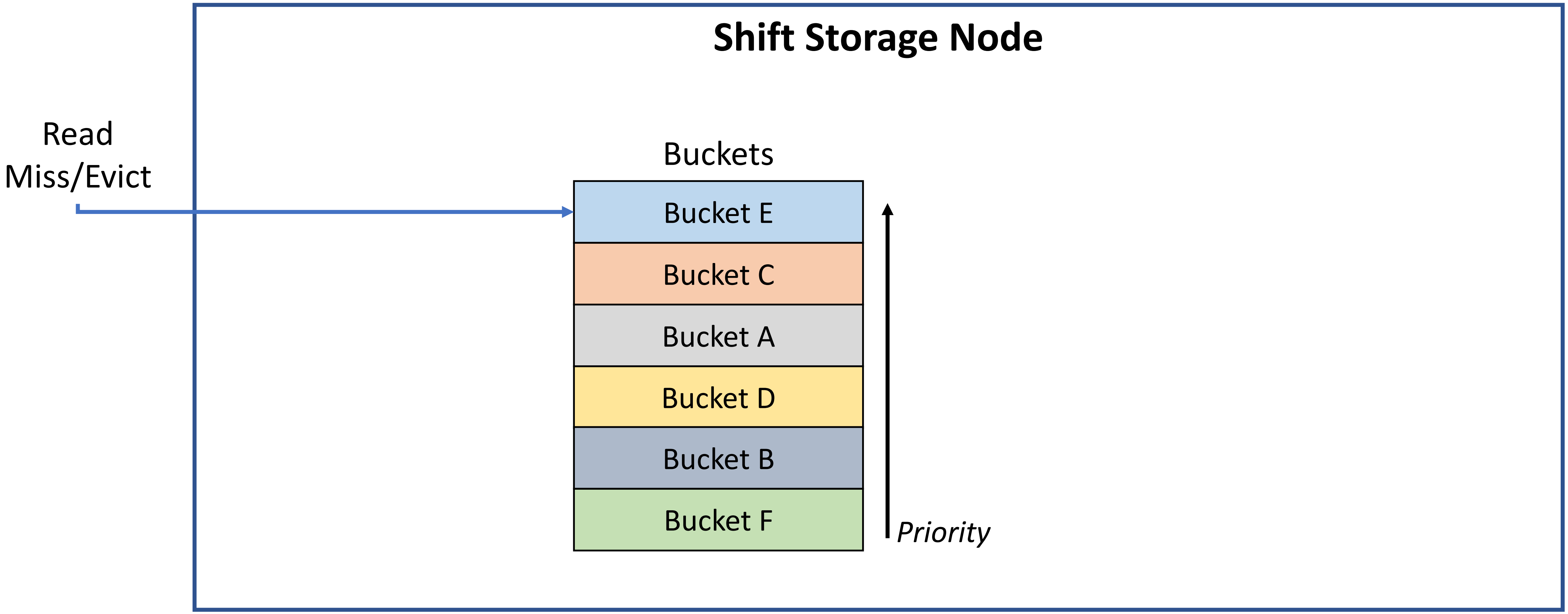
Absorbing IOPS with intelligent *Shift* policies

