SEA Conference 2018

Decoupled MapReduce using MPI One-Sided

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Introduction > The relevance of I/O

Scientific applications running on current Petascale Supercomputers demand high-performance I/O to read their ever-increasing input sets and store detailed results. Some of these applications include:

HPC Applications

- Space Weather

- Neuroscience

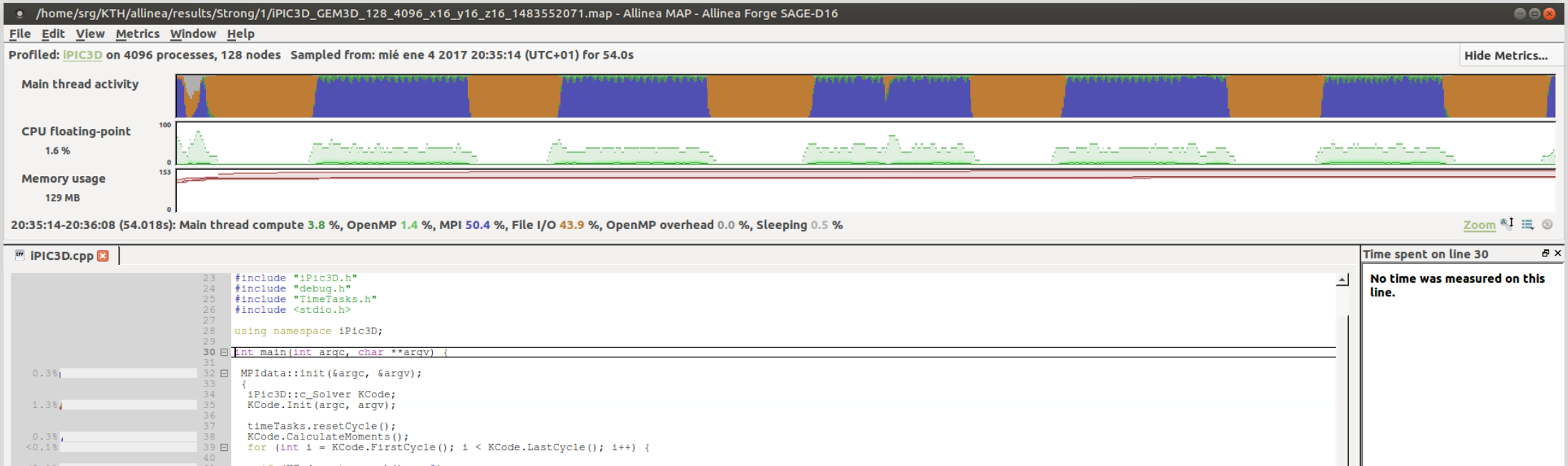
- Visualization

- Others

Image Source: (1) ESA (2) biology.nd.edu (3) TACC Stallion (4) FEniCS-HPC

Introduction > Science demands high-performance I/O

Scientists are aggressively taking advantage of the large available computing power to run larger scale and high-fidelity simulations, requiring the movement of large files to / from storage. For instance, most of the scientific applications **use storage devices for pre-/post-processing, and fault tolerance:**



