



Insight of Medea and Neptune

Scheduling of Long Running Applications &
Scheduling Suspensible Tasks for Unified Stream/Batch Applications



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Medea

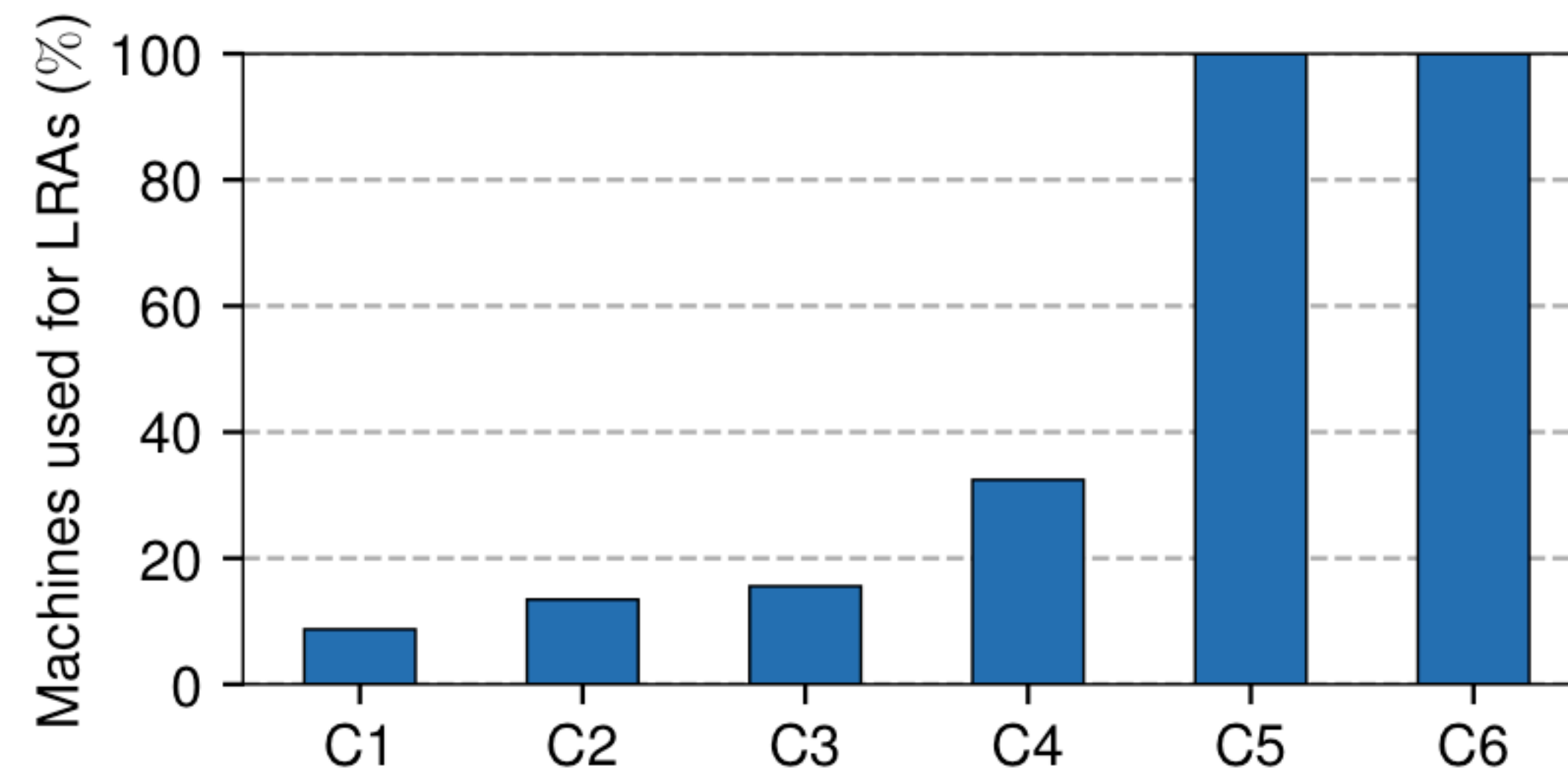
Scheduling of Long Running Applications
in Shared Production Clusters

Long-Running Applications (LRAs)

- **Interactive data-intensive** applications
 - Spark, Hive LLAP
- **Streaming** systems
 - Flink, Storm, SEEP
- **Latency-sensitive** applications
 - HBase, Memcached
- **ML** frameworks
 - TensorFlow, Spark ML-lib

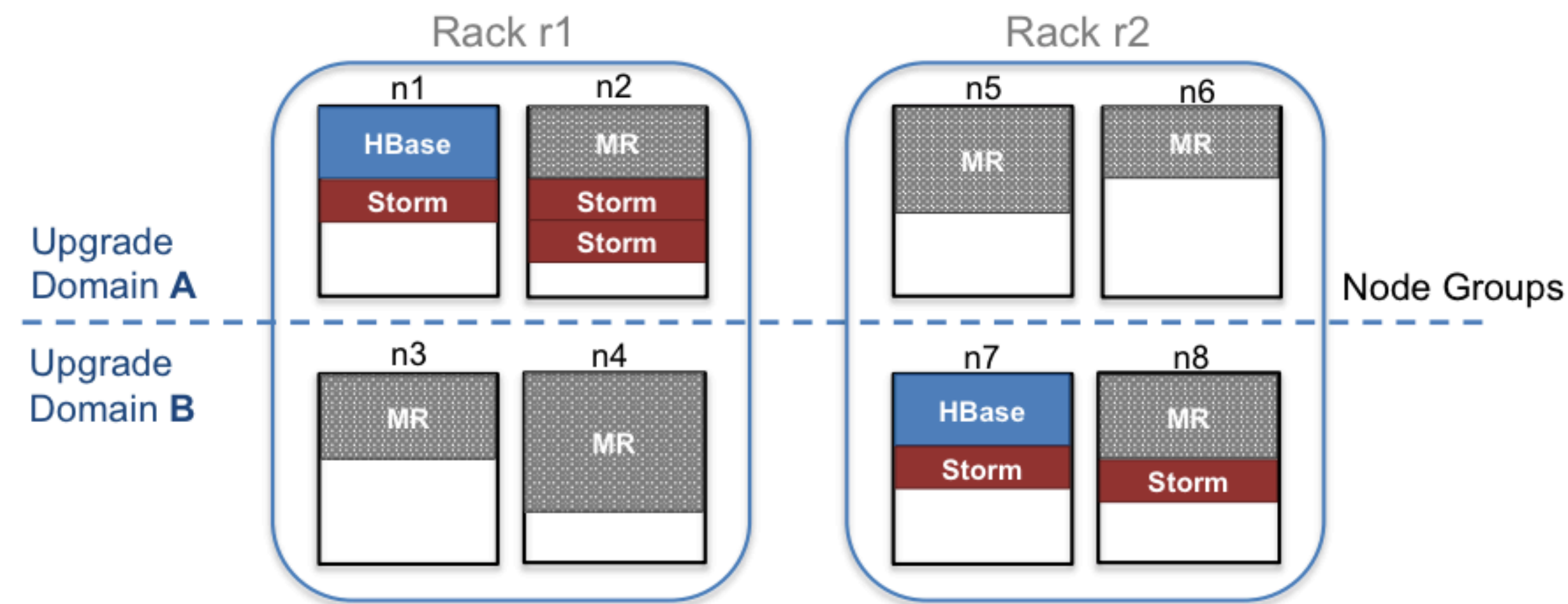
LRAs = applications
with long-running containers
(running from hours to months)

LRAs in Microsoft's analytics clusters



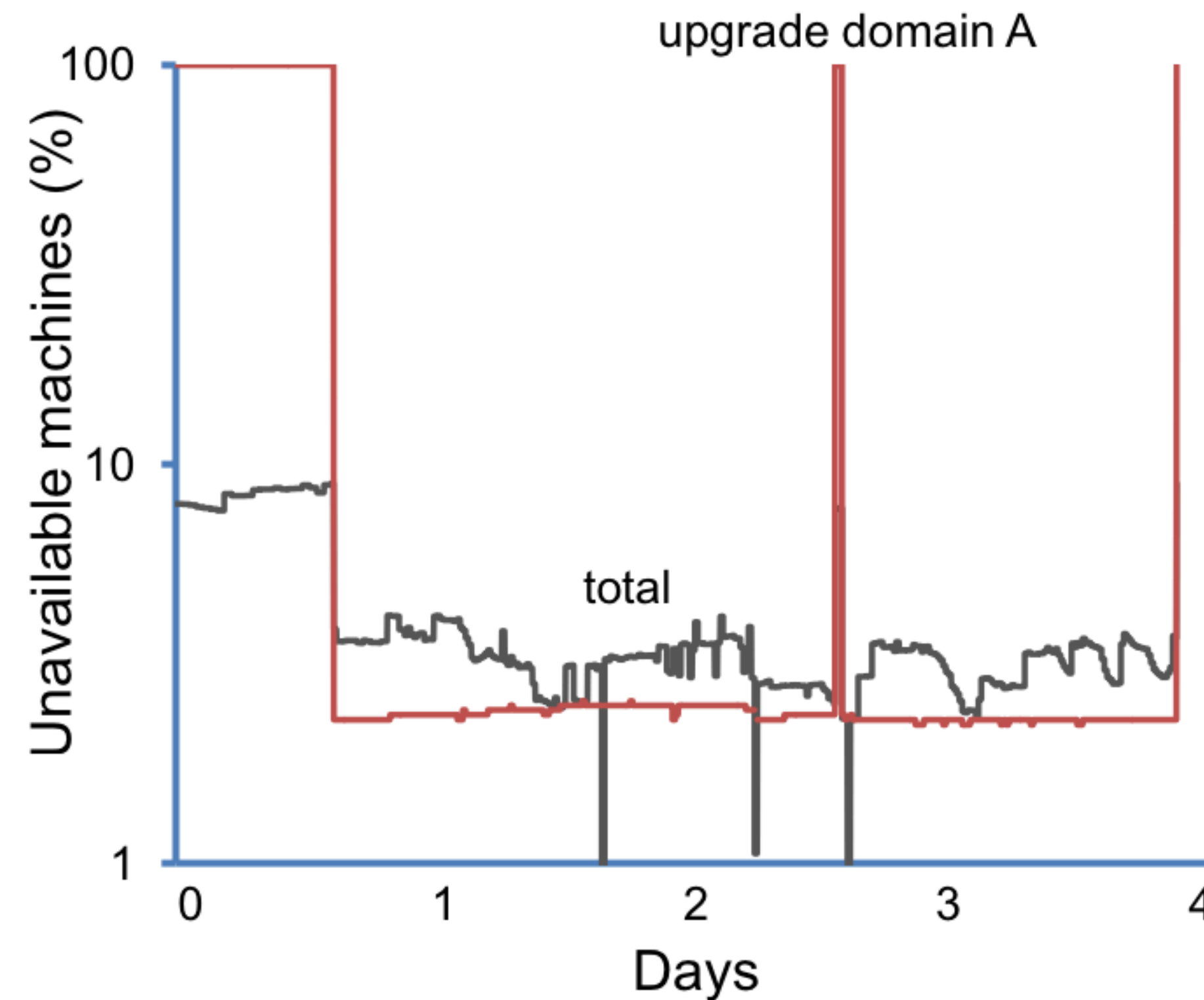
LRA placement is important

LRA scheduling problem



- **Performance:** “Place Storm containers in the same rack as HBase”
- **Cluster objectives:** “Minimize resource fragmentation”
- **Resilience:** “Place HBase containers across upgrade domains”

Machine unavailability in a Microsoft cluster



With **random placement**, an LRA might lose all containers at once

Challenges

- How to **relate containers** to node groups?
- How to **express** different types of constraints related to LRA containers?
- How to achieve **high quality placement** without affecting task-based jobs?

