Memory Deduplication for Serverless Computing with Medes

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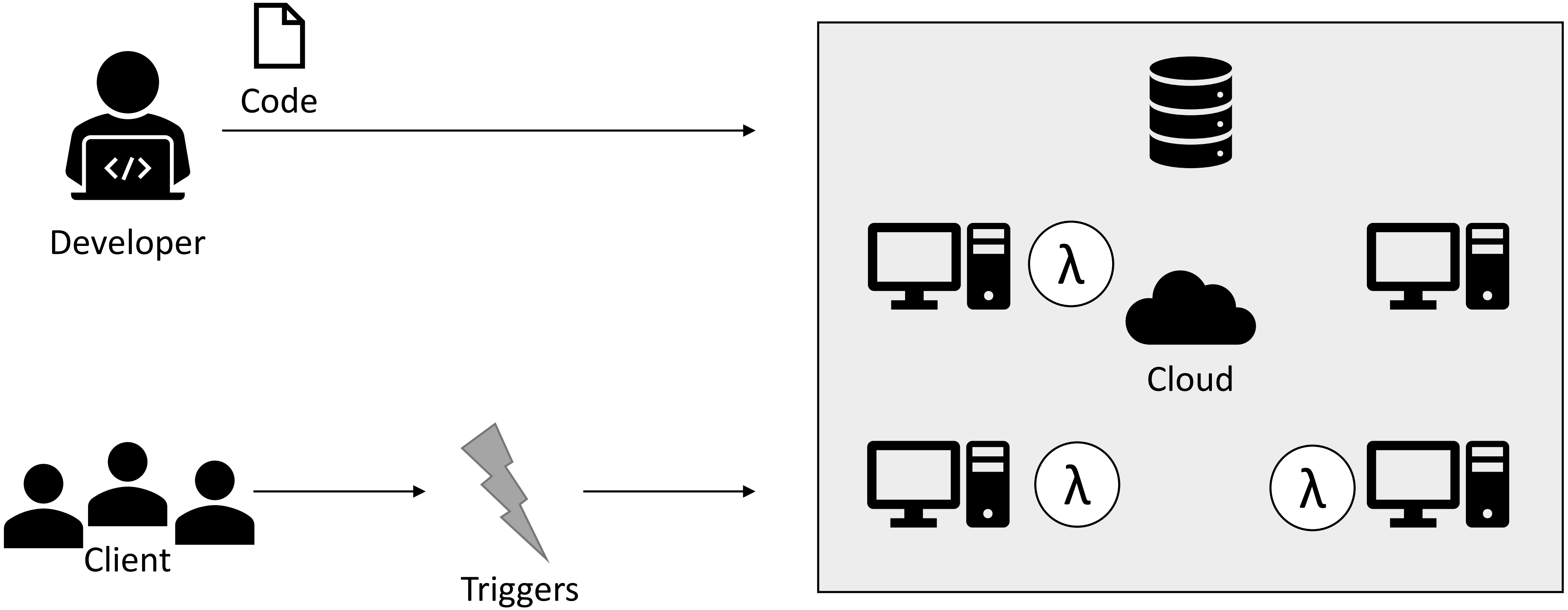
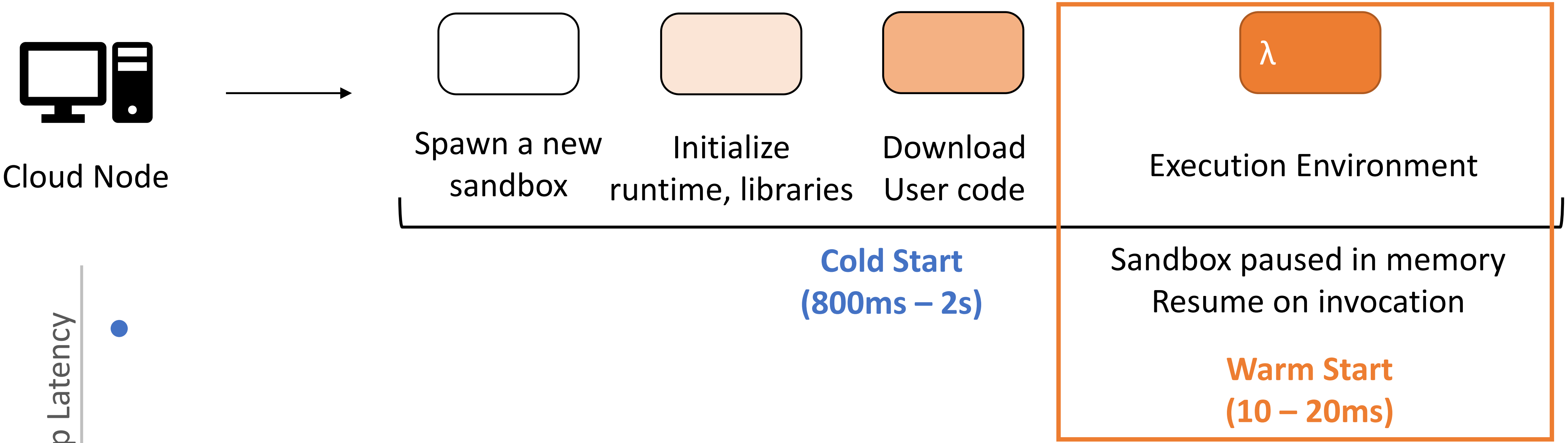
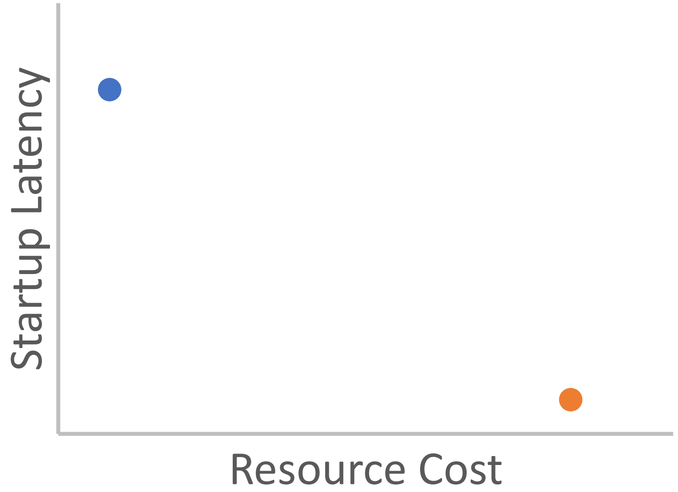
Serverless – Introduction



Serverless – Deep Dive

What exactly happens when a function is invoked on a serverless platform?





Keeping warm sandboxes is prohibitively memory expensive!