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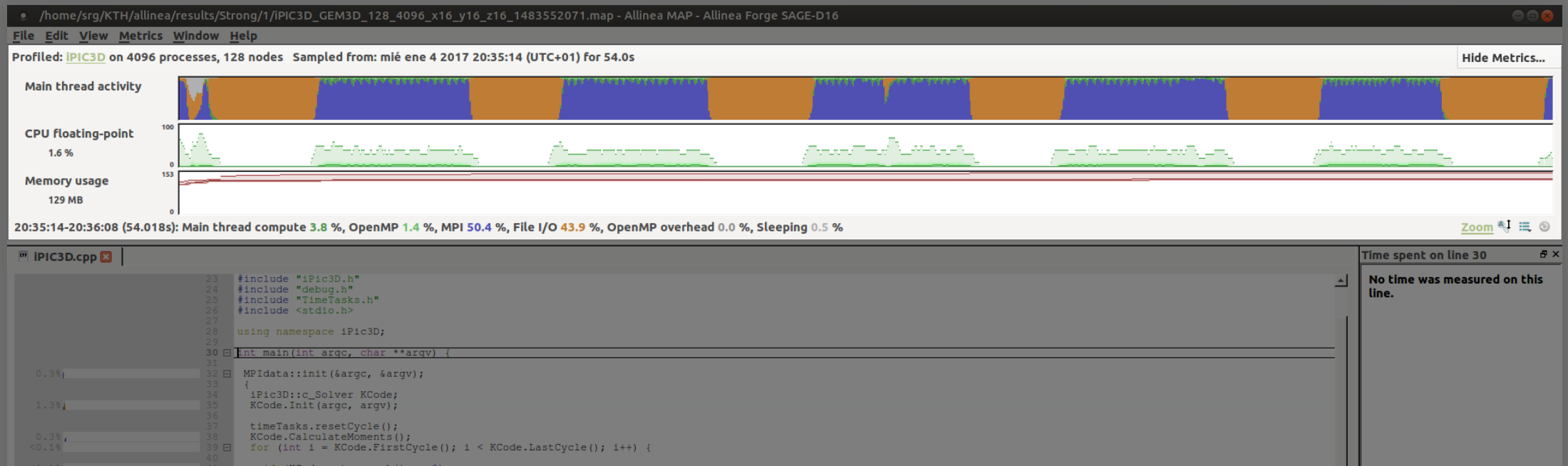


Introduction > Increasing use-cases on HPC

In addition to traditional scientific applications, emerging graph analytics and machine learning applications are becoming common on supercomputers, motivated by the advances in deep learning and convolutional networks:

Big Data & Machine Learning
are trending on HPC

The irregular nature of data analytics pose a large stress on the I/O subsystem, mainly because of the high number of small I/O transactions. In addition, **some of these use-cases require out-of-core execution as well**.

Introduction > Moving away from separate HPC for I/O

Historically, HPC systems have been commonly designed as a large system for computing, and a separate large system that offers persistency support (e.g., through a Distributed File System):

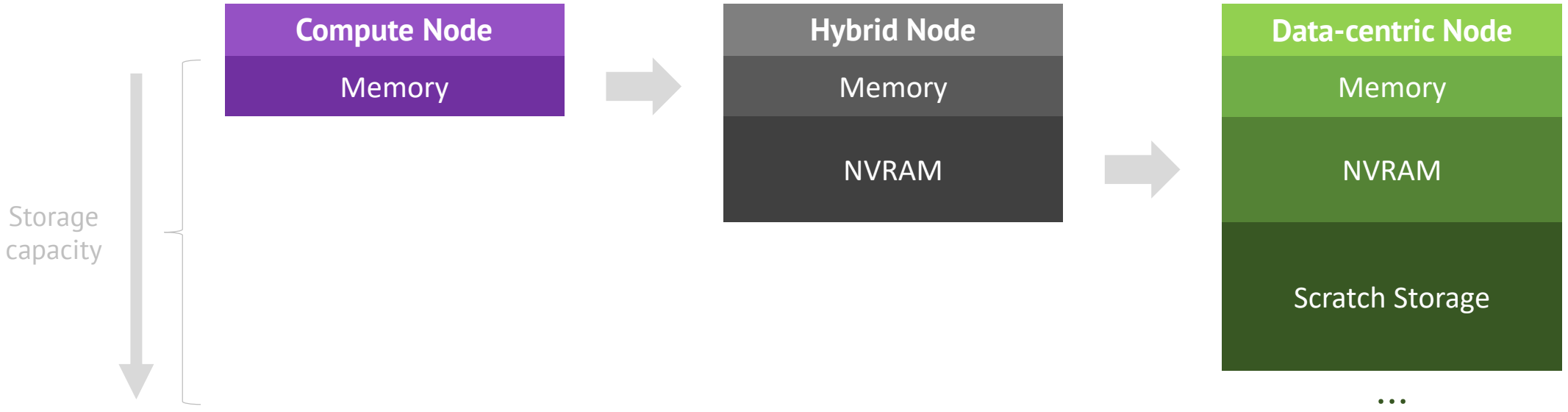
Traditional HPC Systems

Specialized HPC System

The trend for large-scale computer design is diverging from the traditional compute-only node approach, to **hybrid solutions where the data is moved next to the computation**.