1. Group similar accesses (e.g., table partition) to ***buckets***



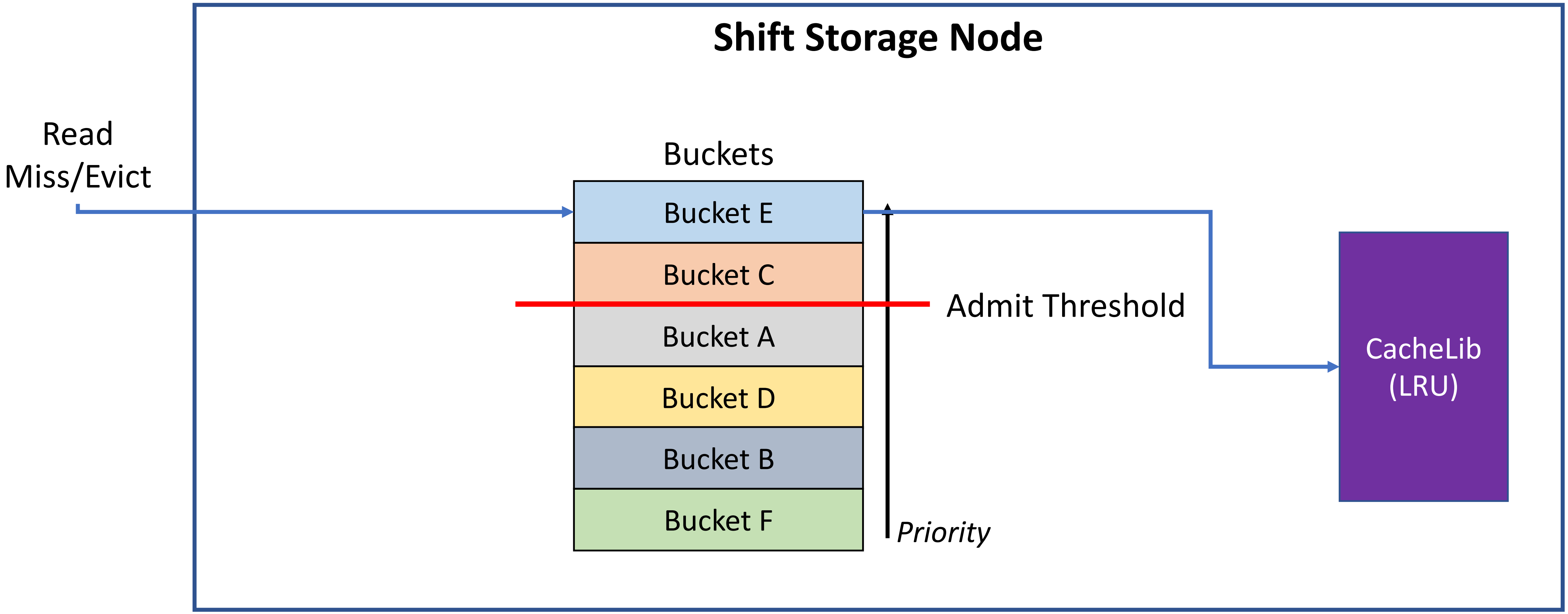
Absorbing IOPS with intelligent *Shift* policies

2. Prioritize buckets based on ***historic*** and ***derived future*** accesses



Absorbing IOPS with intelligent *Shift* policies

3. Admit buckets based on **threshold** to avoid thrashing and flash burn



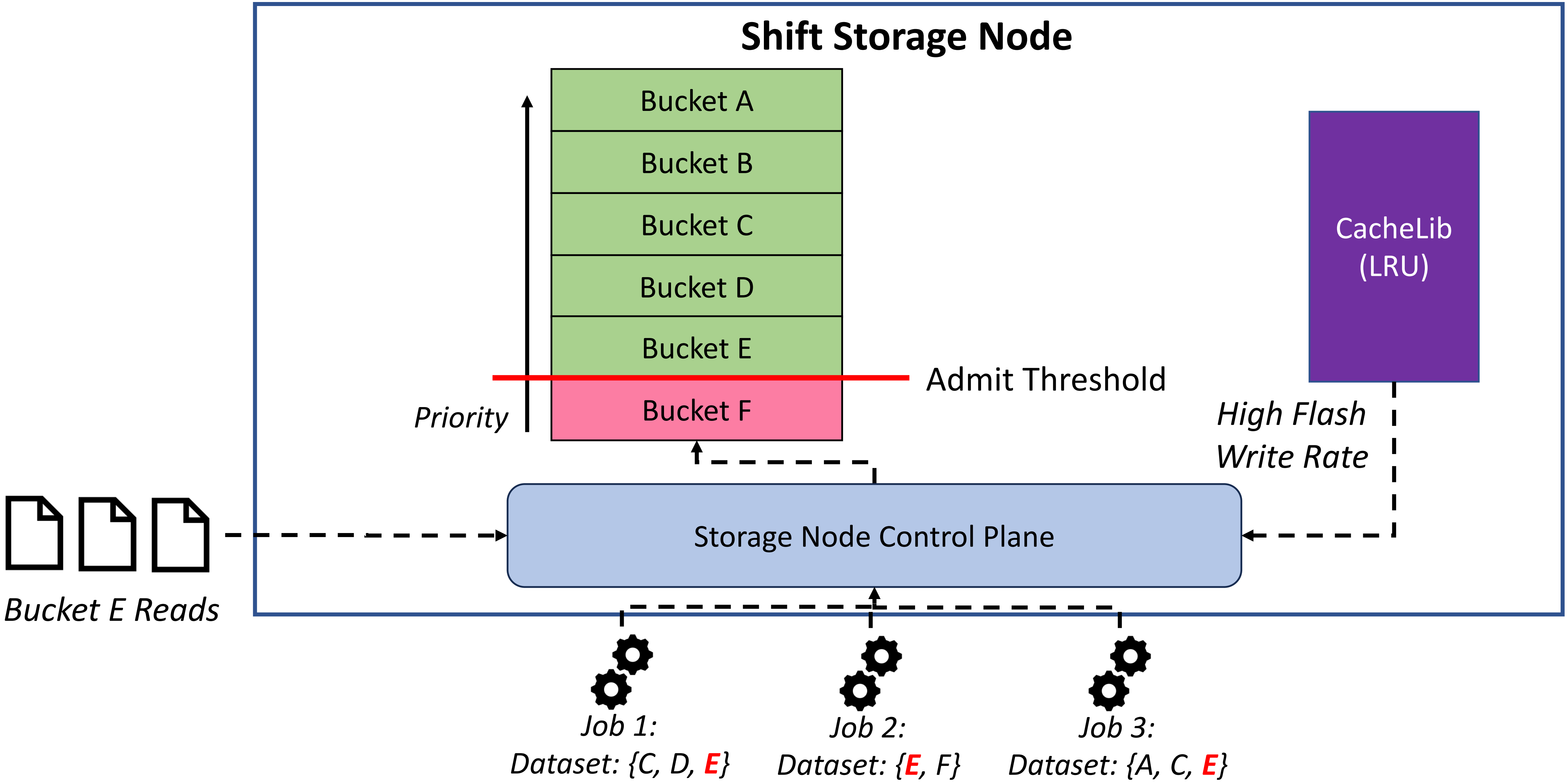
Bucket priorities: Predicting the future