Medea

- How to **relate containers** to node groups?
- Support container tags and logical node groups
- How to **express** different types of constraints related to LRA containers?
- Introduce expressive cardinality constraints
- How to achieve **high quality placement** without affecting task-based jobs?
- Follow a two-scheduler design

Medea Design

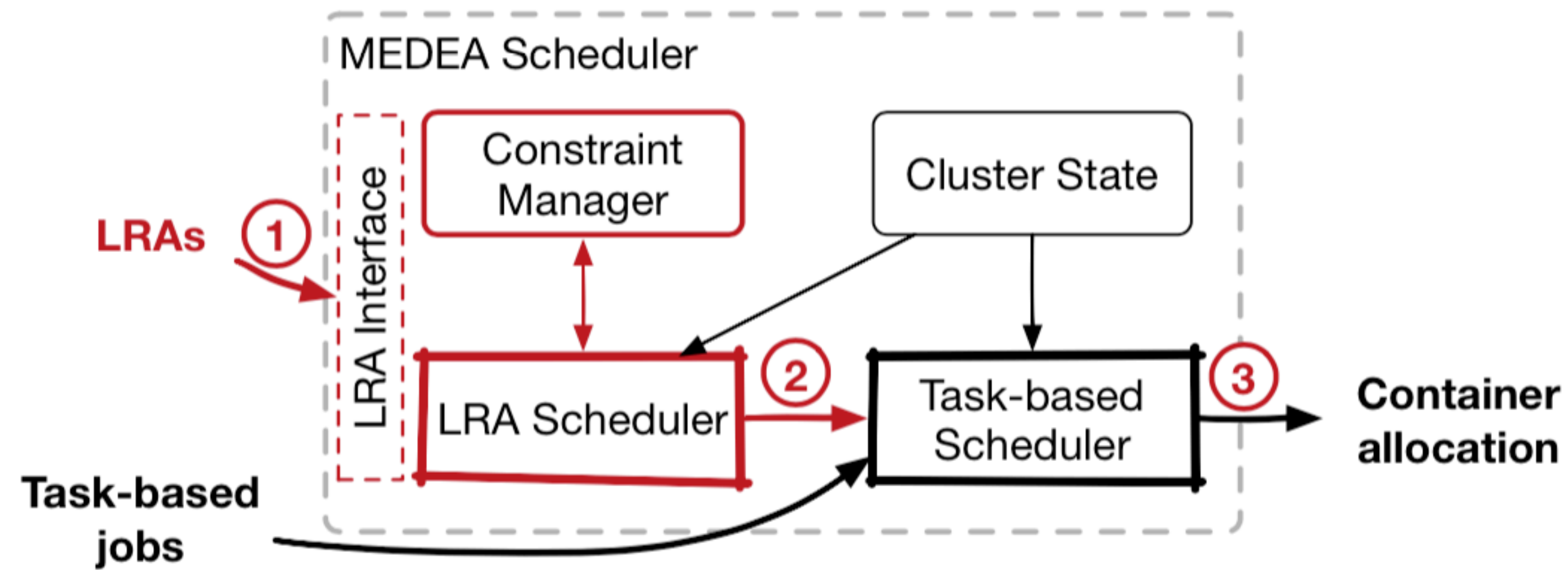
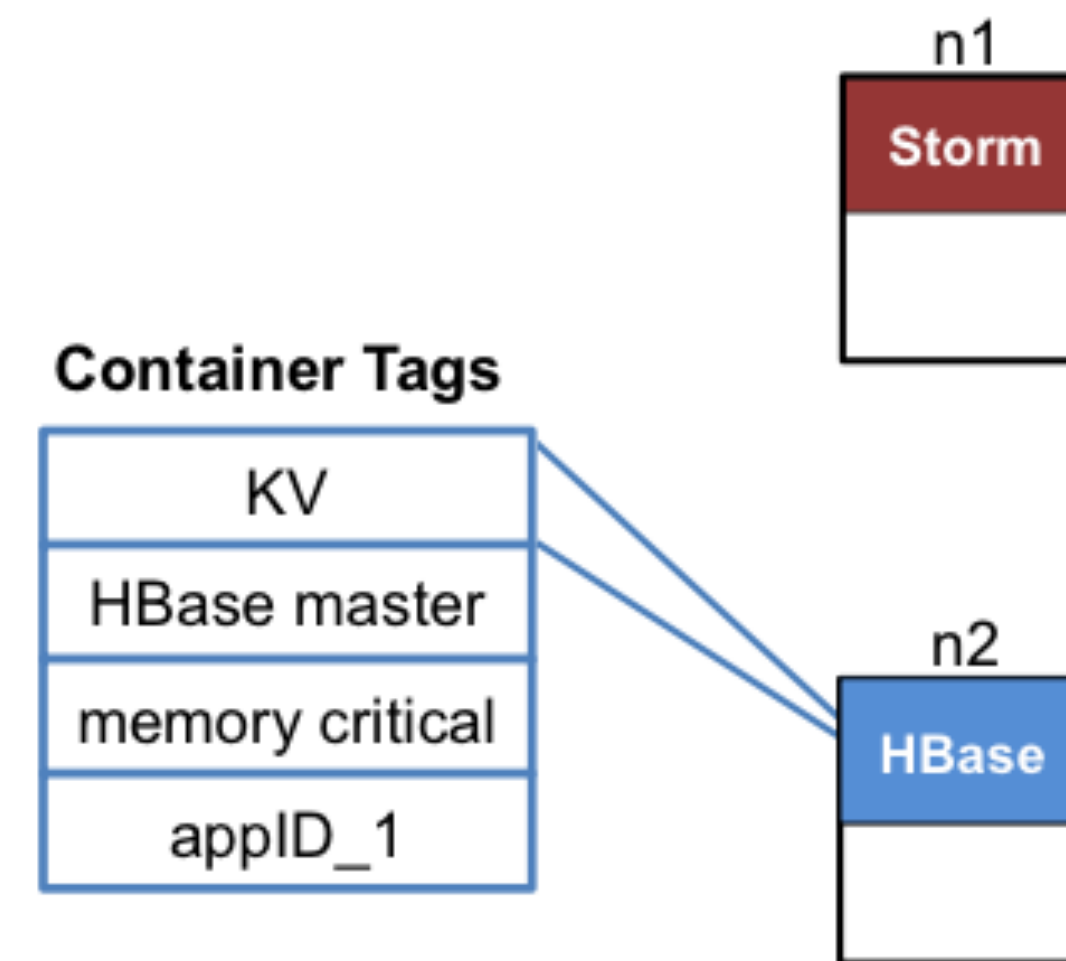


Figure 4: MEDEA scheduler design

Container tagging

- **Idea:** use **container tags** to refer to group of containers

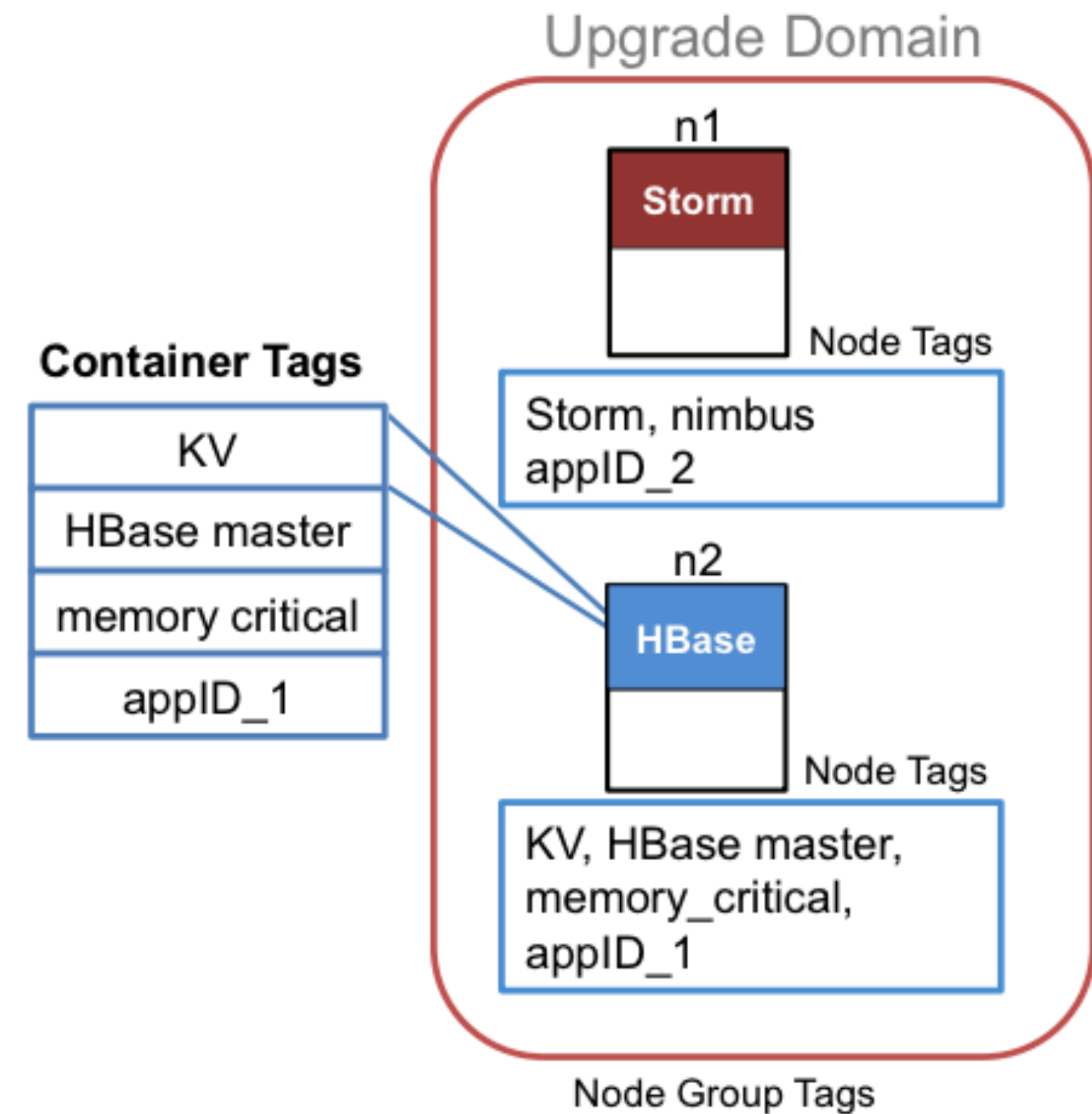
- Describe
 - application type
 - application role
 - resource specification
 - global application ID



- Can refer to any current or future LRA container

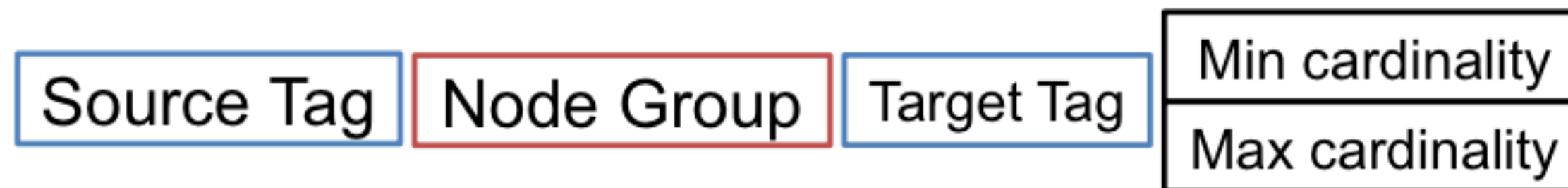
Hierarchical grouping of nodes

- **Idea:** logical node groups to refer to dynamic node sets
- E.g. node, rack. Upgrade domain
- Associate nodes with all the container tags that live there
- Hide infrastructure “spread across upgrade domains”



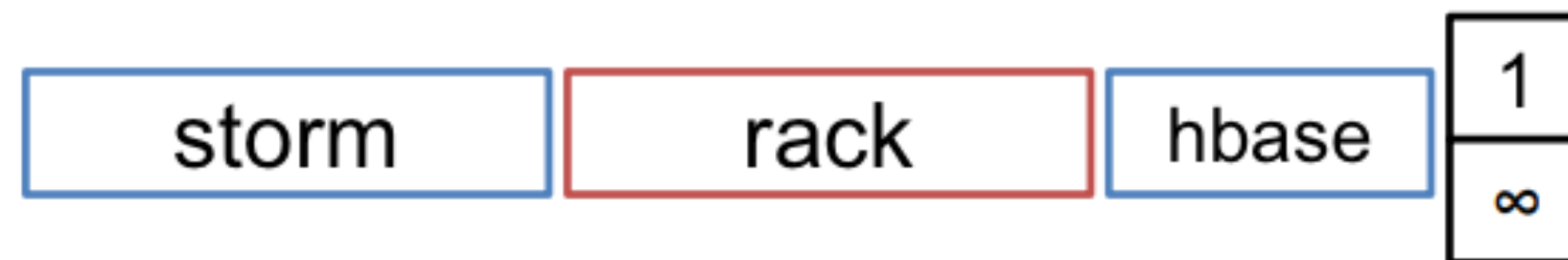
Defining constraints

- Generic constraints to capture a variety of cases

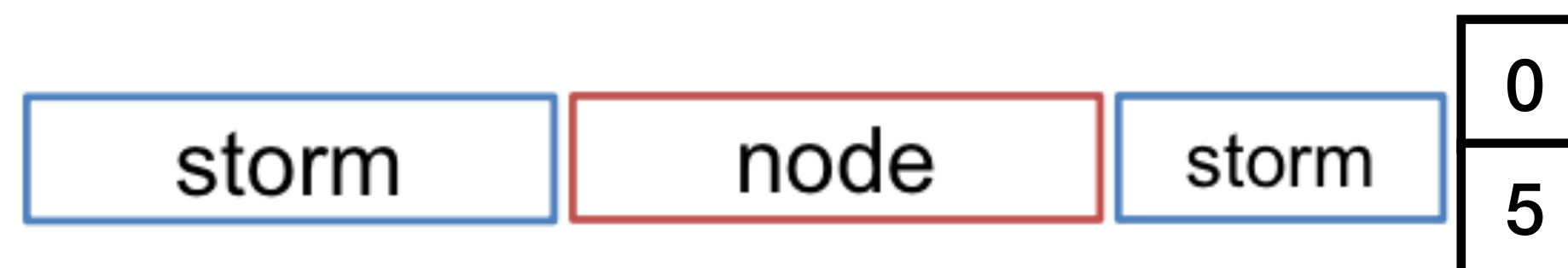


- $\text{Min cardinality} \leq \text{occurrences (Target Tag)} \leq \text{Max cardinality}$