Introduction > Increasing heterogeneity per node

Emerging storage technologies are evolving so rapidly that the existing gap between main memory and I/O subsystem performances is thinning. Next-generation supercomputers will feature a variety of Non-Volatile RAM (NVRAM), with different performance characteristics, next to traditional DRAM:



Introduction > Challenges of data-centric trends

Now that data-intensive workloads have become an integral part of large-scale scientific computing, **several challenges arise that must be considered on programming models of upcoming HPC clusters**:

Complexity	Performance	Scalability
Applications becoming extremely complex	High-Performance cannot be guaranteed	Future clusters to feature a concurrency of 100-1000×

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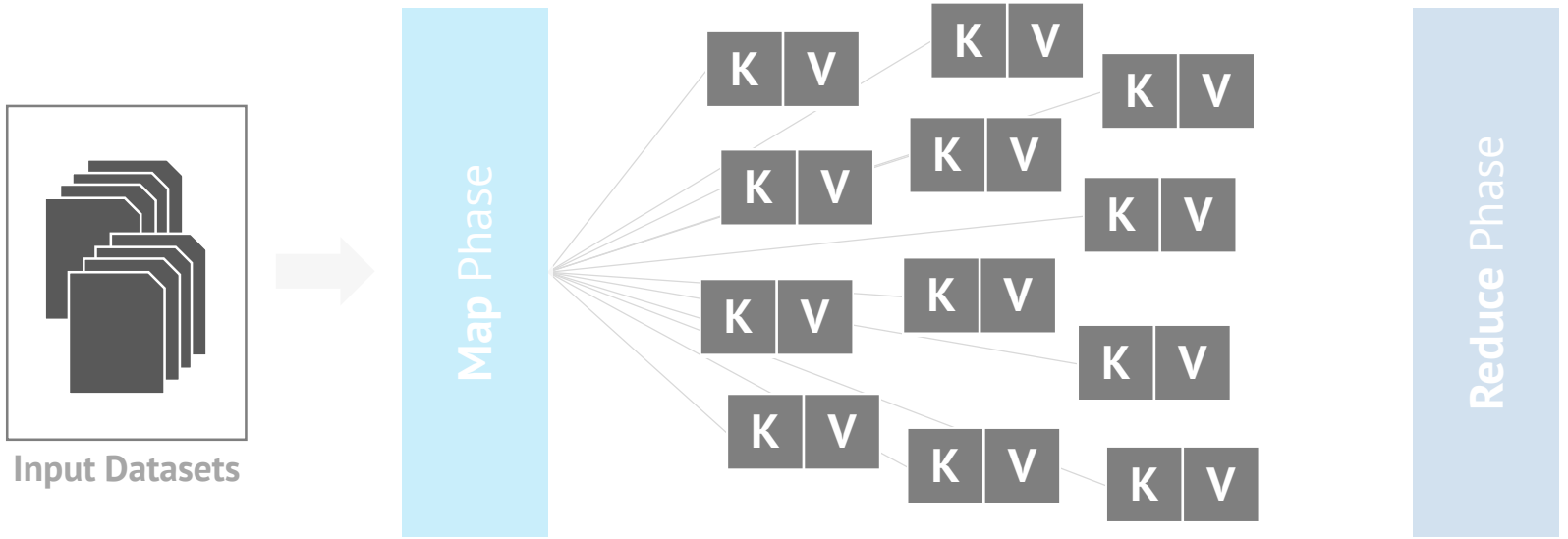