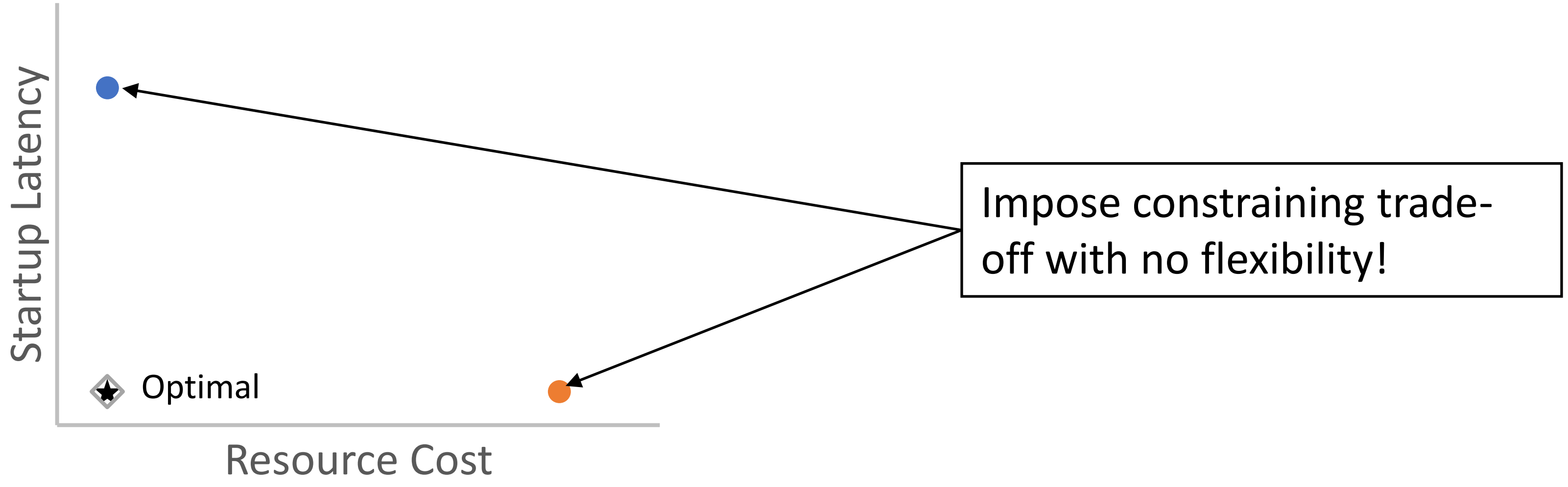
Serverless – Existing Techniques

- Fixed (AWS) or Adaptive (Hybrid Histogram$_{(ATC20)}$) keep-alive durations
- Provision sandbox resources in anticipation of future invocations $_{(ATC20,\ SoCC20)}$

Erratic serverless workloads are difficult to generalize!

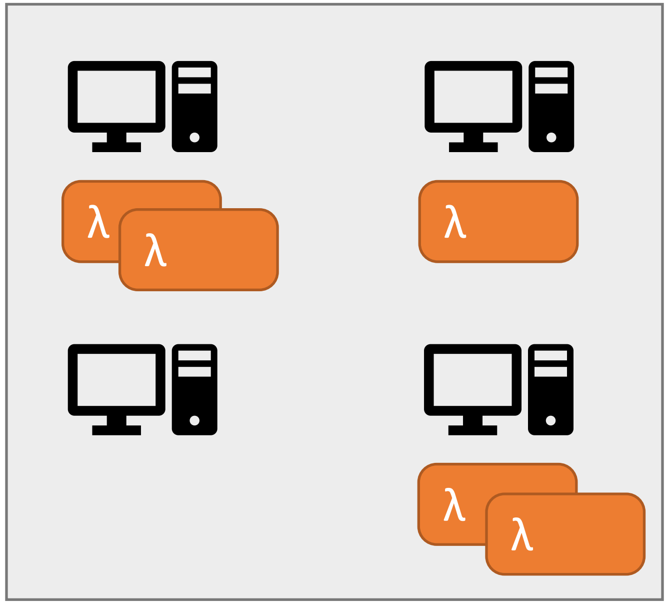
- Snapshot-restore techniques (Catalyzer$_{(ASPLOS20)}$, SEUSS$_{(EuroSys20)}$)

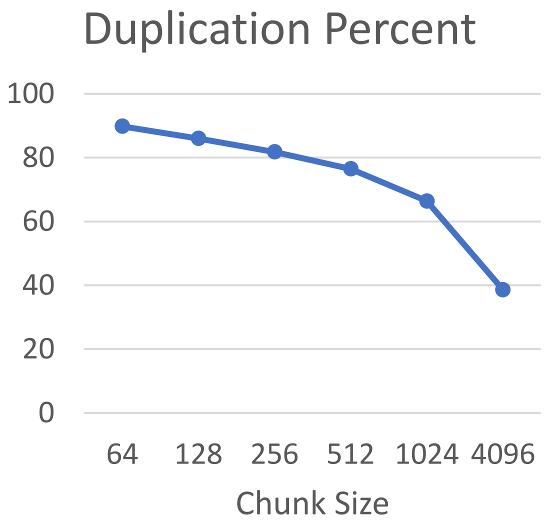
Cold starts still significantly slower than warm starts, or sacrifice isolation