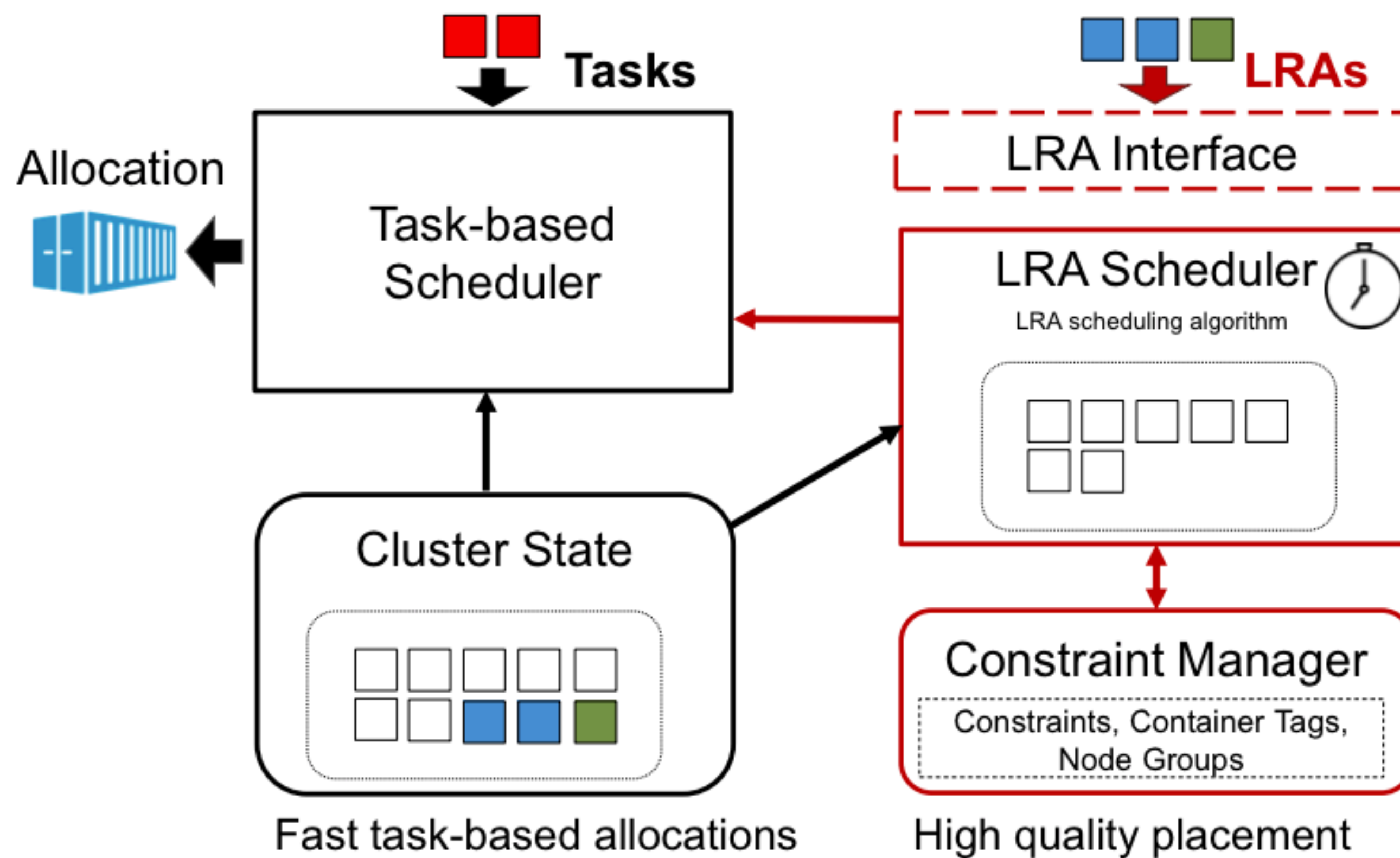
- Affinity “Place Storm containers in the same rack as HBase”



- Cardinality “Place up to 5 Storm containers in the same node”



Two-scheduler design



ILP-based scheduling algorithm

$$\text{maximize } \frac{w_1}{k} \sum_{i=1}^k S_i + \frac{w_2}{m} \sum_{l=1}^m v_c^l + \frac{w_3}{N} \sum_{n=1}^N z_n \quad (1)$$

$$\text{subject to: } \forall i, j : \sum_{n=1}^N X_{ijn} \leq 1 \quad (2)$$

$$\forall n : \sum_{i=1}^k \sum_{j=1}^{T_i} r_{ij} \cdot X_{ijn} \leq R_n^f \quad (3)$$

$$\forall i : \sum_{n=1}^N \sum_{j=1}^{T_i} X_{ijn} - T_i S_i = 0 \quad (4)$$

$$\forall n : \sum_{i=1}^k \sum_{j=1}^{T_i} r_{ij} \cdot X_{ijn} - B_n(1 - z_n) \leq R_n^f - r_{min} \quad (5)$$

For each constraint $C_l = \{s_tag, \{c_tag, c_{min}^l, c_{max}^l\}, G\}$,
 \forall container $t_{ijs} \in s_tag, \forall$ node set $S \in G$:

$$\sum_{n \in S} \left(\sum_{\substack{i,j:tag \in t_{ij} \\ t_{ij} \neq t_{ijs}}} X_{ijn} + D_n(1 - X_{ijsn}) \right) - c_{min}^l + c_{min}^{l,v} \geq 0 \quad (6)$$

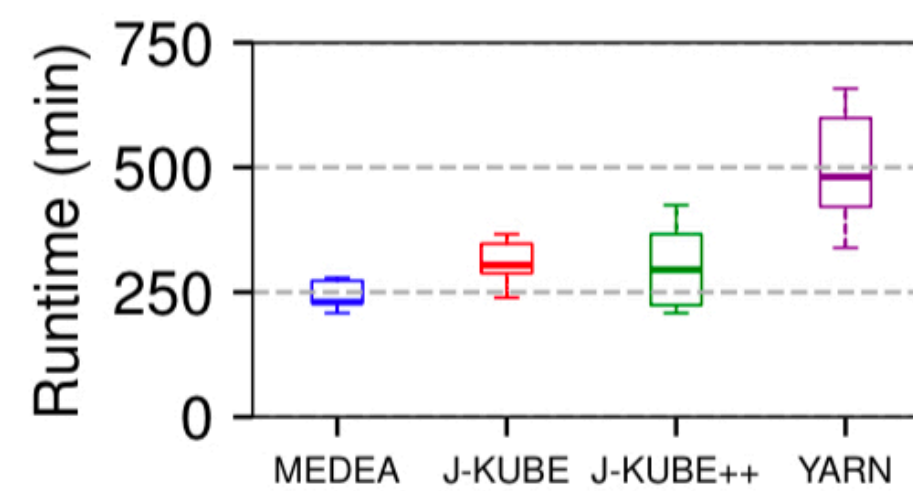
$$\sum_{n \in S} \left(\sum_{\substack{i,j:tag \in t_{ij} \\ t_{ij} \neq t_{ijs}}} X_{ijn} - D_n(1 - X_{ijsn}) \right) - c_{max}^l - c_{max}^{l,v} \geq 0 \quad (7)$$

$$v_c^l = \frac{c_{min}^{l,v}}{c_{min}^l} + \frac{c_{max}^{l,v}}{c_{max}^l} \quad (8)$$

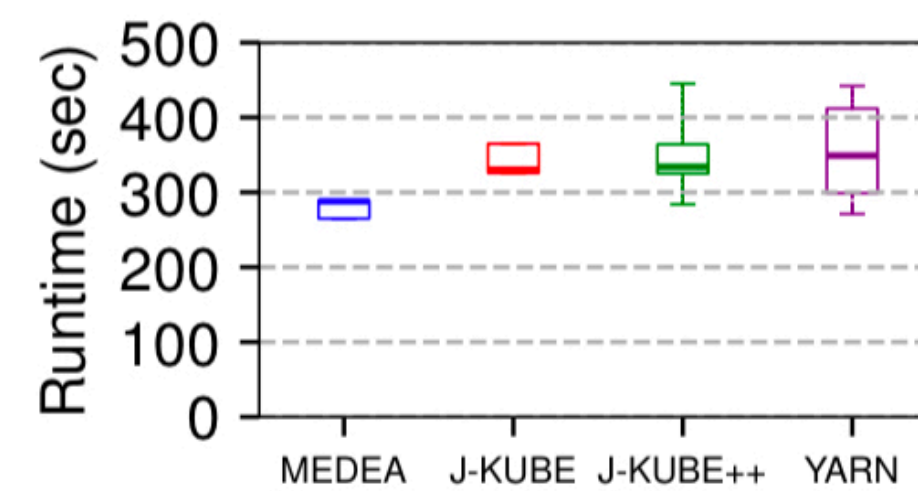
Symbol	Description
k	Number of LRAs to be placed
N	Number of cluster nodes
T_i	Number of containers of LRA i
R_n^f, R_n^u	Free, used resources of node n ⁶
m	Total number of constraints
w_i	Weights of components in objective function
B_n, D_n	Sufficiently large integers, used in inequalities
S_i	1 if all containers of LRA i are placed; 0 otherwise
X_{ijn}	1 if container j of LRA i placed at node n ; 0 otherwise
r_{ij}	Resource demand of container j of LRA i
r_{min}	Minimum resource demand
$c_{min}^{l,v}, c_{max}^{l,v}$	Violation of cardinalities c_{min}, c_{max} for constraint C_l
v_c^l	Violation for constraint C_l
z_n	1 if free resources $\geq r_{min}$ after placement; 0 otherwise

Evaluation

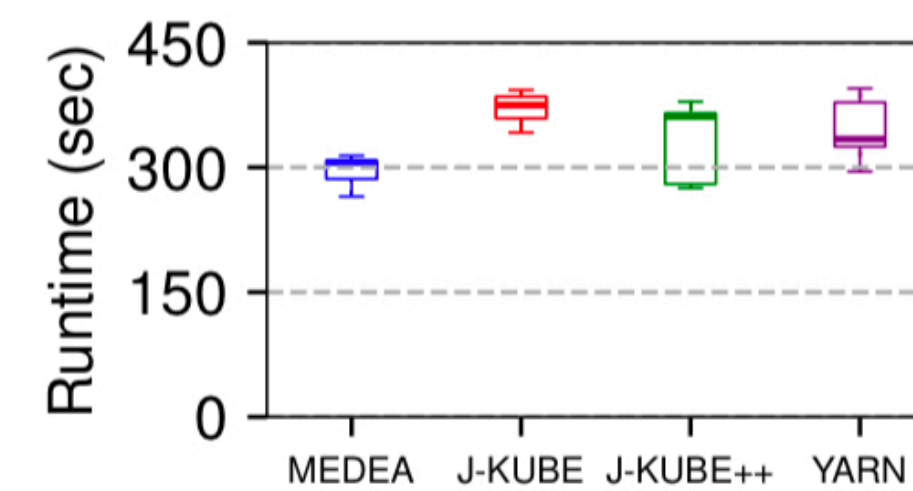
A 400 node pre-production cluster grouped into 10 racks, supplemented by simulation.



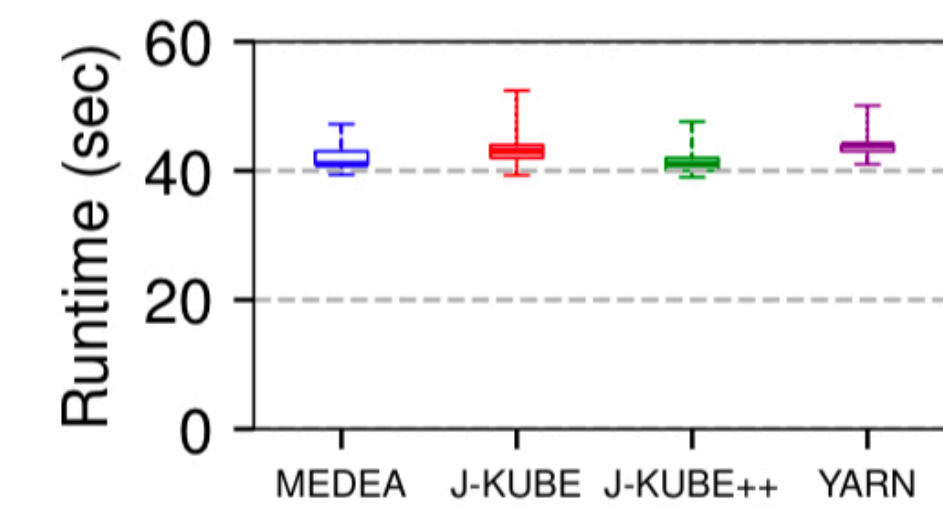
(a) TensorFlow



(b) HBase insert



(c) HBase workloadA



(d) GridMix workload

Figure 7: Application performance (lower is better)

Evaluation

A 400 node pre-production cluster grouped into 10 racks, supplemented by simulation.