Calculate bucket priorities based on...

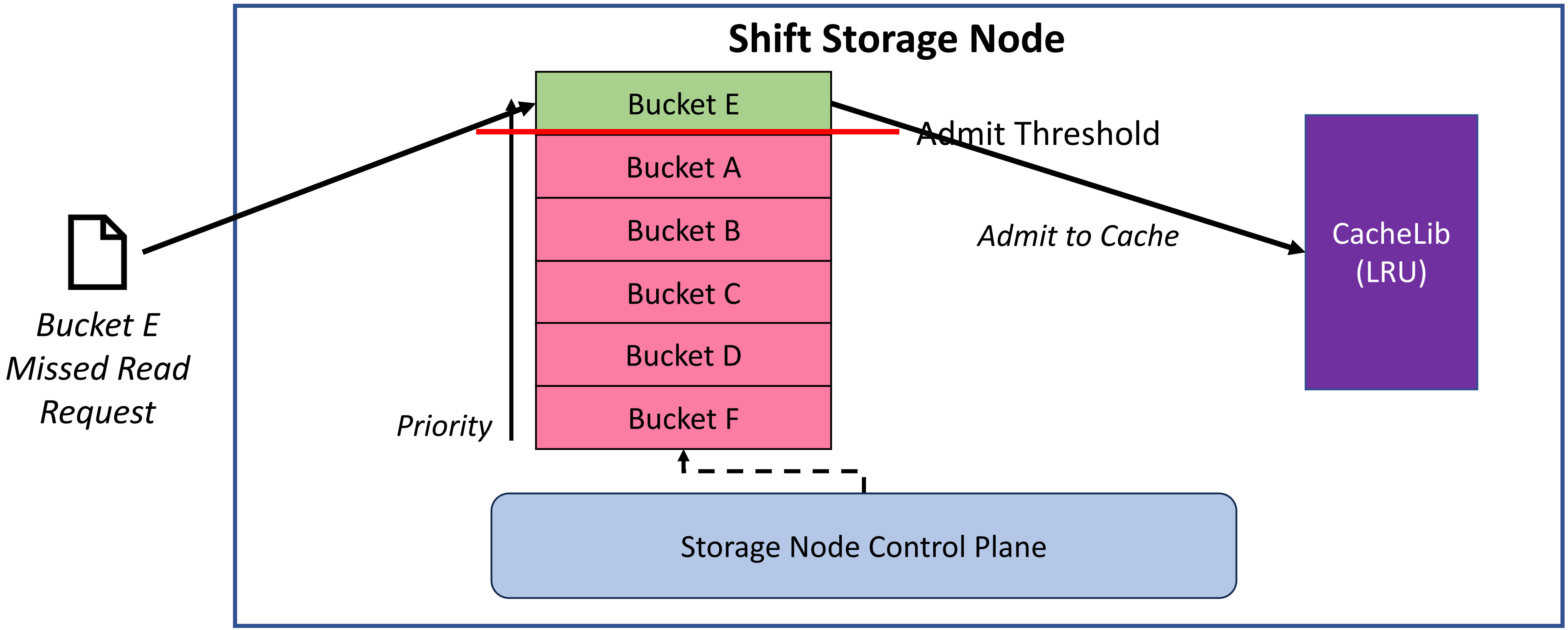
- Historic accesses
  - Log of recent per-bucket accesses
- Key insight: Future accesses
  - Derived from **dataset specifications**

```
class DLRMDataset(...):
  def __init__(self, table, rows, cols):
    ...
  def __iter__(self):
    # return iterator over table rows/cols
...

ds = DLRMDataset(
  table_t,
  [date_d, ...],
  [feature_f, ...]
)
loader = DataLoader(ds, ...) # DPP client

for sample in loader:
  # read sample from storage
  # train model
```