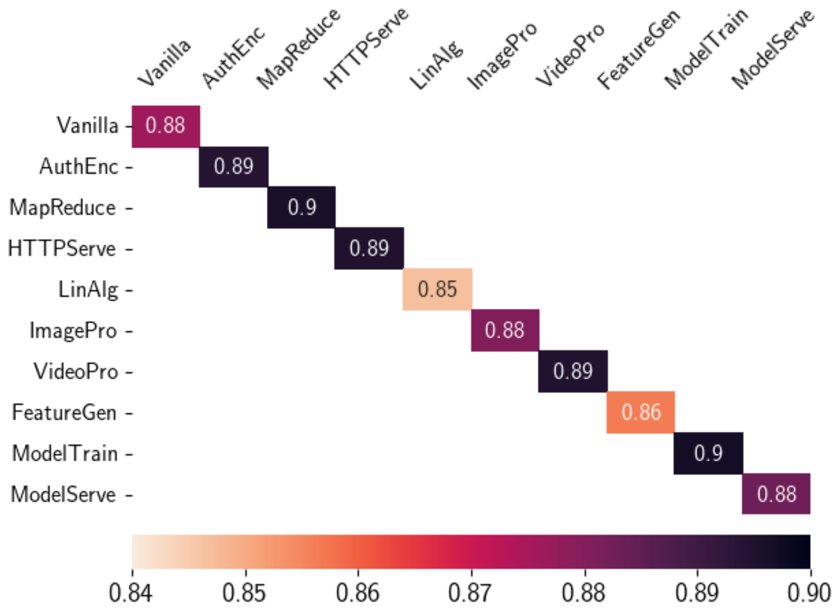


Key Insight

At any point, several "warm" sandboxes are in memory







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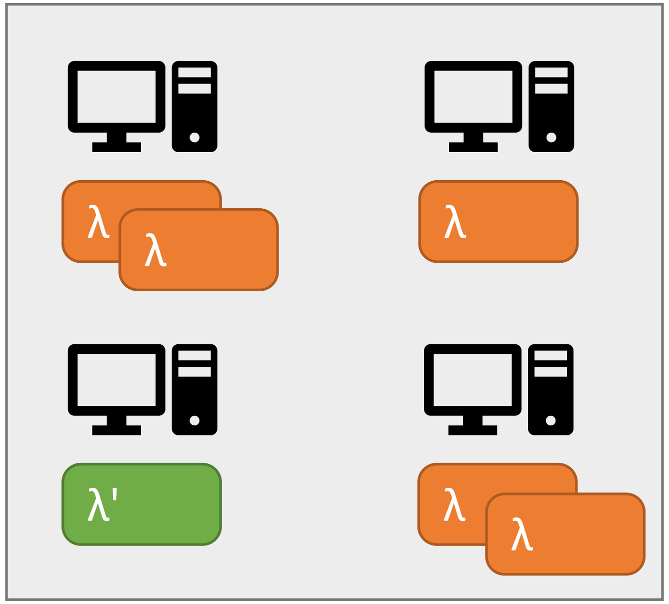
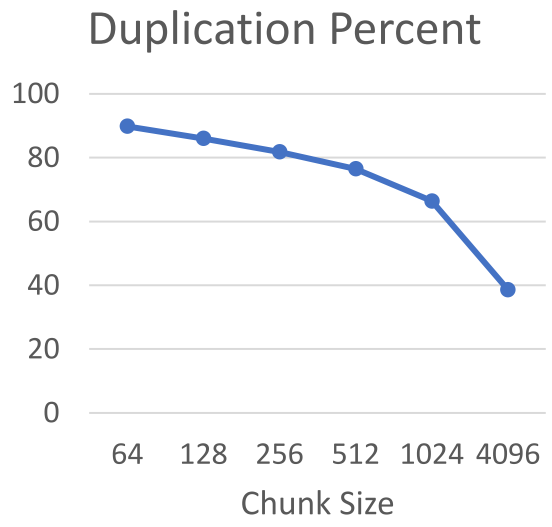
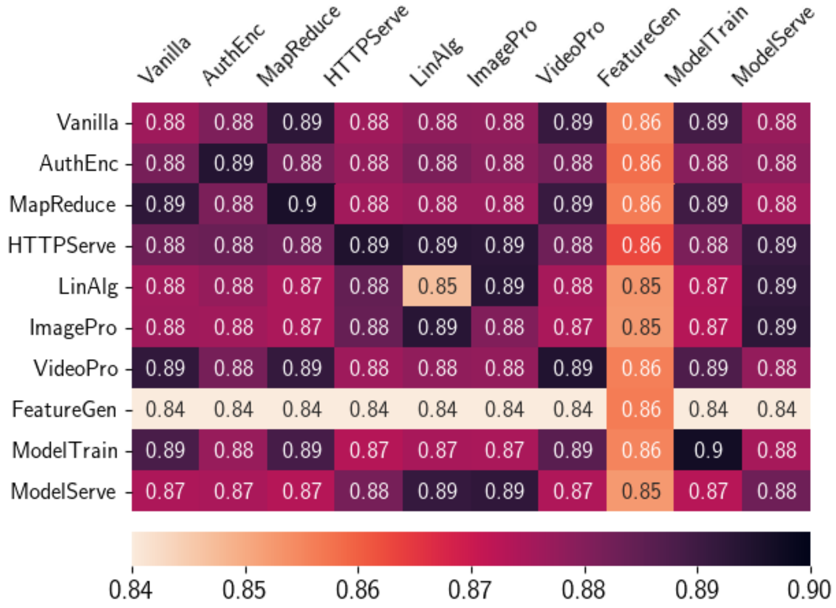