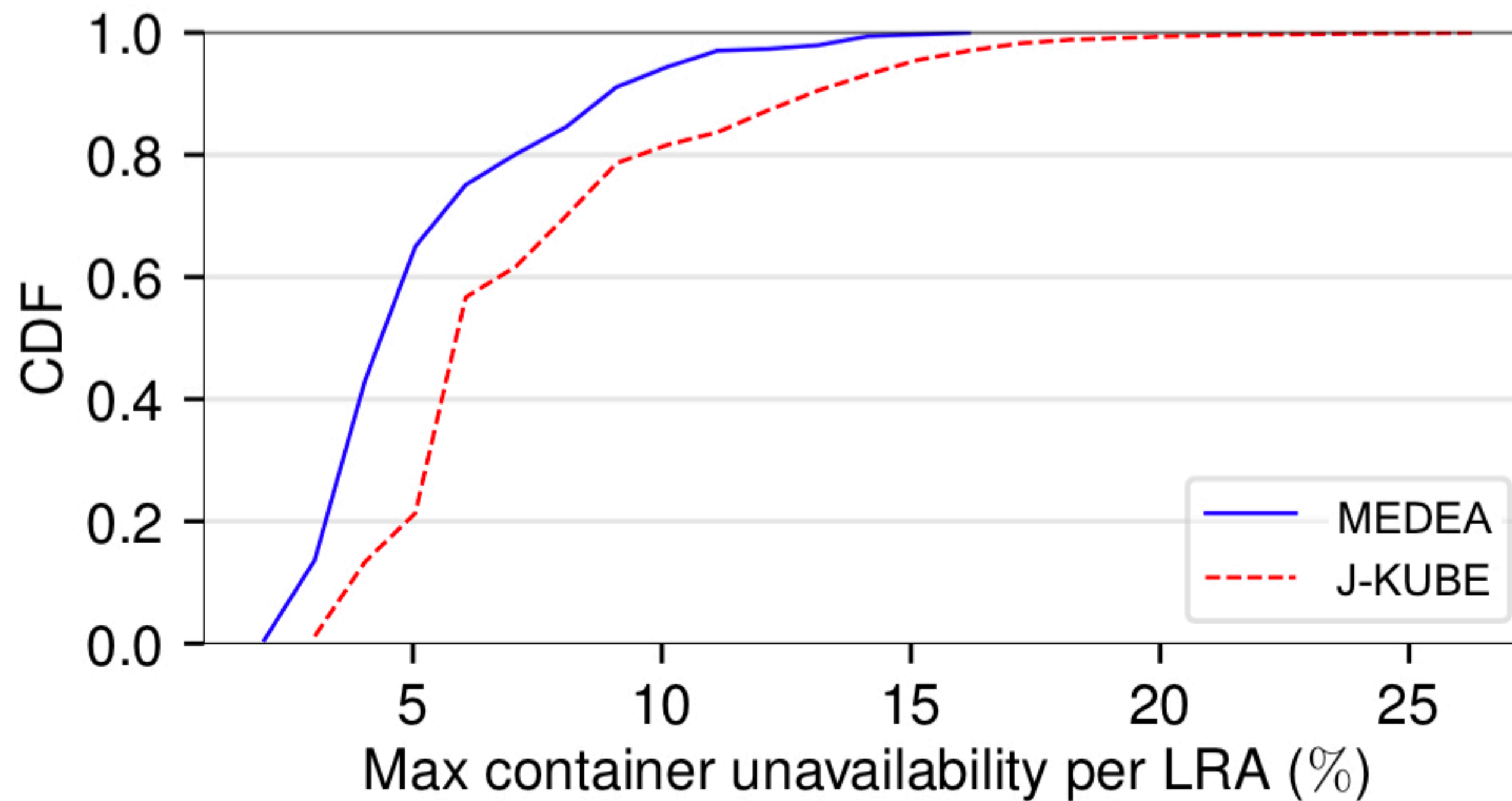


Figure 8: Application resilience over 15 days

Evaluation

A 400 node pre-production cluster grouped into 10 racks, supplemented by simulation.

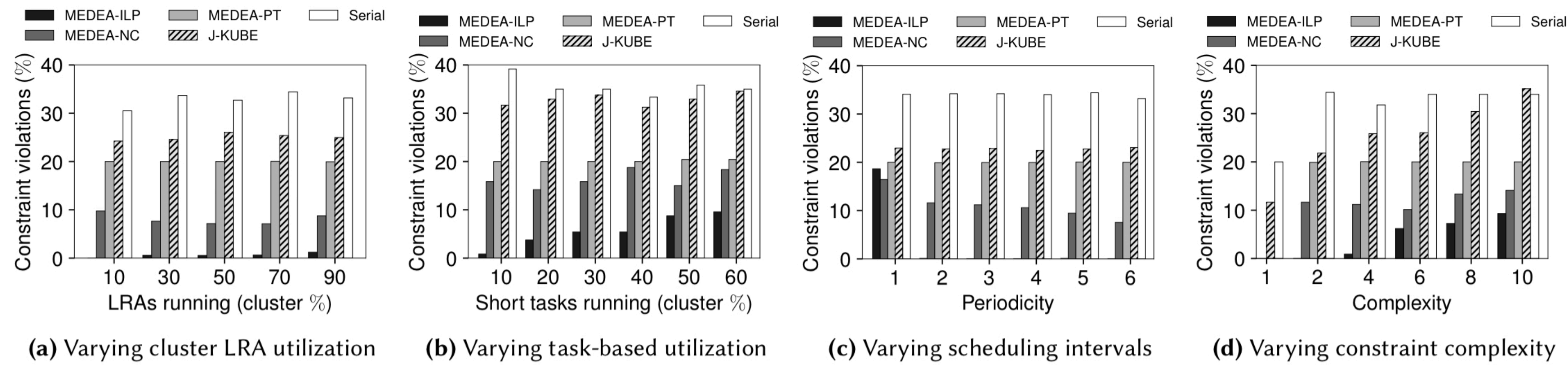


Figure 9: Constraint violations

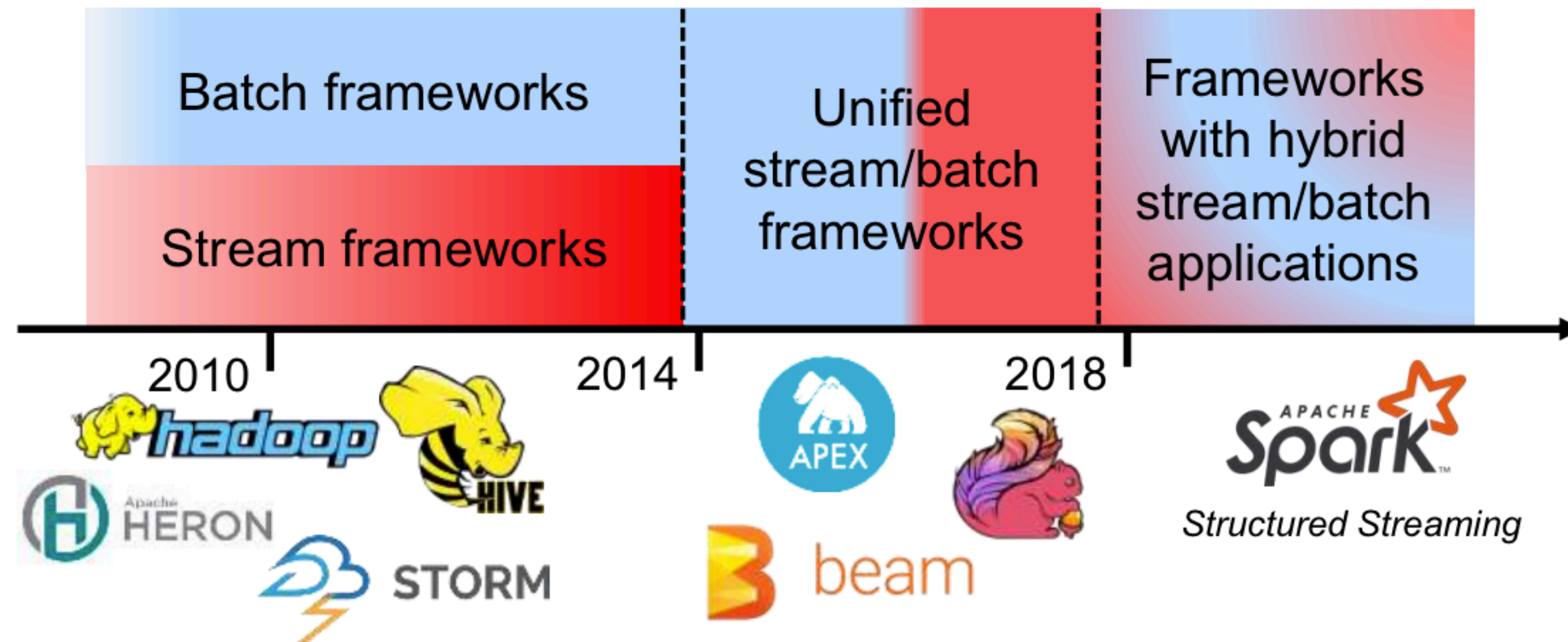


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Neptune

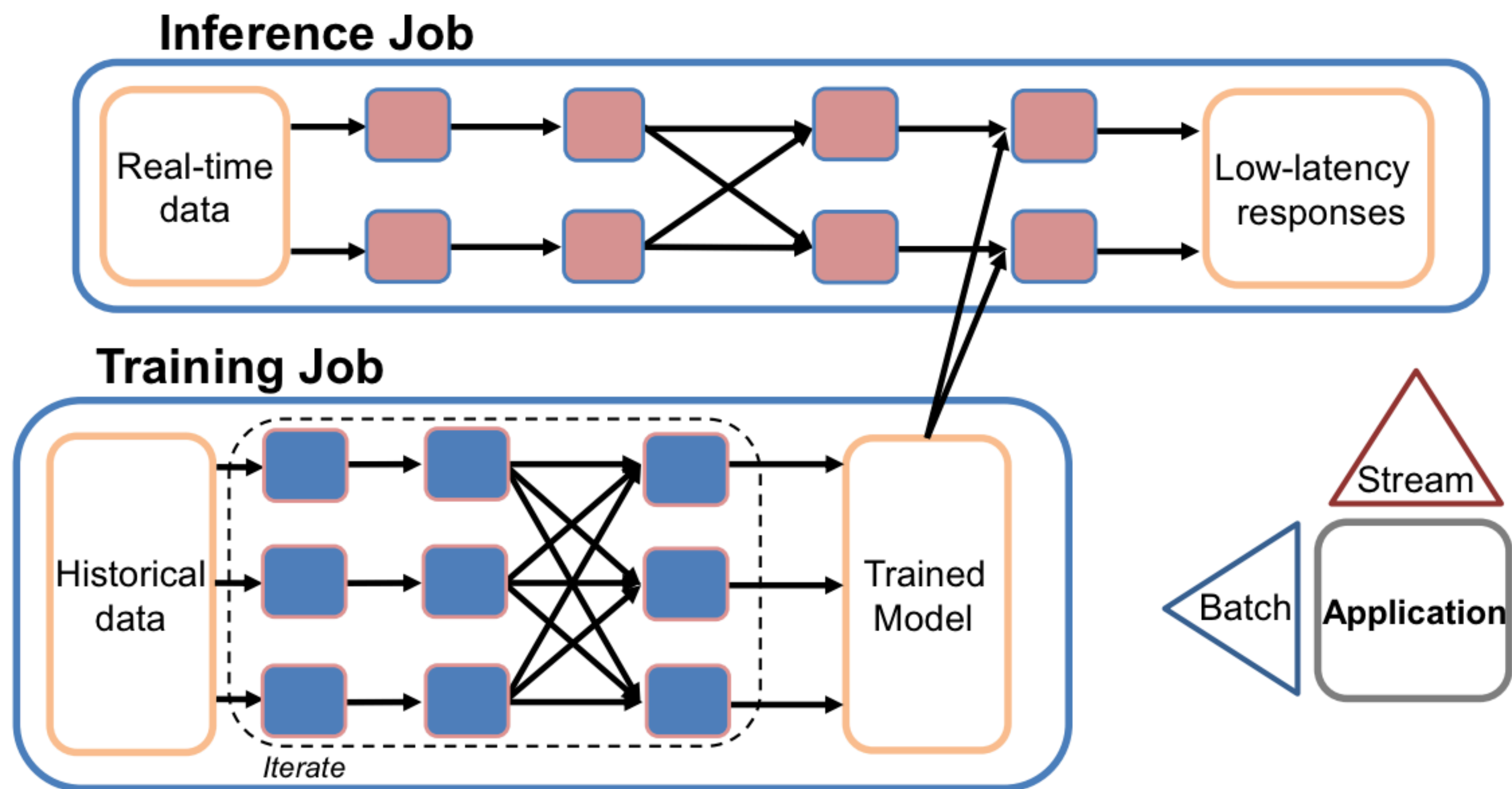
Scheduling Suspendable Tasks
for Unified Stream/Batch Applications