Dynamic priority and threshold tuning

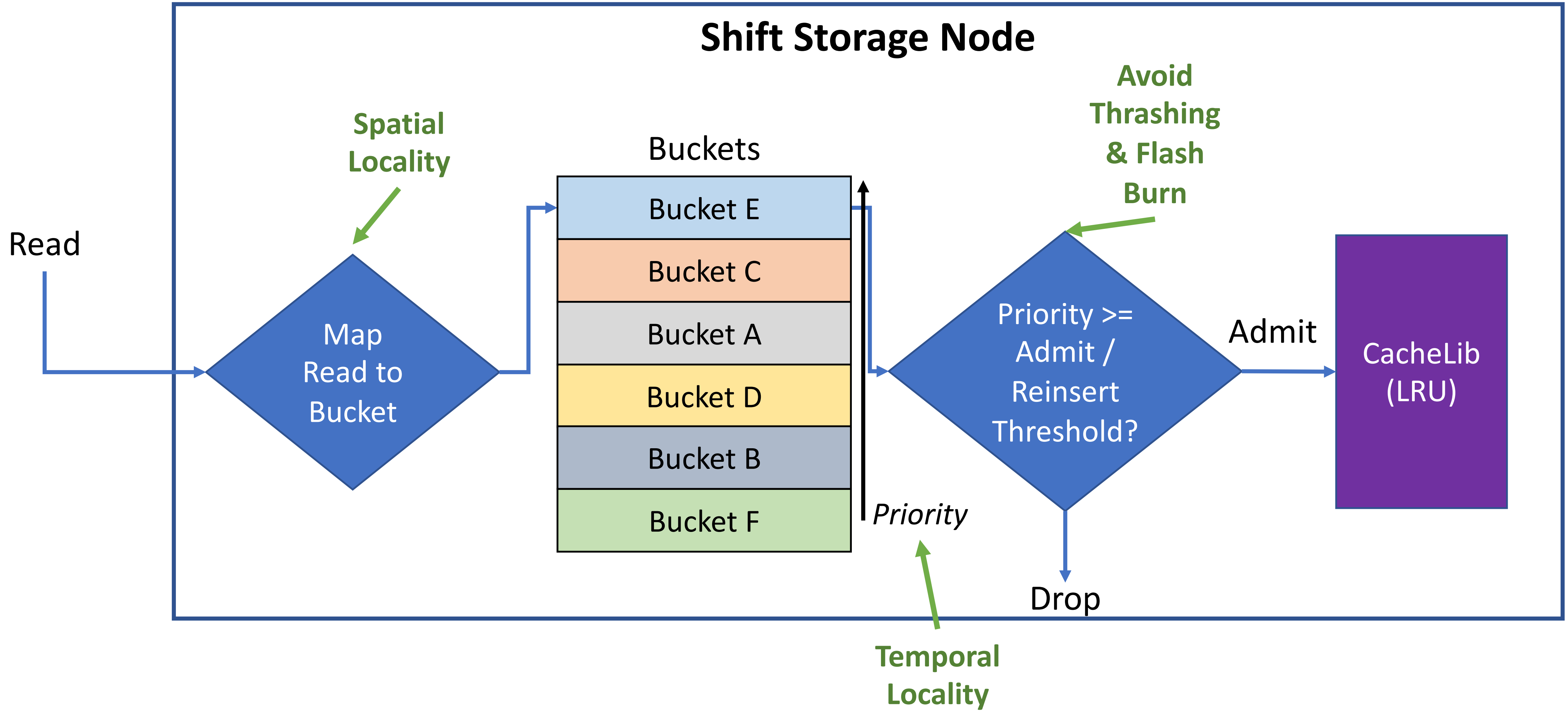


Dynamic priority and threshold tuning



Shift dynamically adjusts admission policies to keep high-priority data in cache, while minimizing thrashing and flash writes.