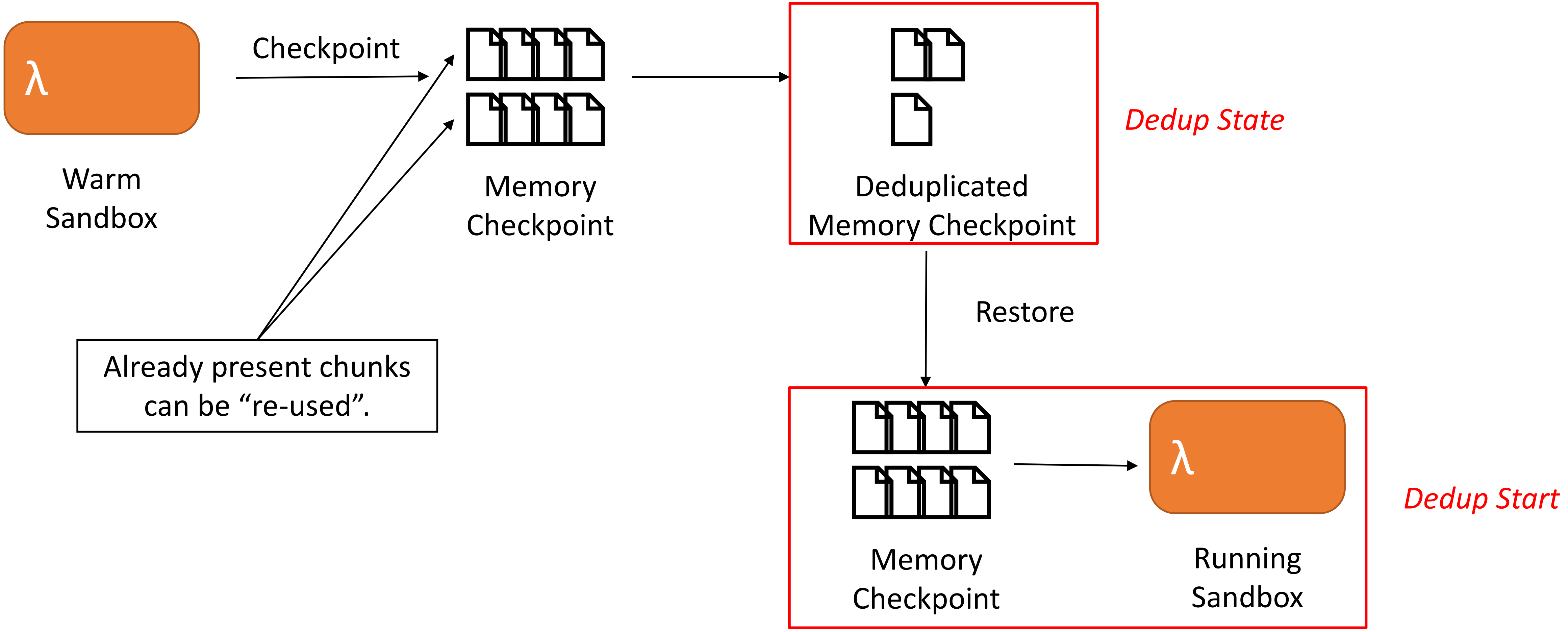




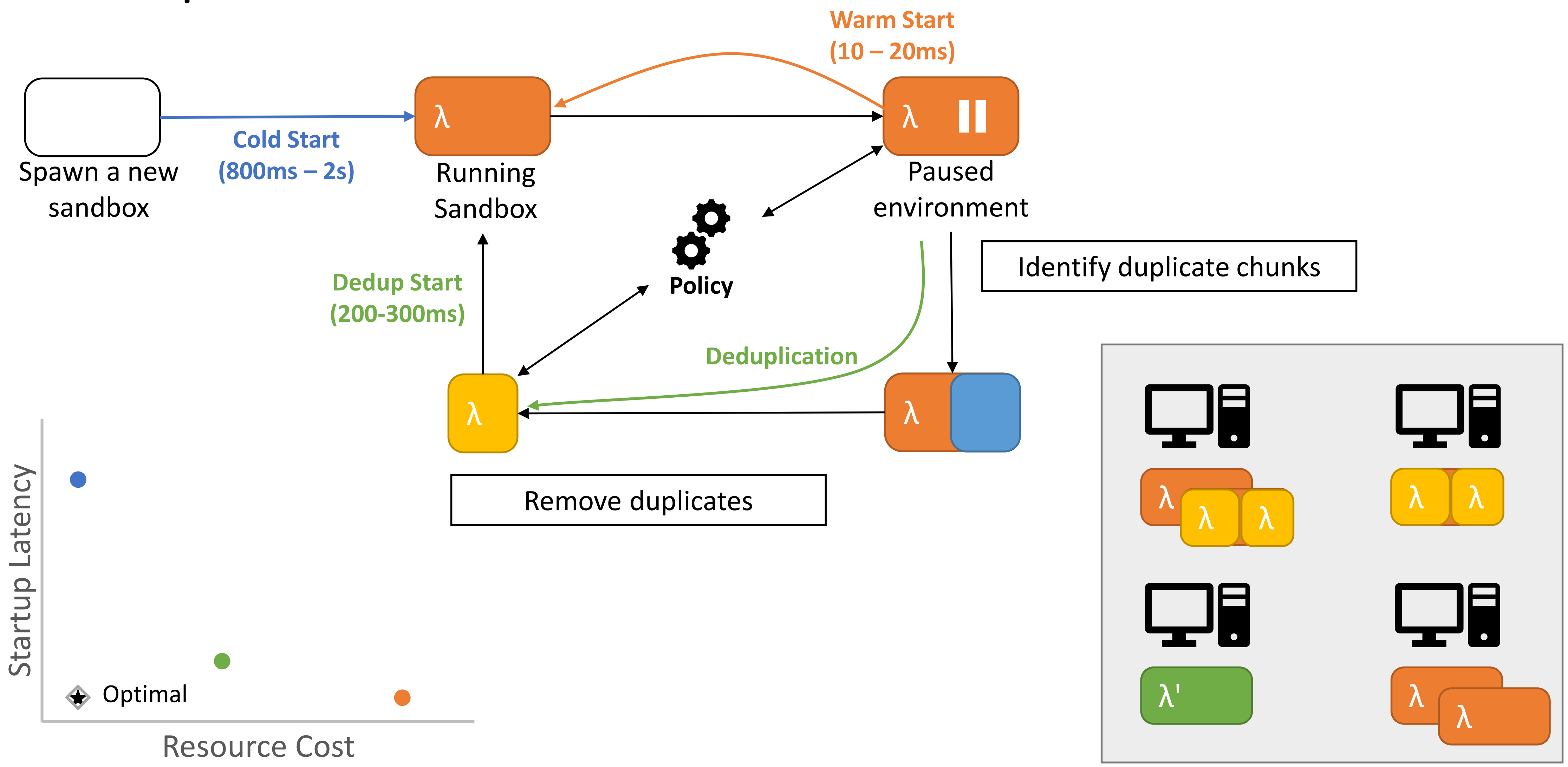
Duplication due to common runtime and libraries

Memory redundancy can be exploited to reduce sandbox footprints

Reusable Sandbox Chunks



Dedup Starts



Medes – System Design

Design Goals

Exploit redundancy across nodes

Efficient and scalable redundancy identification

Fast Dedup sandbox restores

Flexibility in navigating trade-offs

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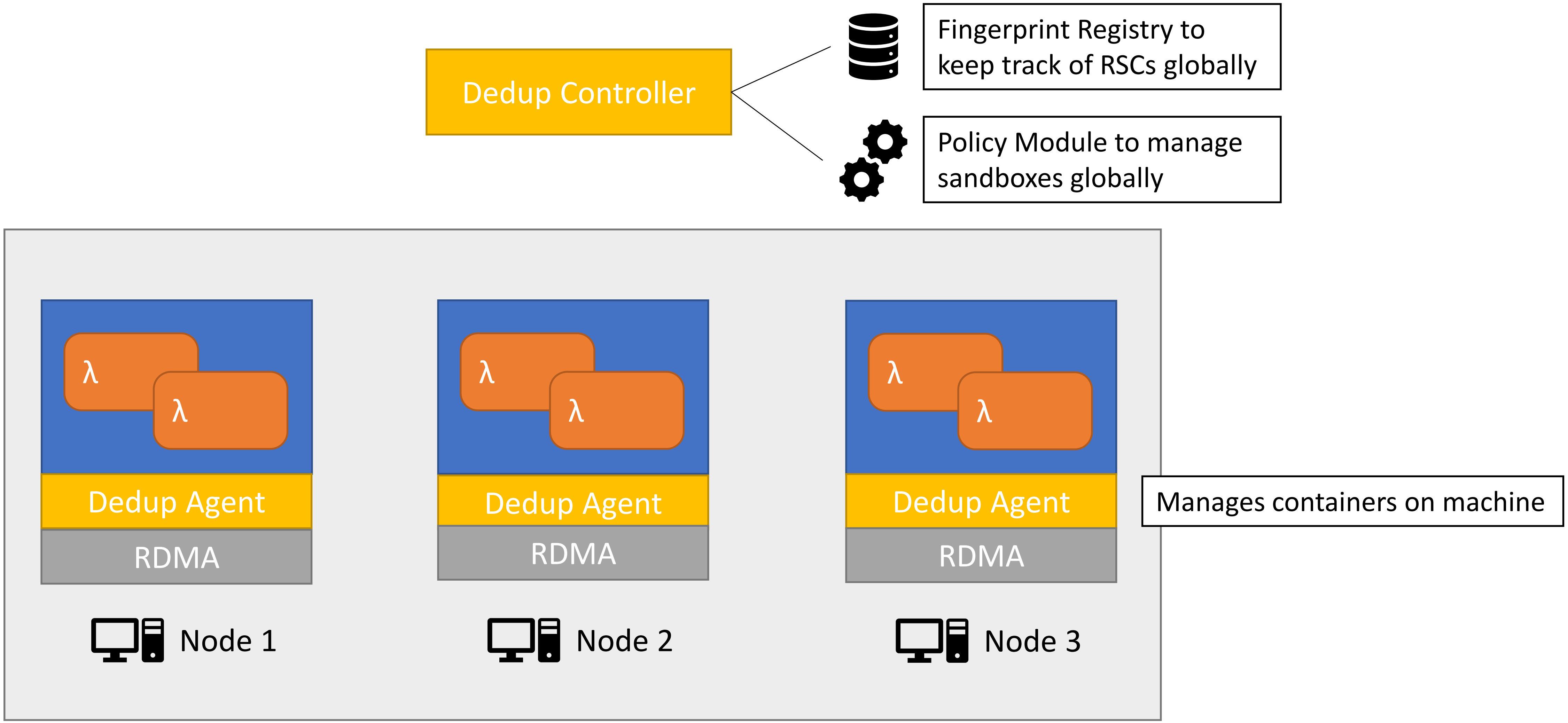
Maintain a global view of the cluster