Evolution of analytics frameworks



UNIFICATION

Unified application example



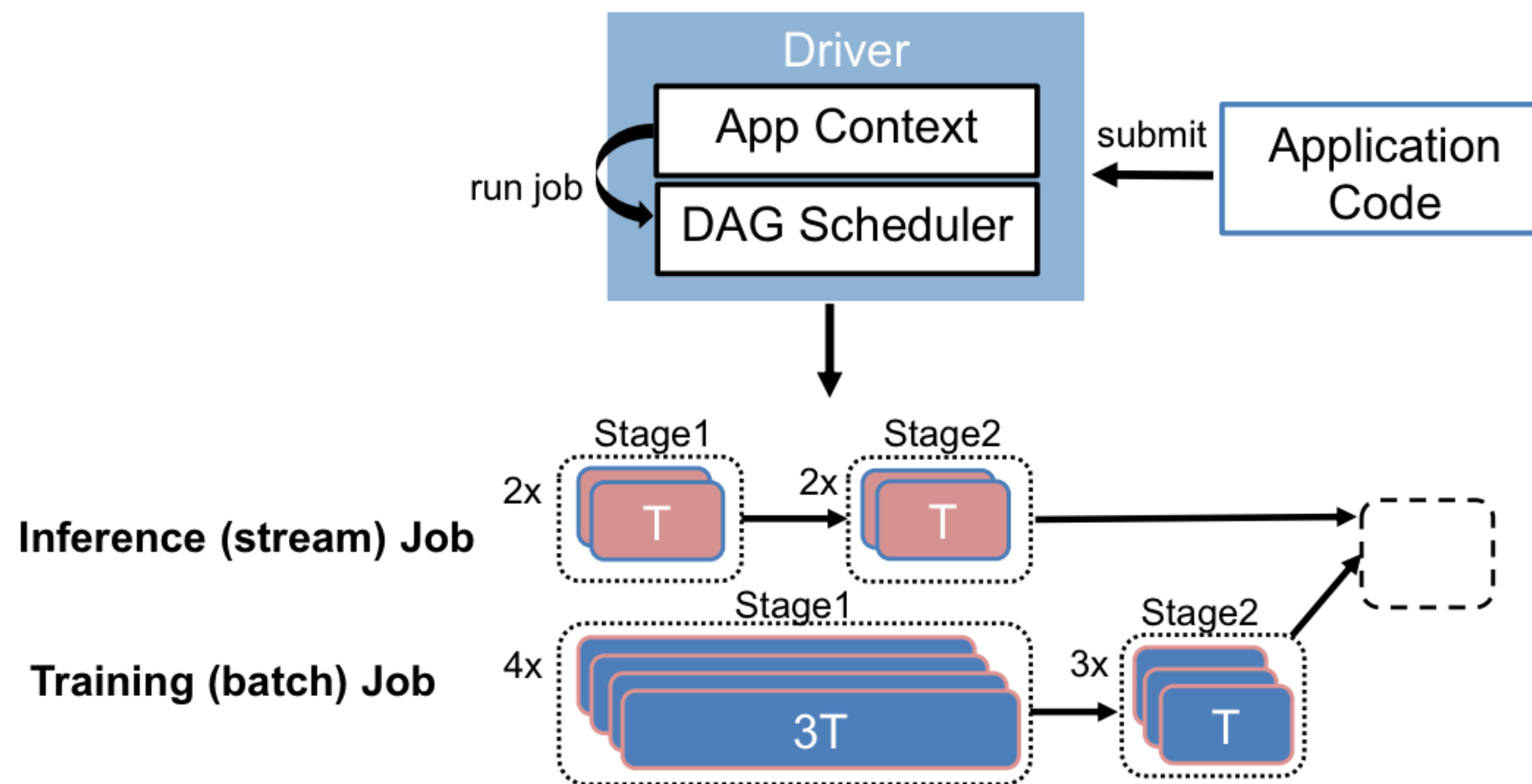
Stream/Batch application requirements

- **Requirements**

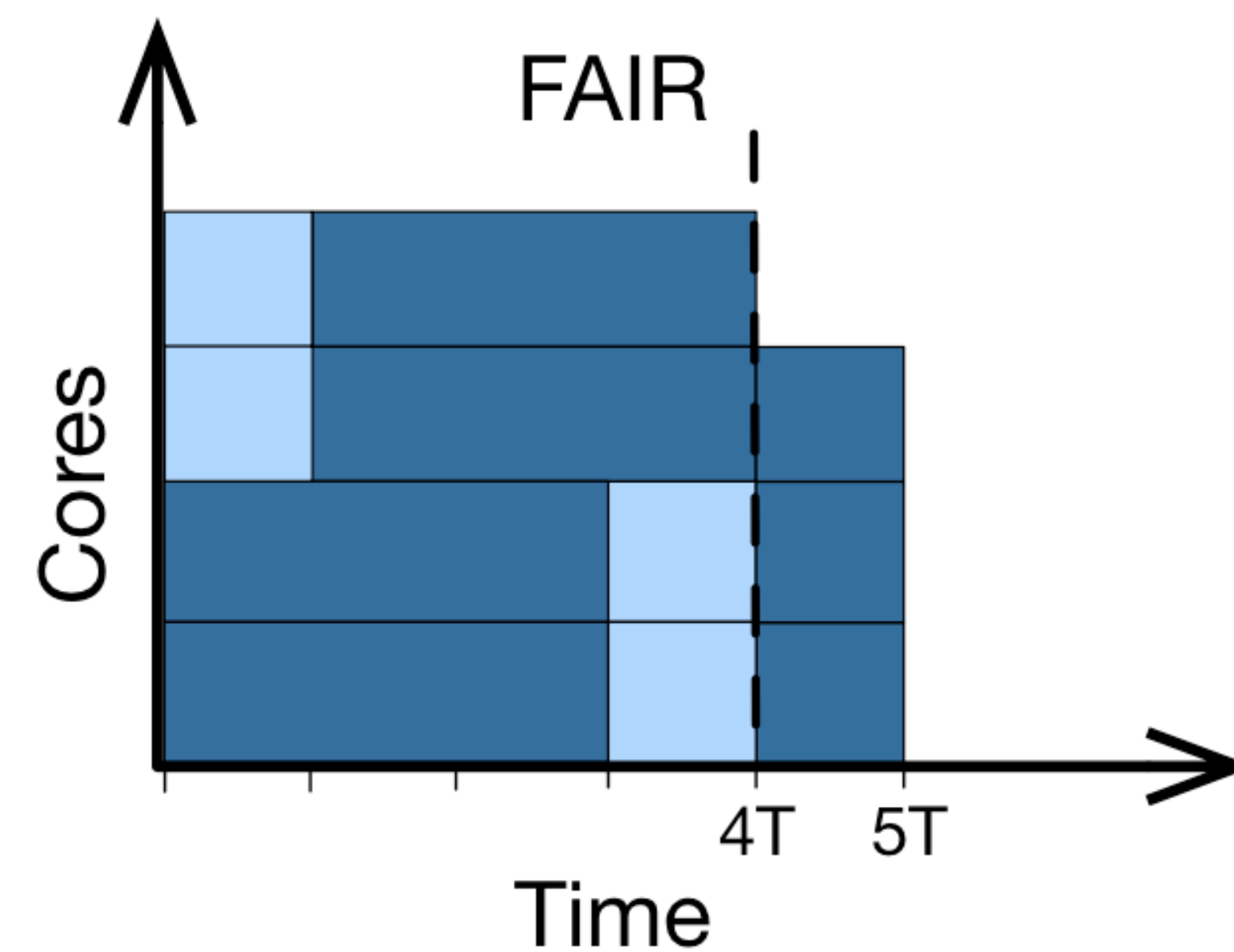
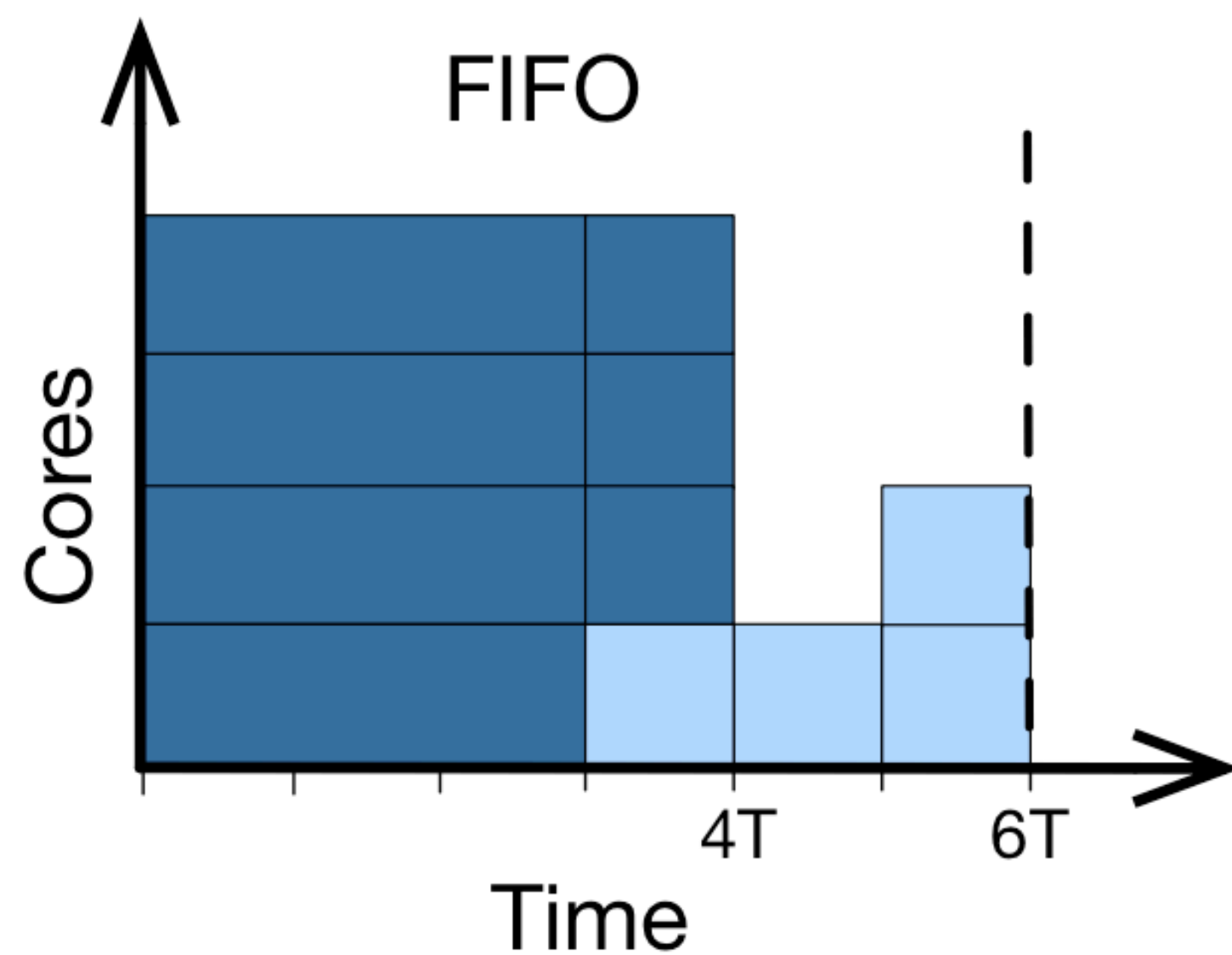
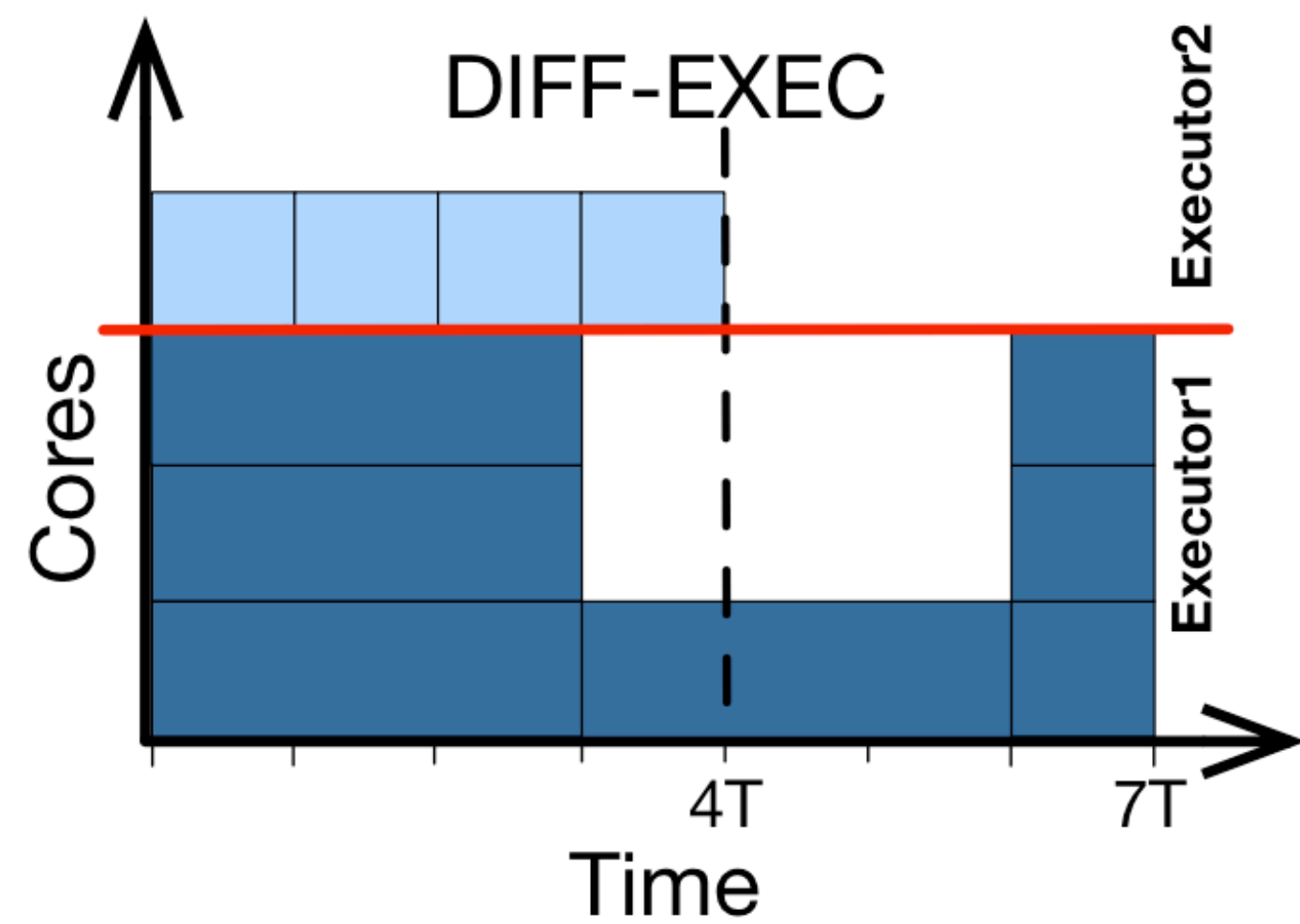
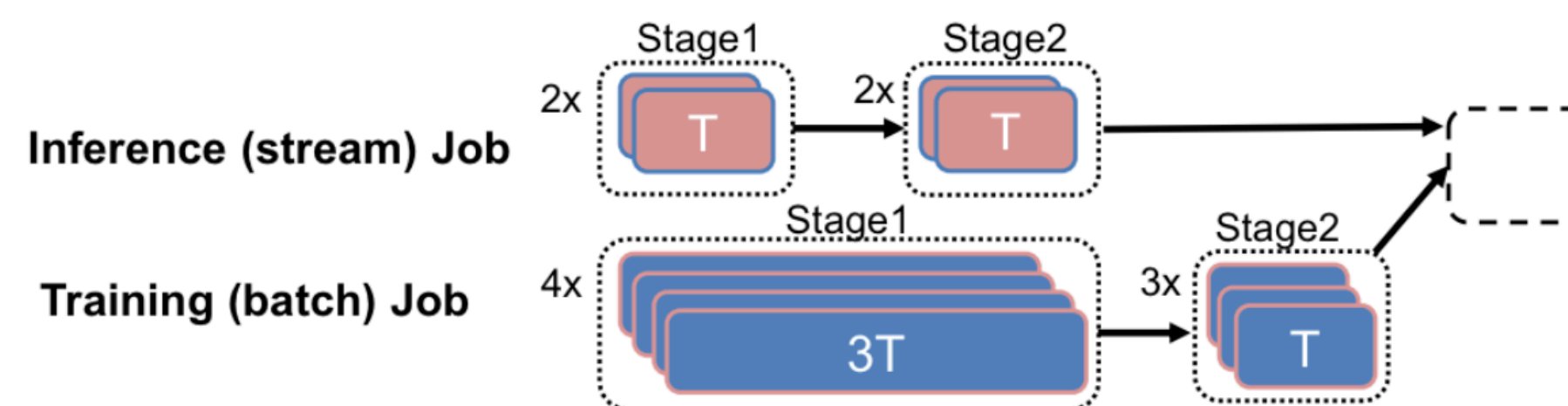
- Latency: Execute inference job with minimum delay
- Throughput: Batch jobs should not be compromised
- Efficiency: Achieve high cluster resource utilization