Putting it all together



Shift admission policies improve IOPS absorption

- Benchmark setup
  - Three production DLRM training workloads
  - 6-node *Shift* cluster
- Policy evaluation
  - CacheLib LRU, FIFO eviction only
  - Historic admission: bucket priority from recent accesses
  - Future admission: bucket priority from future accesses derived from Dataset
  - Historic & Future admission: bucket priority from max of Historic, Future

Average Normalized IO Absorption Across Benchmarks				
LRU Eviction	FIFO Eviction	Historic Admission + LRU Eviction	Future Admission + LRU Eviction	Historic & Future Admission + LRU Eviction
1.00	1.31	1.51	3.28	1.67

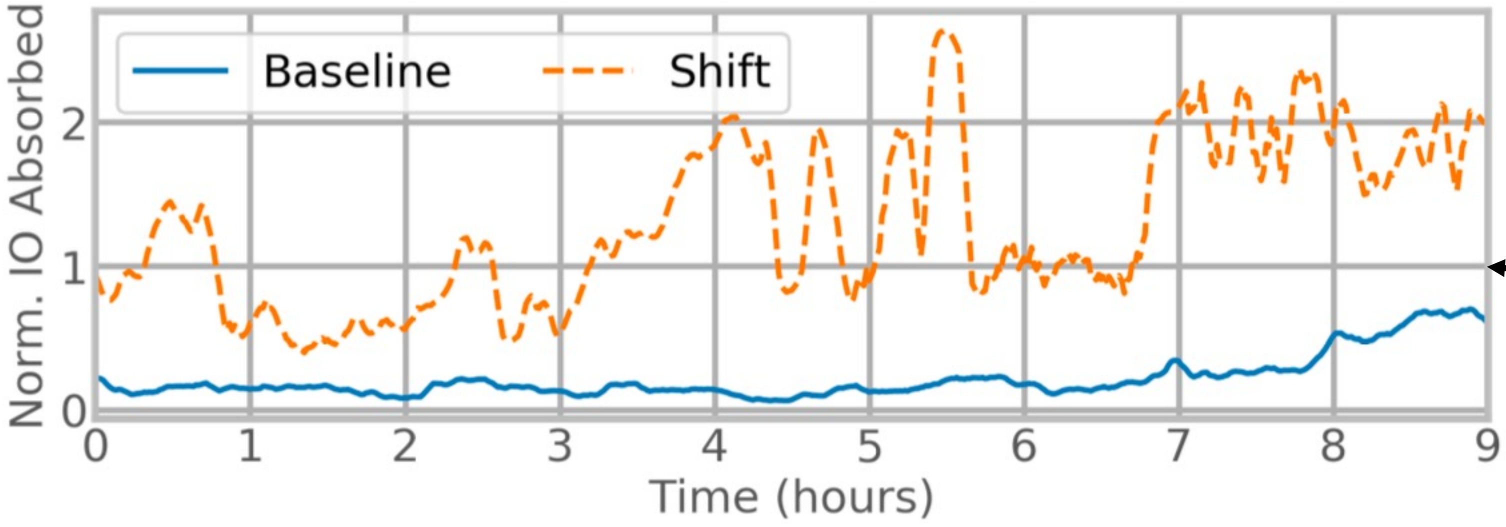
Shift admission policies manage flash endurance

- Need to limit flash write rates in production
  - Evaluation: 100 MB/s average write rate limit

Average IO Absorption & NVM Write Rate for *Synchronized* Workload						
	CacheLib Dynamic Admission	Reject First	Admit All	Historic Admission	Future Admission	Historic & Future Admission
IO Absorption (norm. to Dynamic)	1.00	1.51	2.66	2.14	3.07	2.99
NVM Write Rate (norm. to 100 MB/s limit)	0.96	8.39	22.05	1.01	1.01	1.00

Production deployment

Shift has been deployed across DCs at PB scale since early 2022, saving significant amounts storage infrastructure power.



Shift saves 29% power relative to only HDDs. Massive @ DC scale.

Conclusion

- Modern ML training clusters require massive storage IOPS.
- *Tectonic-Shift* meets IOPS demand by combining *Tectonic* with *Shift*, an IOPS-efficient flash storage tier.
- *Shift* maximizes absorbed IOPS (1.5-3.3x over LRU) using intelligent policies leveraging historic and derived future access patterns.
- *Tectonic-Shift* serves as Meta's ML storage fabric, improving storage efficiency (29% in our trace) across multiple datacenters.

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