Medes System Design – Global View



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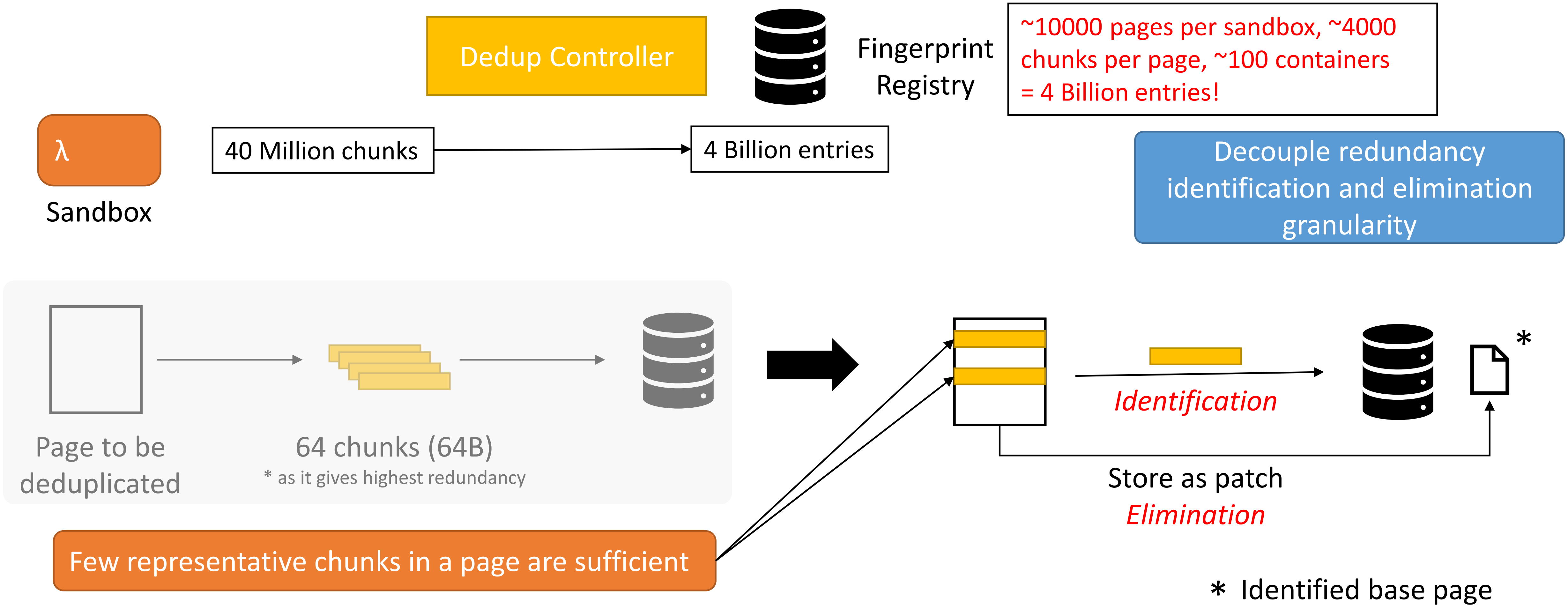
Two Tier Architecture

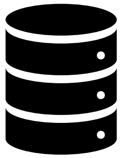
- Needs to be computationally lightweight
- And have low metadata overhead

Efficient Redundancy Identification

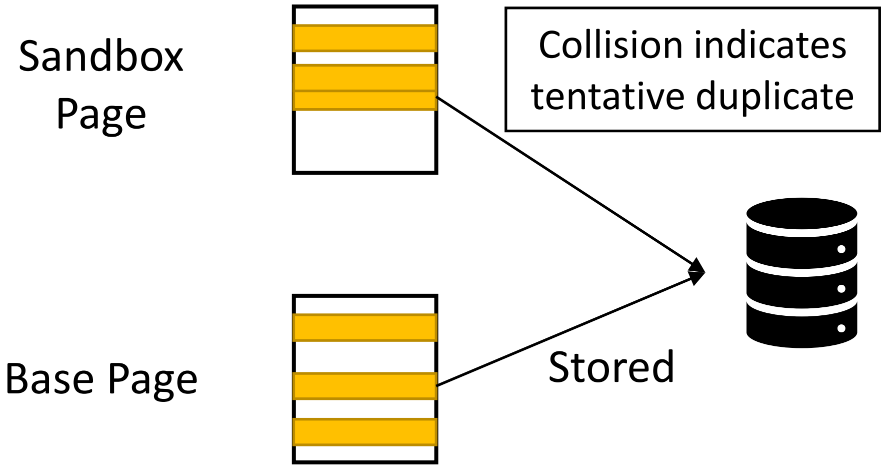


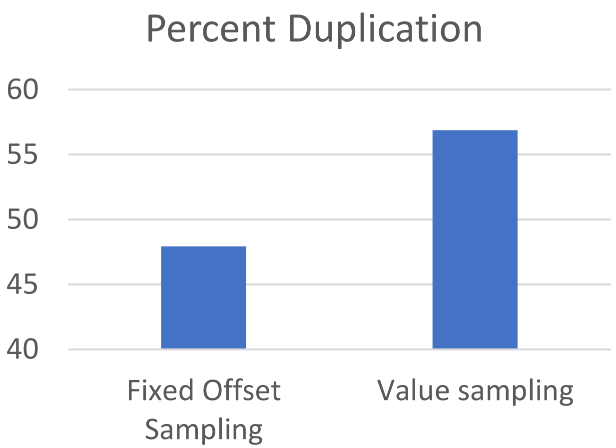
Efficient Redundancy Identification

Dedup Controller



Fingerprint Registry

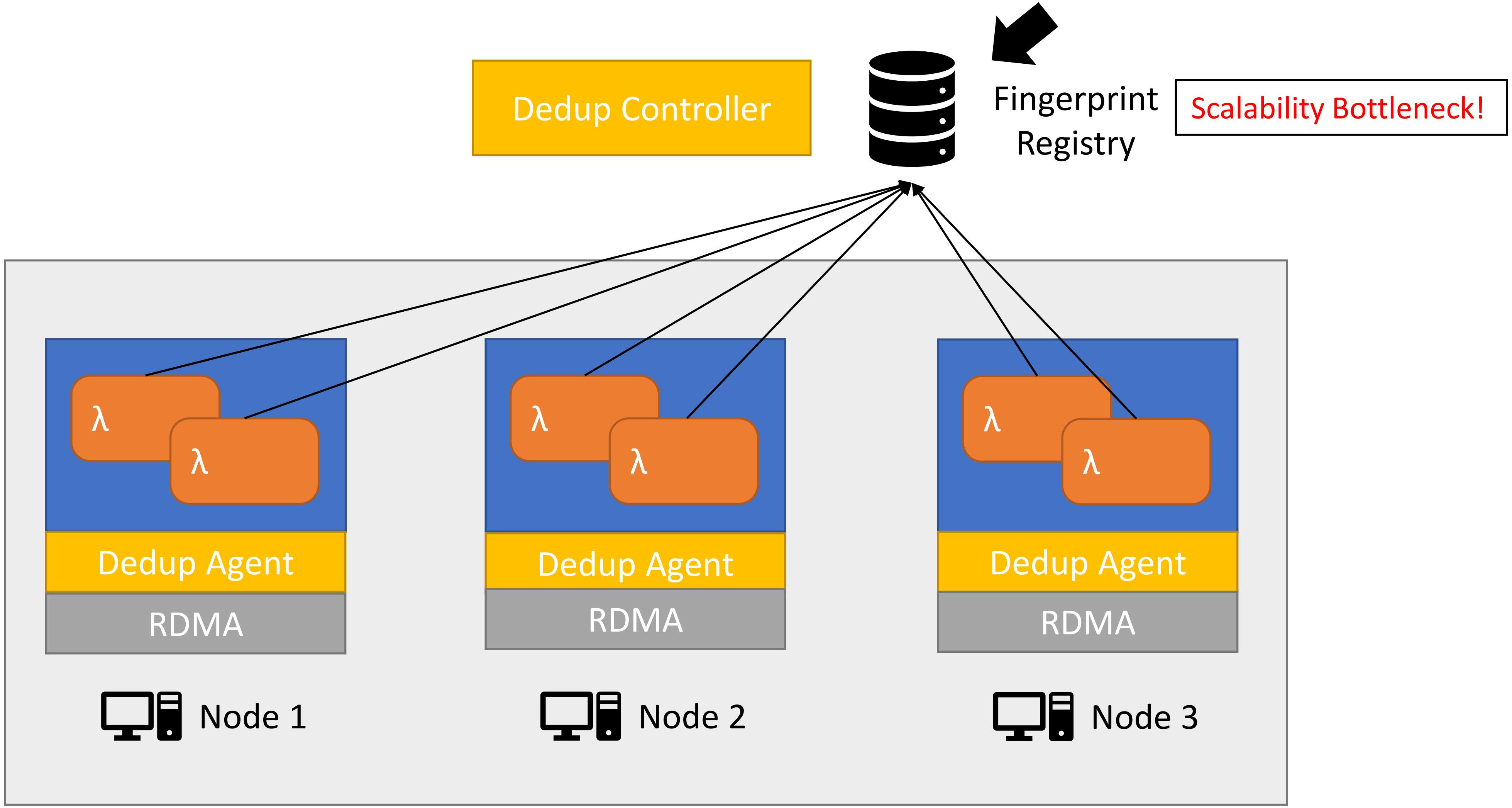




Value sampled fingerprinting

Use value sampling – choose only those chunks that have the last byte to be a particular marker.