Challenge: schedule stream/batch jobs to satisfy their diverse requirements

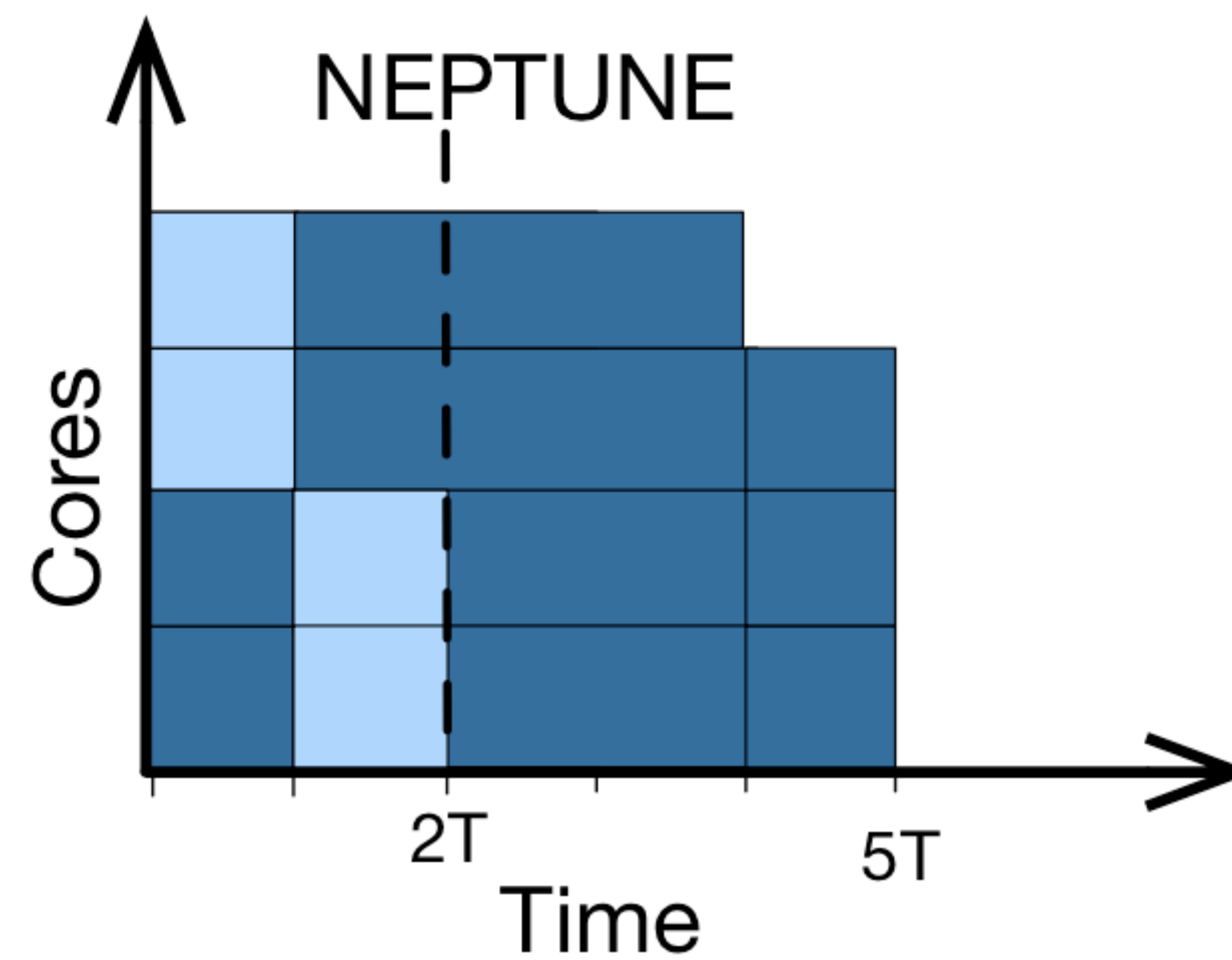
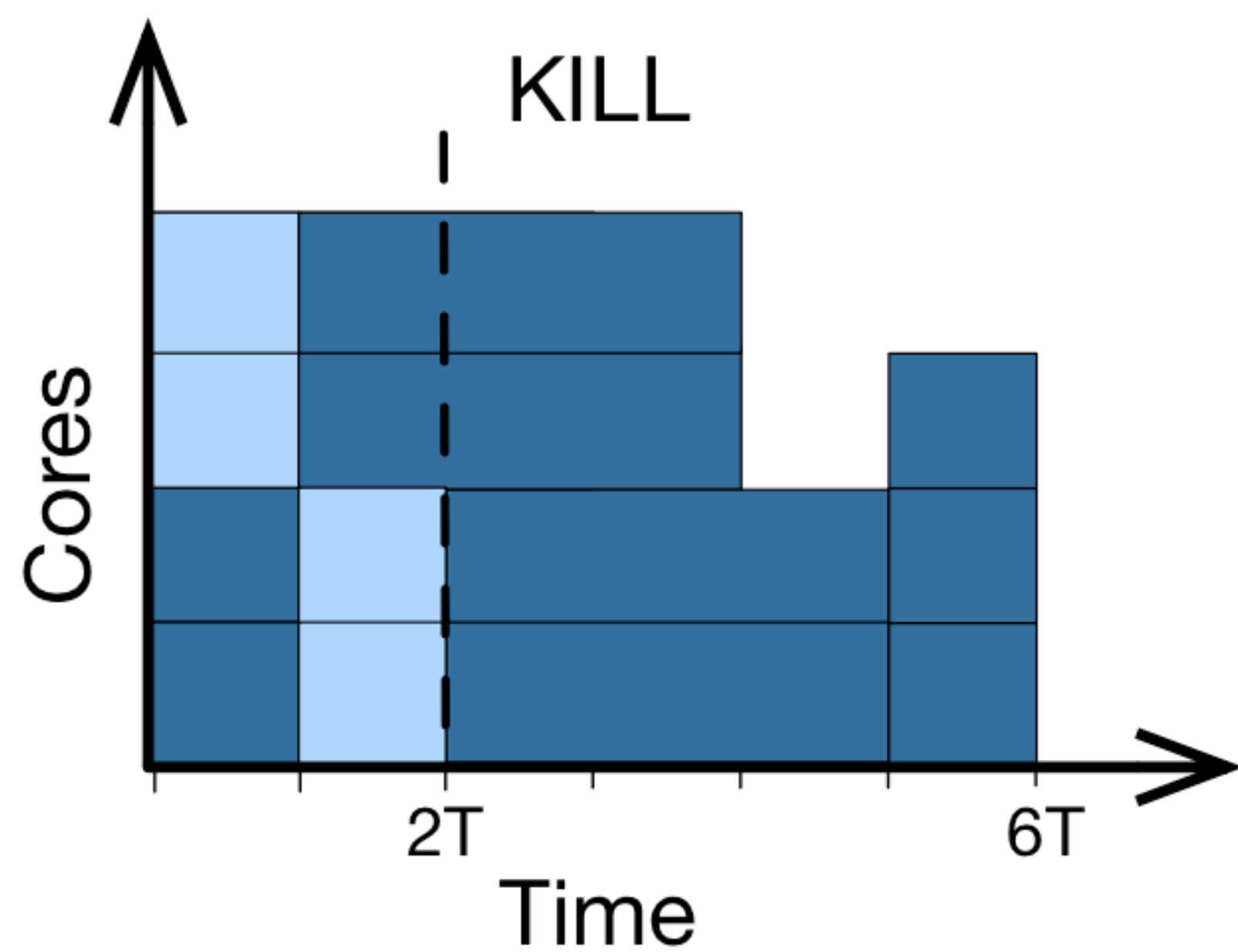
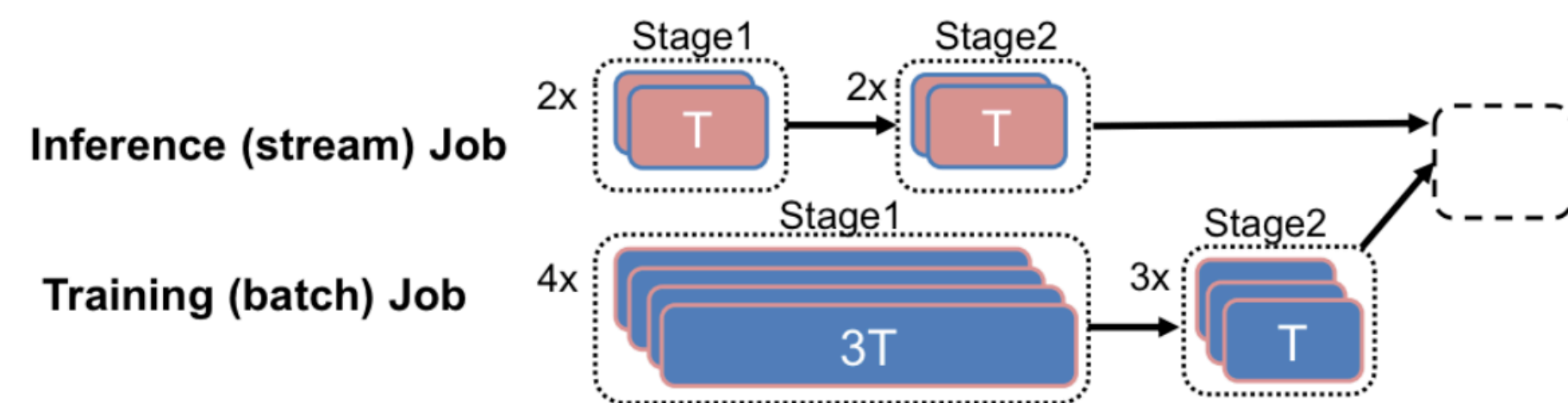
Stream/Batch application scheduling



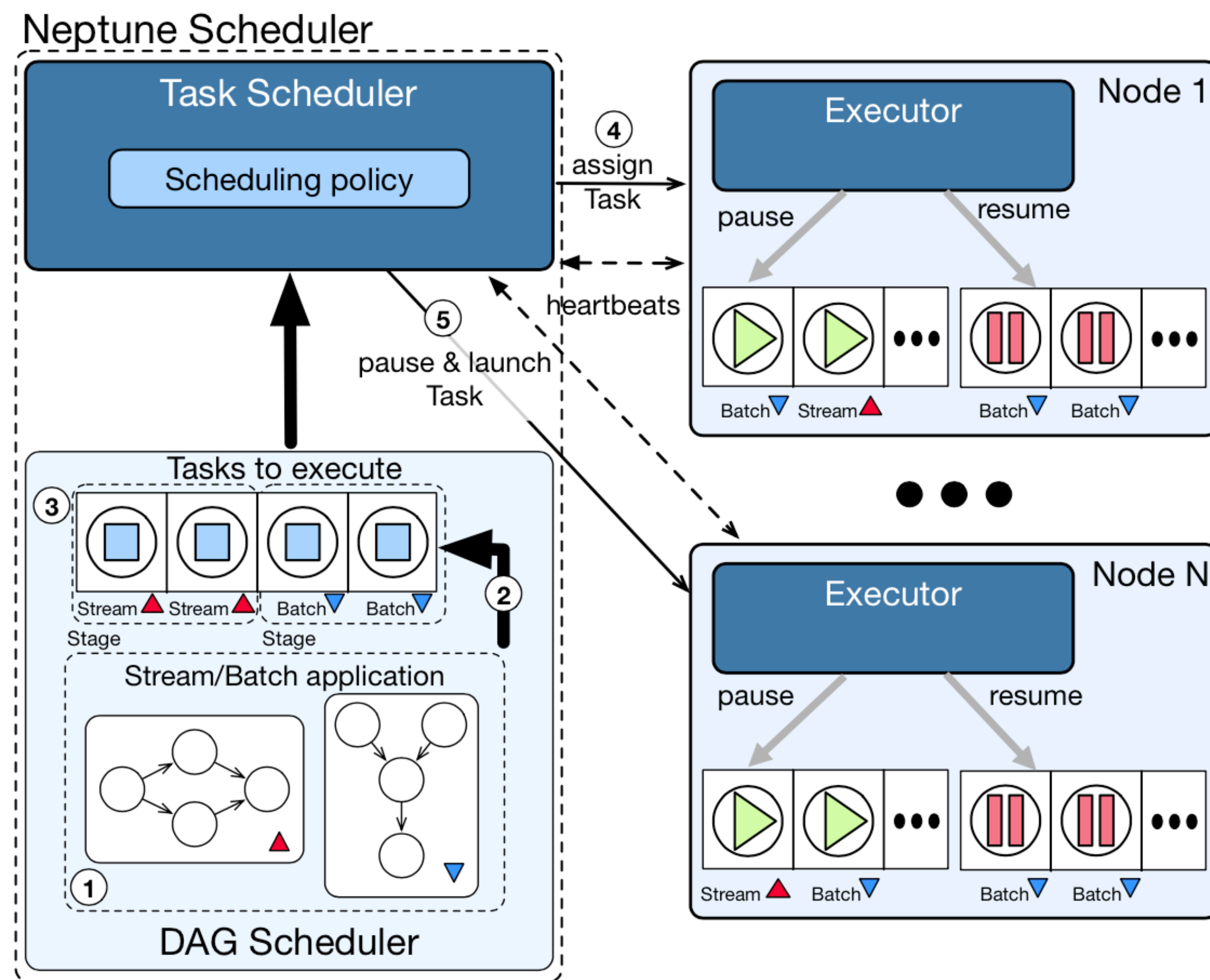
Stream/Batch application scheduling



Stream/Batch application scheduling



Neptune Design



Suspendable Tasks

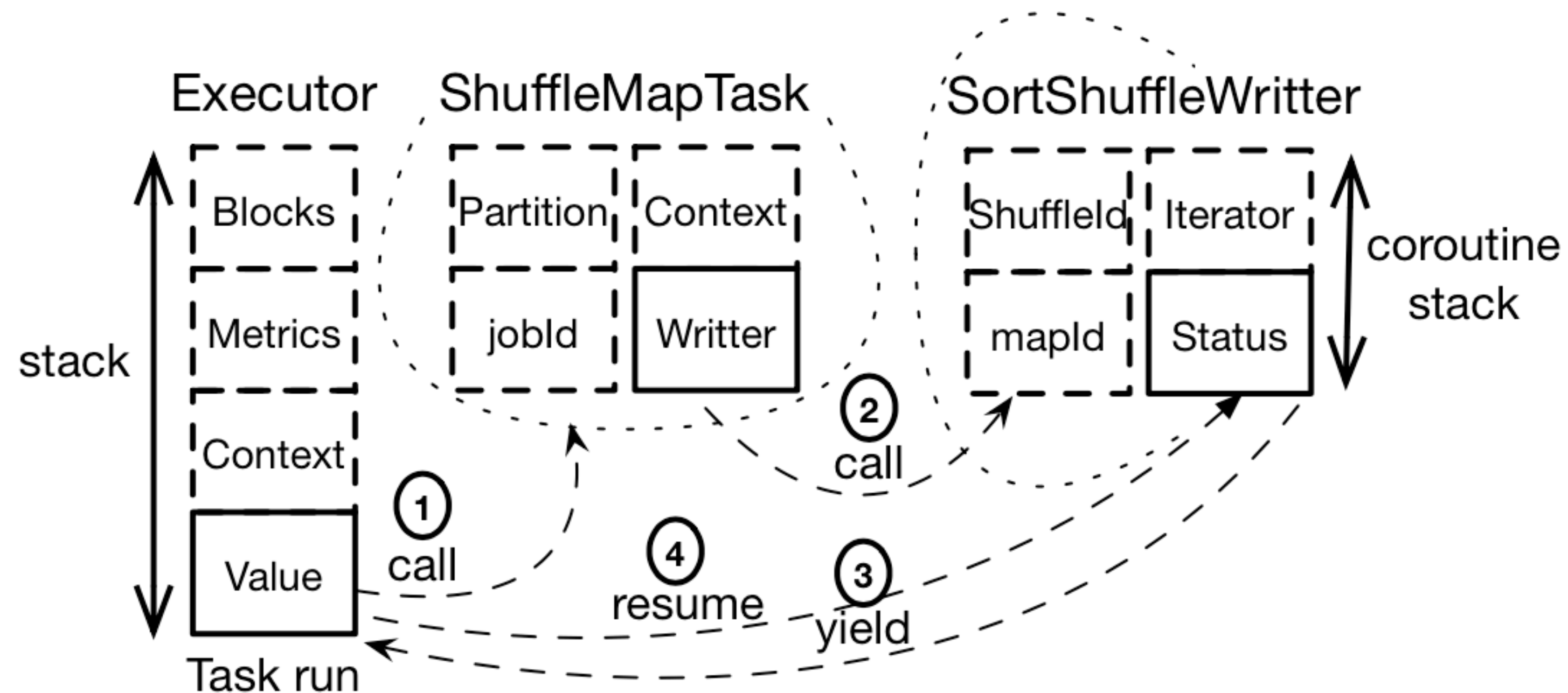
Neptune uses stackful coroutines to implement suspendable tasks, which have a yield point after the processing of each record.

Listing 2: Collect coroutine task

```
1 val collect : (TaskContext, Iterator [T]) -> (Int, Array[T]) =  
2   coroutine {(context: TaskContext, itr : Iterator [T]) =>  
3     val result = new mutable.ArrayBuffer[T]  
4     while (itr.hasNext) /* iterate records */  
5       | result.append(itr.next) /* append record to dataset */  
6       | if (context.isPaused()) /* check task context */  
7         | | yieldval (0) /* yield value to caller */  
8     result.toArray /* return result dataset */
```

Suspendable Tasks

Neptune uses stackful coroutines to implement suspendable tasks, which have a yield point after the processing of each record.



Scheduling policies

- **Idea:** policies trigger task suspension and resumption
 - Guarantee that stream tasks bypass batch tasks
 - Satisfy higher-level objectives i.e. balance cluster load
 - Avoid starvation by suspending up to a number of times
- **Load-balancing** (LB): takes into account executors' memory conditions and equalize the number of tasks per node
- **Locality- and memory aware** (LMA): respect task locality preferences in addition to load-balancing

LMA Scheduling policies

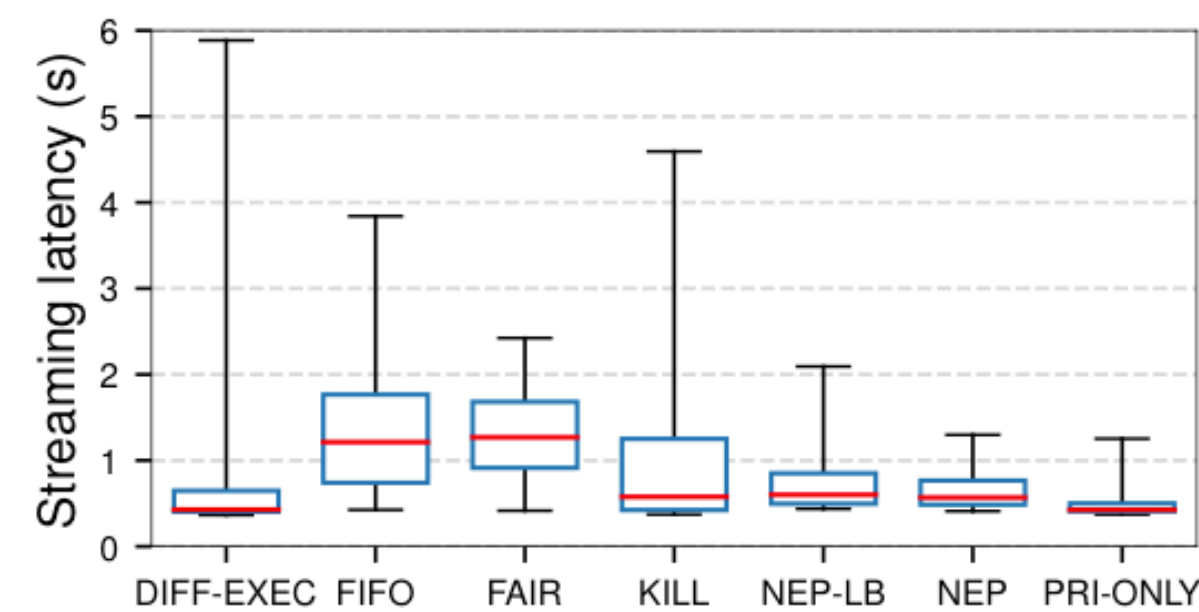
Algorithm 1: LMA scheduling policy

```
Input: List Executors,           // In descending preference order
1  List ExecutorsMetricsWindow    // Executor metrics

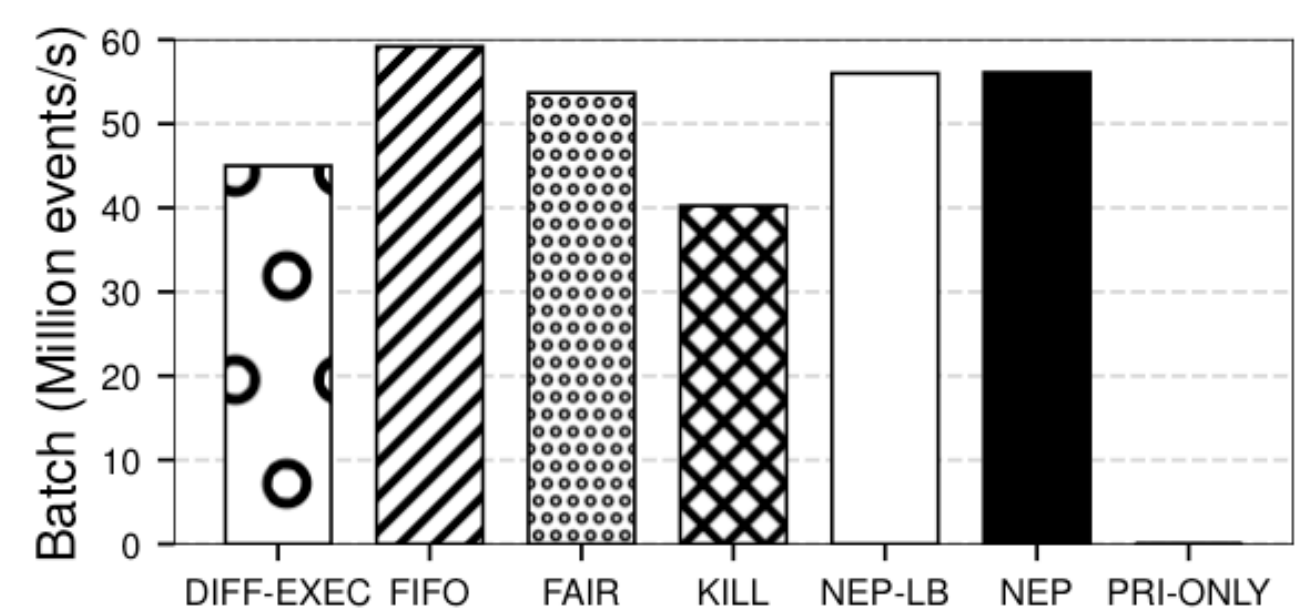
2  Upon event HEARTBEAT hb from EXECUTOR e do
3      ExecutorsMetricsWindow[e].push(hb.metrics)
4      Executors.updateOrdering
5  return

6  Upon event SUBMIT Task t do
7      // Cache local executor
8      Executor  $t_{exec} \leftarrow \text{hostToExecutor.get}(t.\text{cacheLocation})$ 
9      if  $t_{exec}$  is None or  $t_{exec}.\text{freeMemory} < \text{threshold}$  then
10         // Executor with the least pressure
11          $t_{exec} \leftarrow \text{Executors.head}$ 
12     if  $t_{exec}$  has availableCores then
13         // Launch task t on free cores
14          $t_{exec}.\text{Launch}(t)$ 
15     else
16         // Suspend task  $t_p$  and launch t
17         Task  $t_p \leftarrow t_{exec}.\text{tasks.filter}(\text{LowPriority})$ 
18          $t_{exec}.\text{PauseAndLaunch}(t, t_p)$ 
19 return
```