Scalable Redundancy Identification



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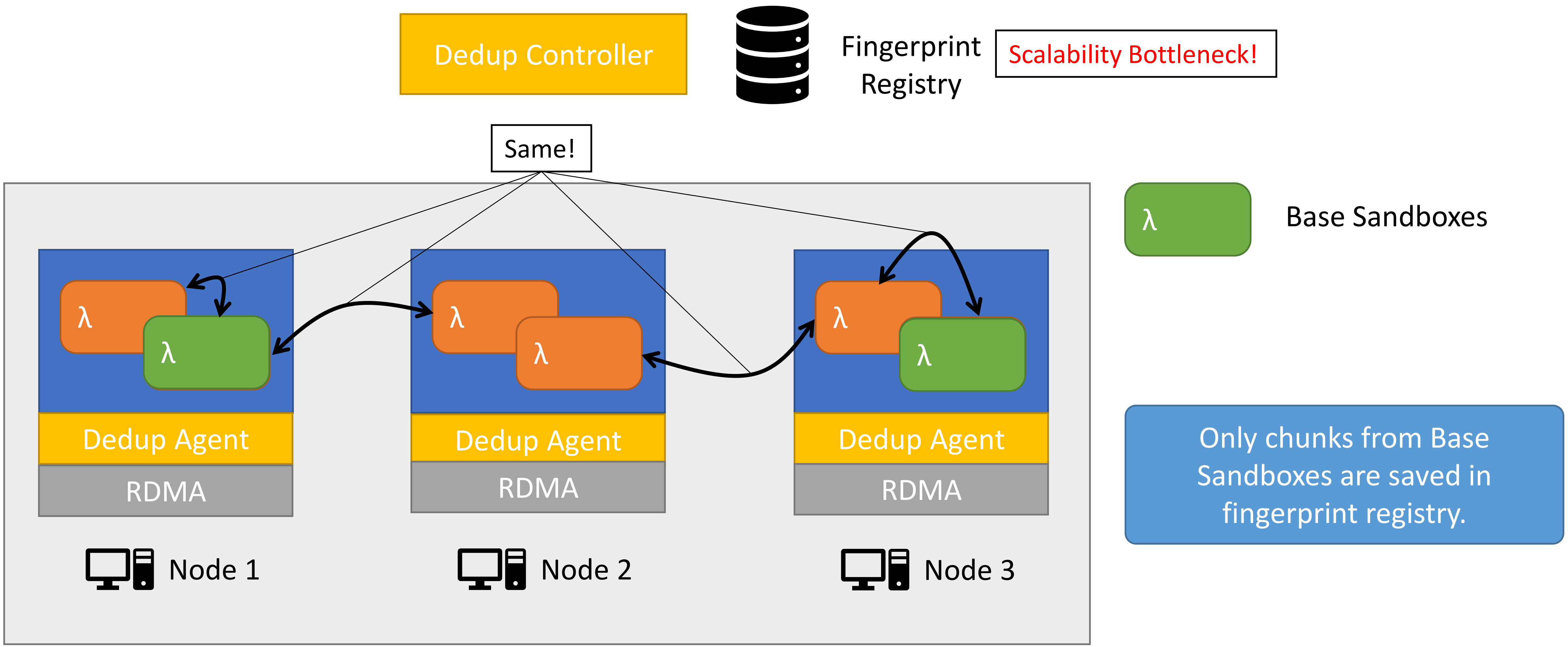

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Two Tier Architecture

- Needs to be computationally lightweight
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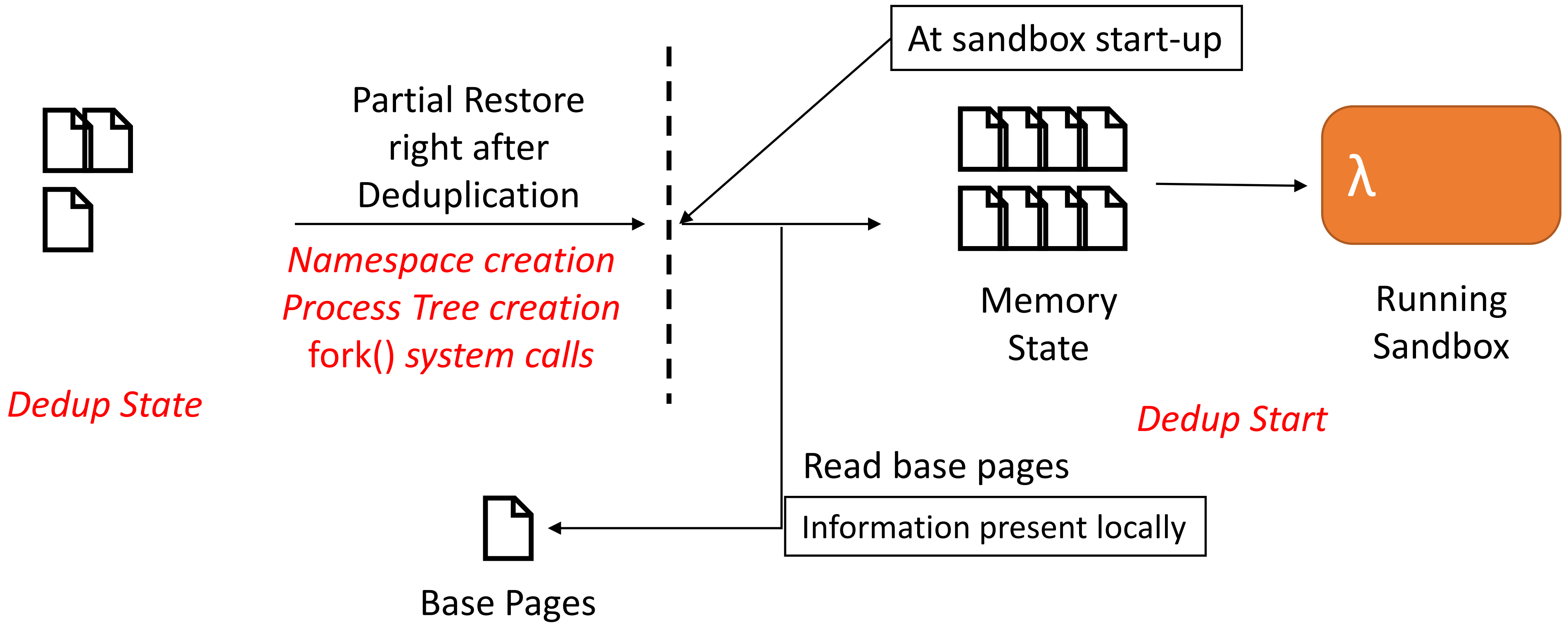
Value sampled fingerprints, decouple redundancy granularity and select base containers