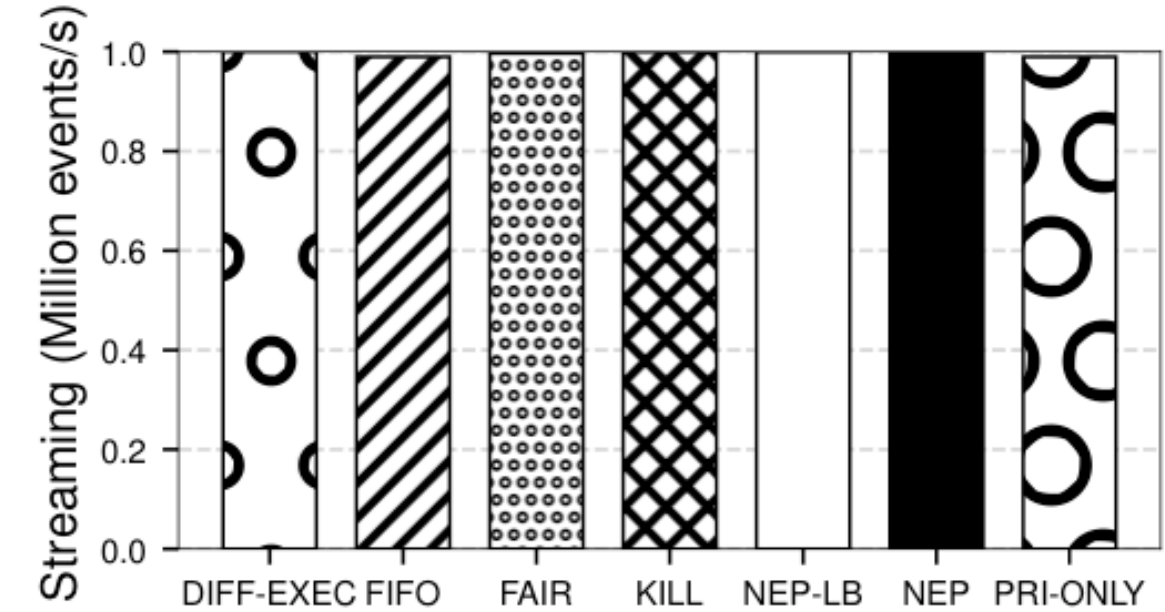
Evaluation



(a) Streaming query latency

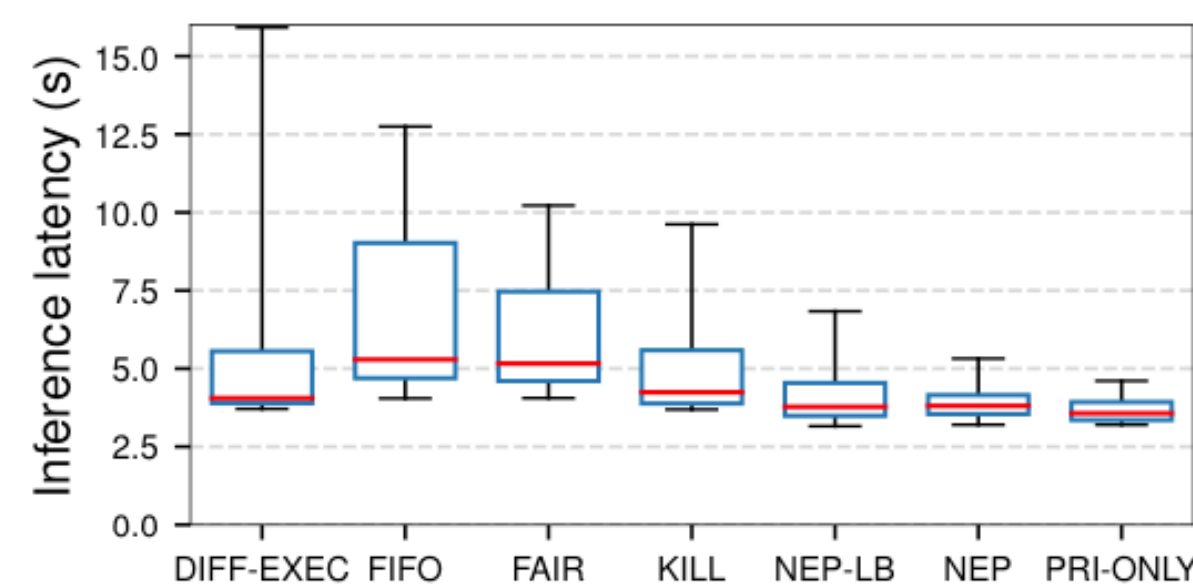


(b) Batch query throughput

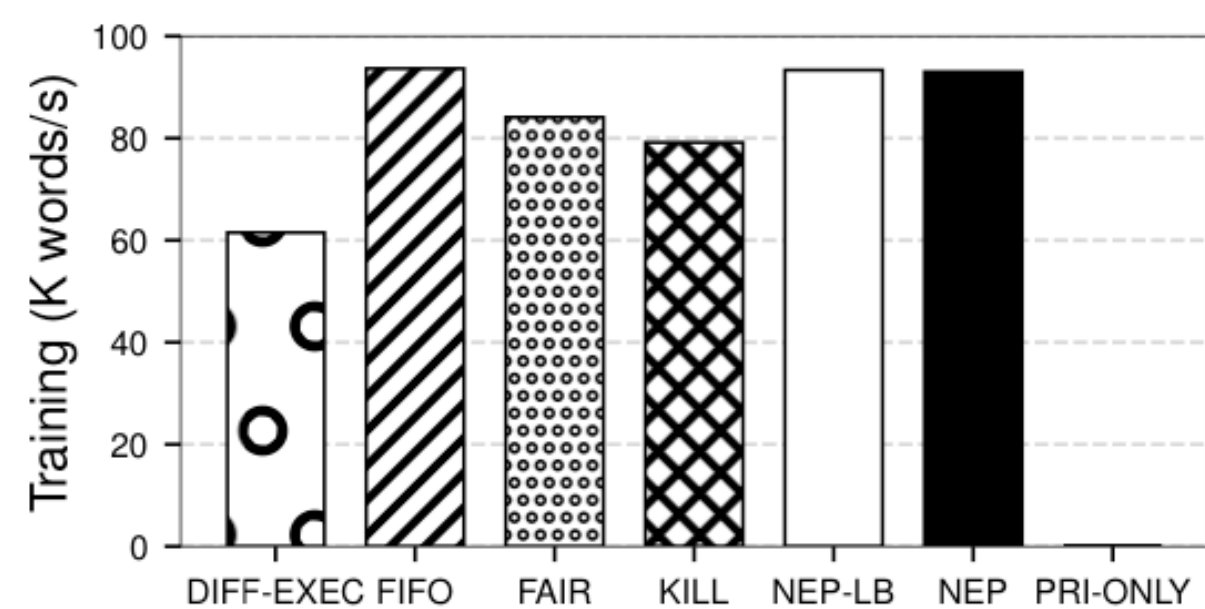


(c) Streaming query throughput

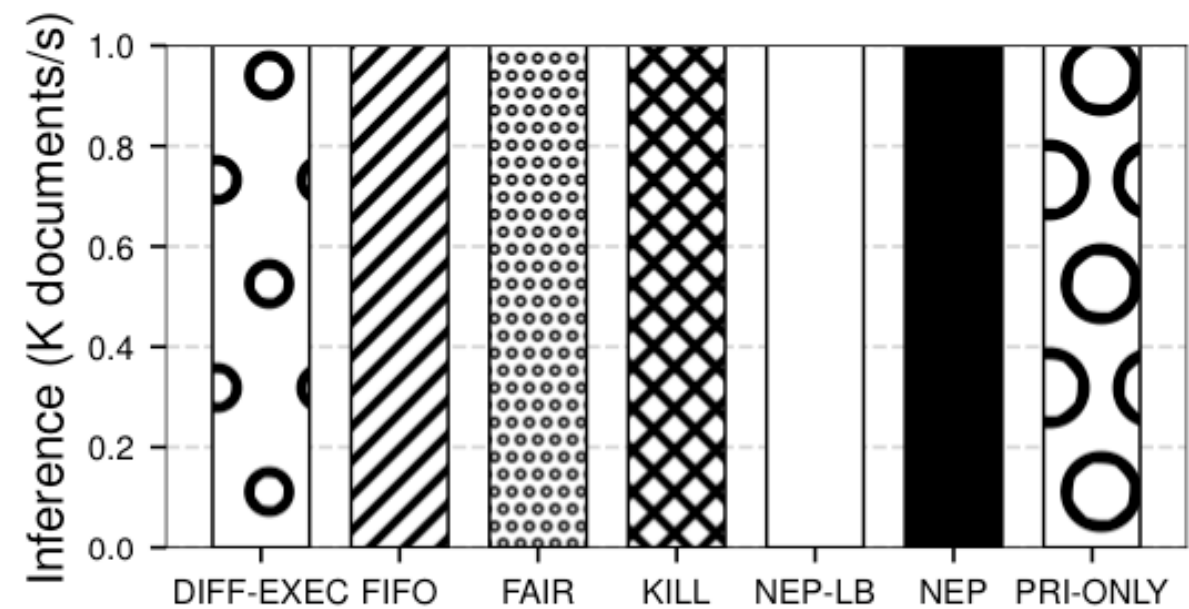
Figure 9: Yahoo Streaming benchmark (streaming + batch)



(a) Inference latency

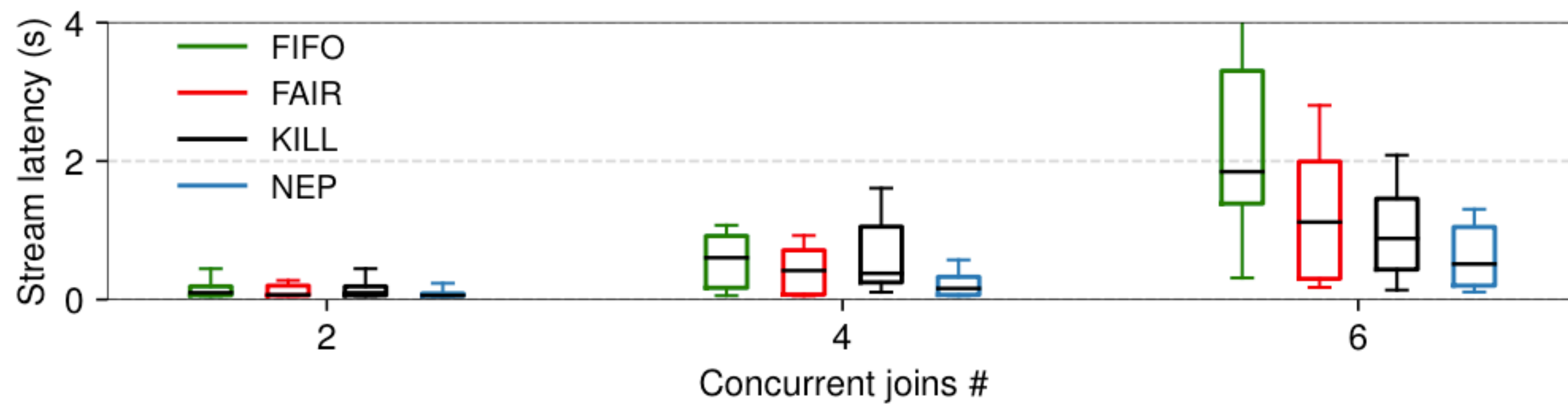


(b) Training query throughput

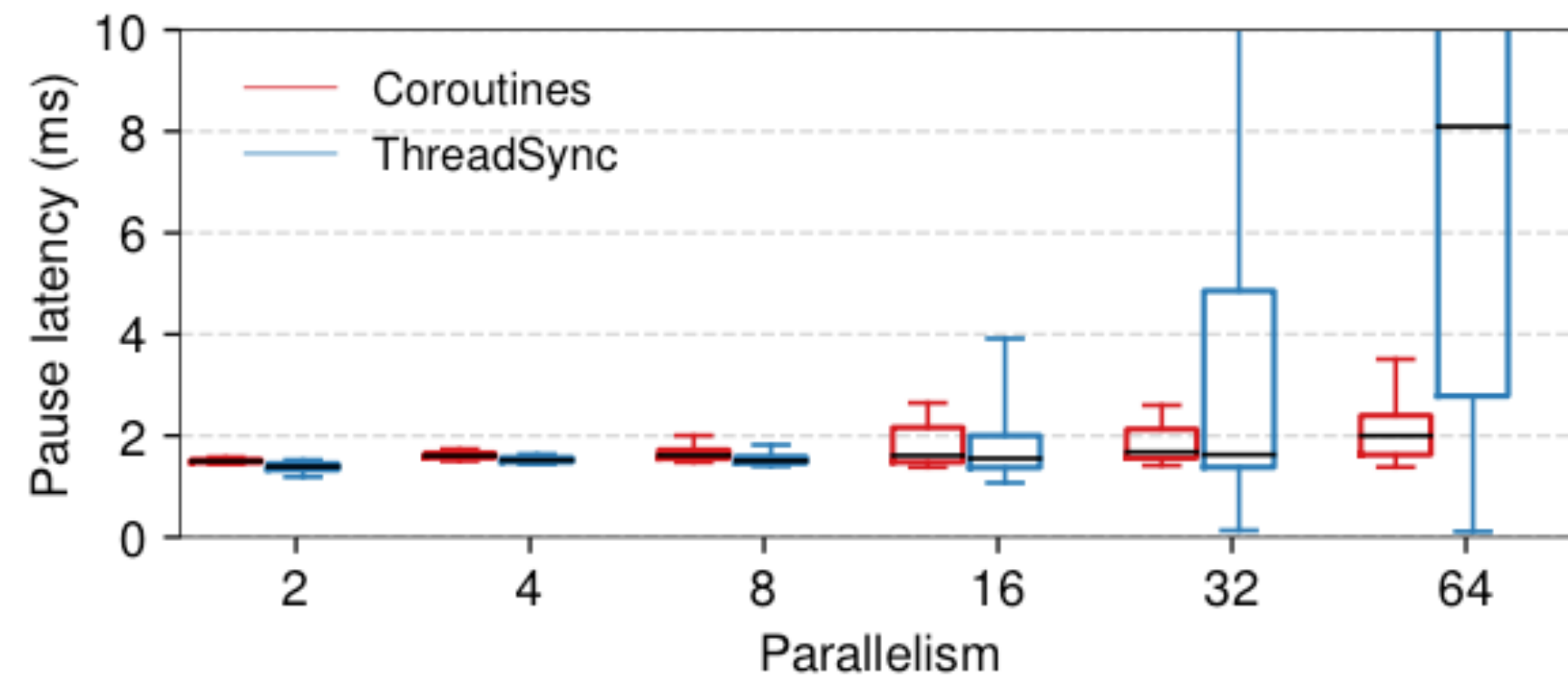


(c) Inference query throughput

Evaluation



Evaluation



Summary

- **Medea:**

- Support container tags and logical node groups
- Expressive cardinality constraints
- Two scheduler design

- **Neptune**

- Suspendable Tasks
- LMA Scheduling policies

Thanks