Dedup Starts should be much faster than cold starts

Fast Dedup Sandbox Restores

- Time consuming steps of sandbox restore performed right at deduplication [Catalyzer$_{(ASPLOS20)}$]



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Value sampled fingerprints, decouple redundancy granularity and select base containers

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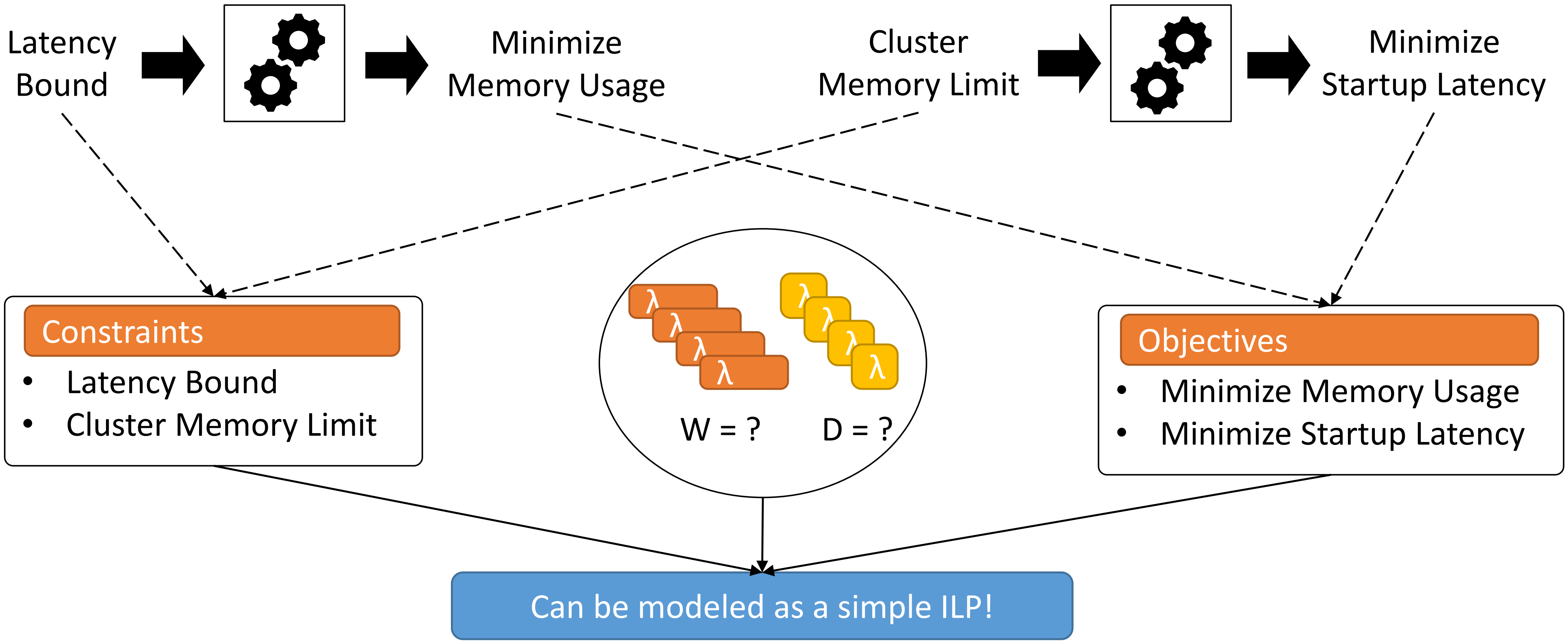
Construct policy that can deduplicate containers as per requirement

Medes – Policy

- Allow operators run their platform in two configurations:



Evaluation

- Can Medes provide improved end-to-end latencies?
- How does Medes perform under memory pressure situations?
- Can Medes help reduce the overall memory footprints?
- Can tuning fixed keep-alive policies achieve the same performance-memory tradeoffs as Medes?

Evaluation - Setup

- Configuration
  - Controller – One xl170 node on Cloudlab (64GB RAM)
  - Nodes – Nineteen xl170 nodes, with 10Gbps NIC
    - Software memory constraint applied during experiments
- Workloads
  - One hour production traces of various applications released by Microsoft Azure
  - Functions from the FunctionBench benchmark suite

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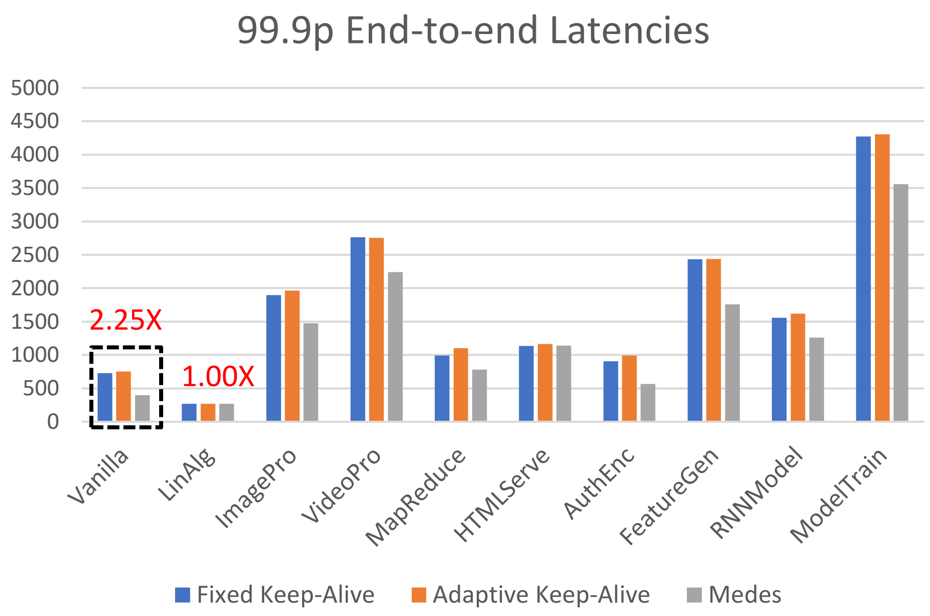
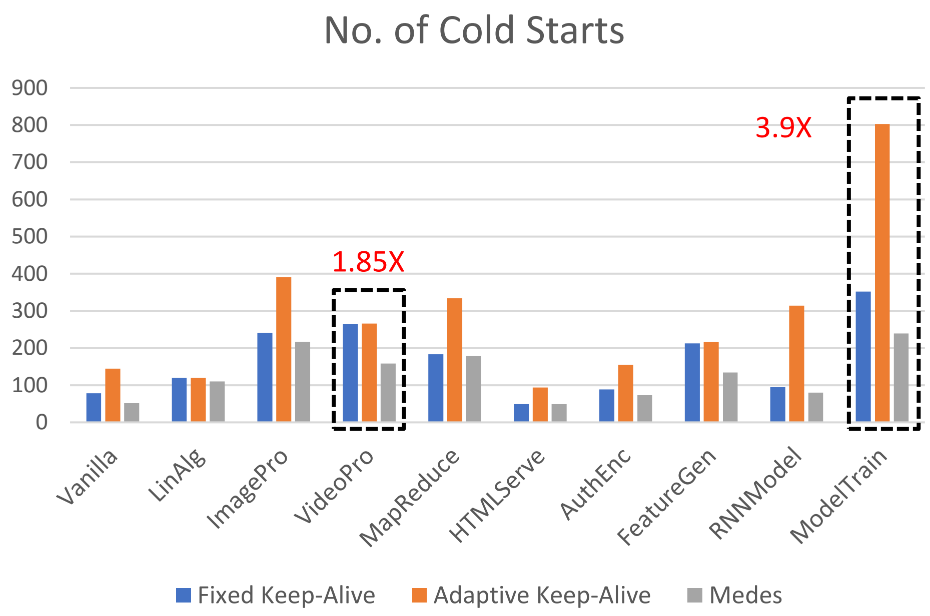
Evaluation – Improved end-to-end latencies





- Tail latencies are improved by a factor of 1-2.25X (1.3X on average).
- Cold starts are reduced up to 1.85X and 3.9X against fixed and adaptive policies.

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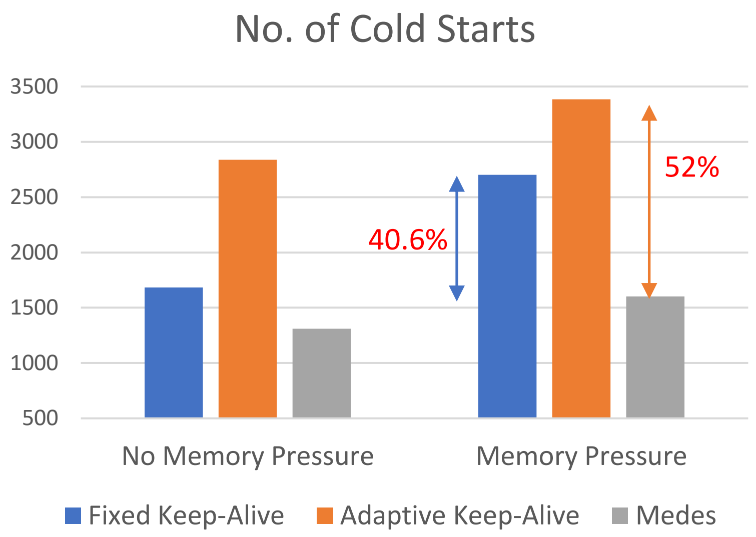
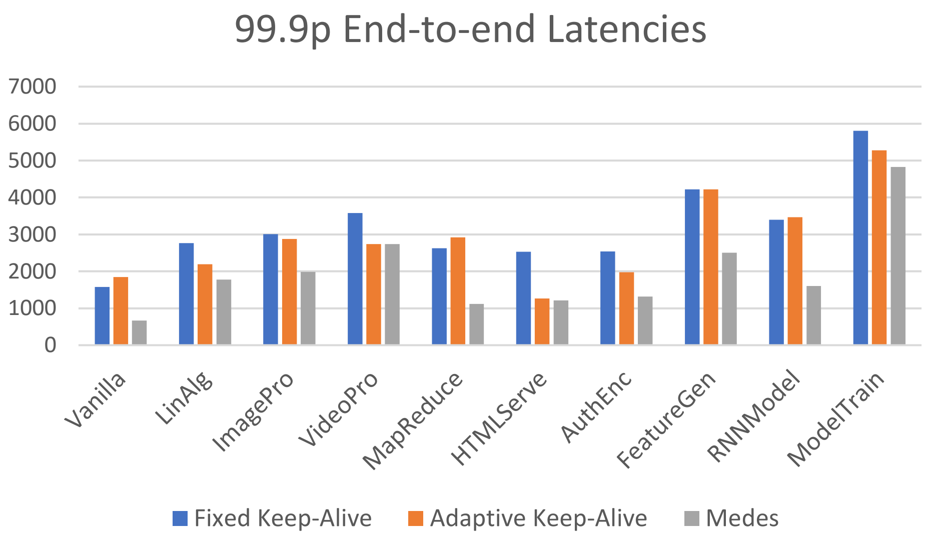
Evaluation – Medes under Memory Pressure





The performance benefits increase under memory pressure.

- Cold starts reduced by 40.6% and 52% against fixed and adaptive keep-alive.
- Tail latencies are improved by a factor of up to 3.8X

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Evaluation – Medes Memory Savings

Function Environment	Percent Savings
Vanilla	$\frac{4.6MB}{17MB} = 27.06\%$
LinAlg	$\frac{10.5MB}{32MB} = 32.81\%$
ImagePro	$\frac{11.36MB}{26.4MB} = 43.03\%$
VideoPro	$\frac{12.22MB}{48MB} = 25.46\%$
MapReduce	$\frac{5.10MB}{32MB} = 15.94\%$
HTMLServe	$\frac{9.88MB}{22.3MB} = 44.30\%$
AuthEnc	$\frac{4.79MB}{22.3MB} = 21.48\%$
FeatureGen	$\frac{25.67MB}{66MB} = 38.89\%$
RNNModel	$\frac{52.23MB}{90MB} = 58.03\%$
ModelTrain	$\frac{26.33MB}{87.5MB} = 30.09\%$

- Medes can reduce 16-58% of the function memory state.

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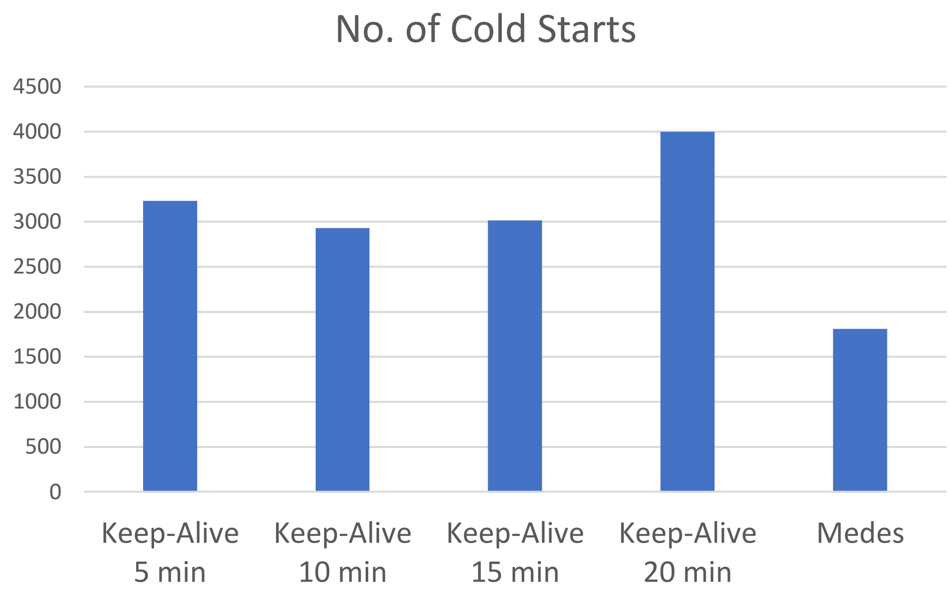
Evaluation – Flexibility achieved by Medes



Medes performs better than any keep alive

Best performing keep-alive

Large keep-alive leads to many evictions

Summary

- Medes can exploit sub-page level redundancy containers across a serverless platform.
- Medes uses:
  - Decoupling of redundancy identification and elimination granularities
  - Value-sampled fingerprints to identify similar pages
  - Fast sandbox restores
  - Flexible policy for sandbox management
- Medes can provide improved end-to-end latencies, memory usage.
- The benefits are enhanced for memory pressure scenarios.