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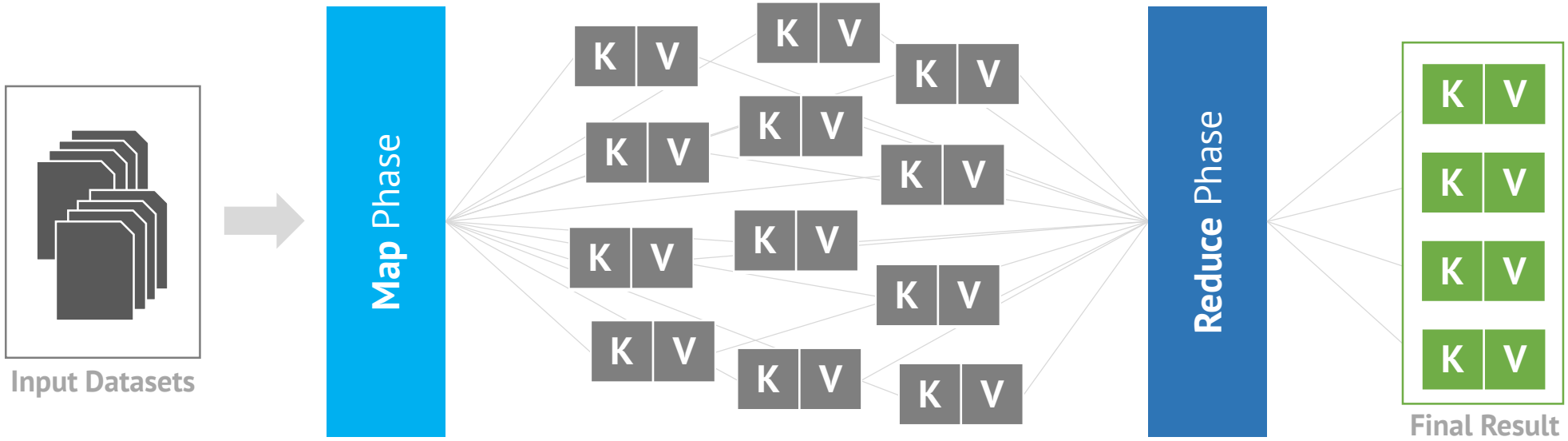

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Each **<key,value>** tuple is ordered within an intermediate Shuffle phase

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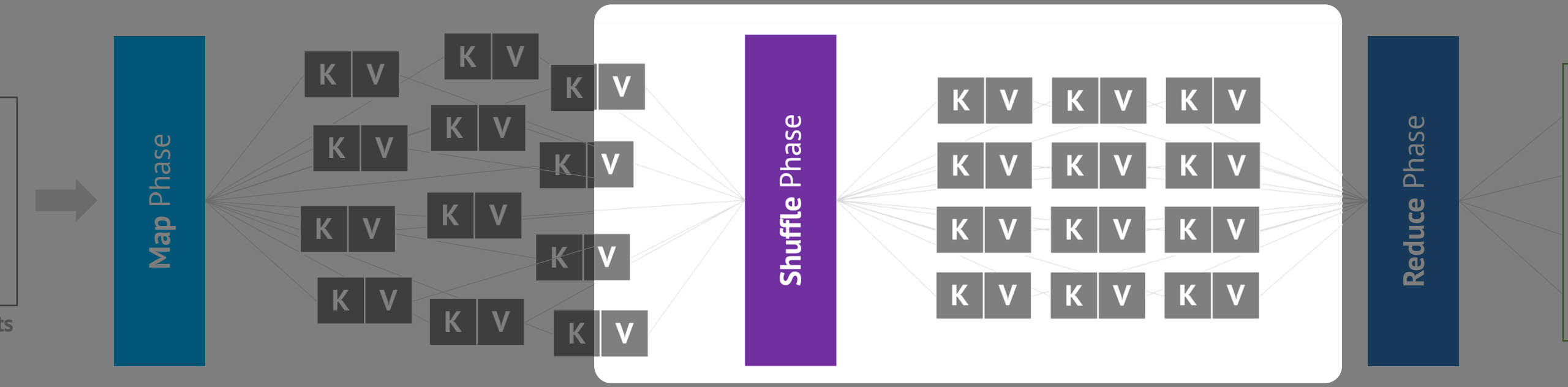

Introduction > MapReduce on HPC

Traditional MapReduce frameworks (e.g., Hadoop MapReduce) **pose numerous constraints on current supercomputers** due to the memory / storage requirements and job scheduling.

As a consequence, **MapReduce implementations on HPC are integrated using state-of-the-art MPI functionality**:

- Tasks are distributed employing a master-slave approach with scatter operations (e.g., `MPI_Scatter`).
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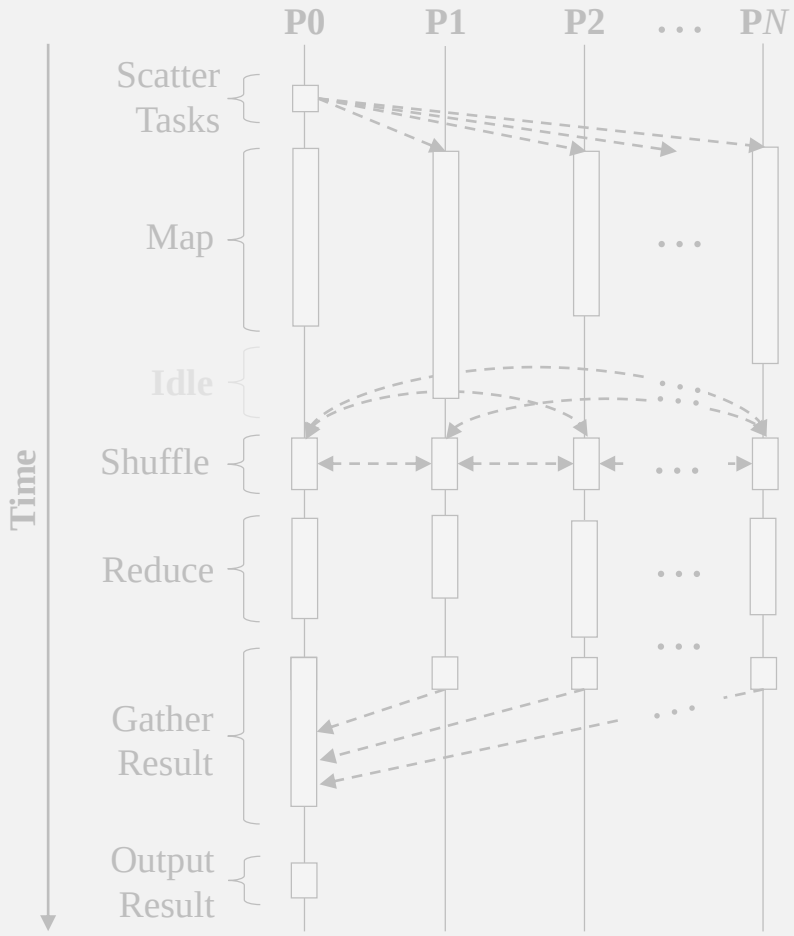

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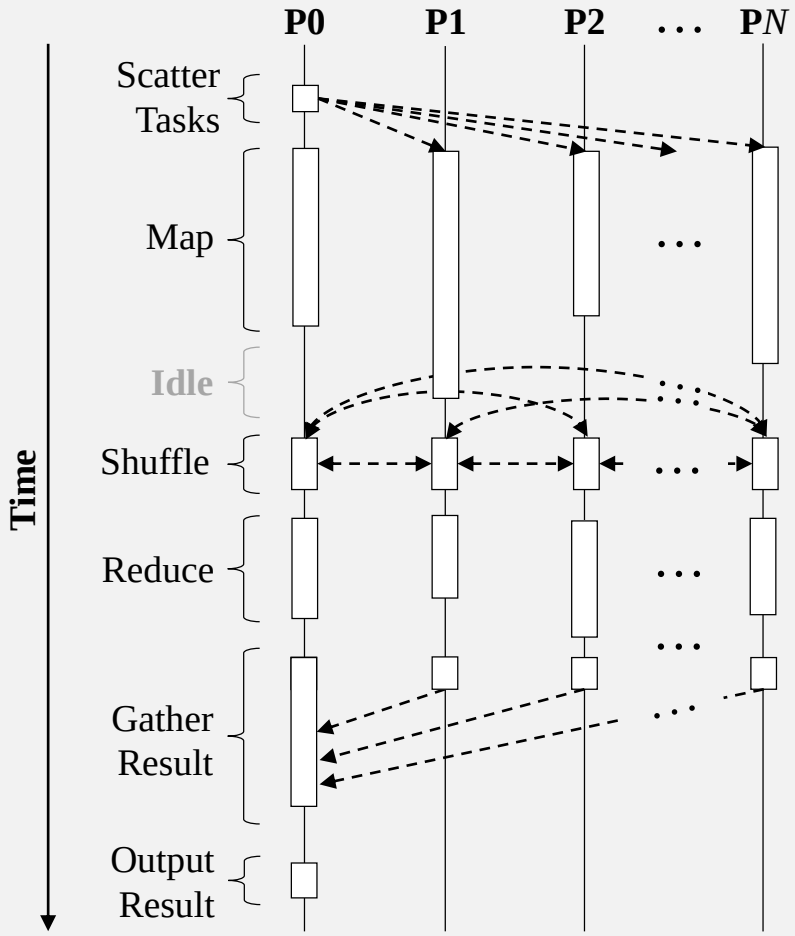

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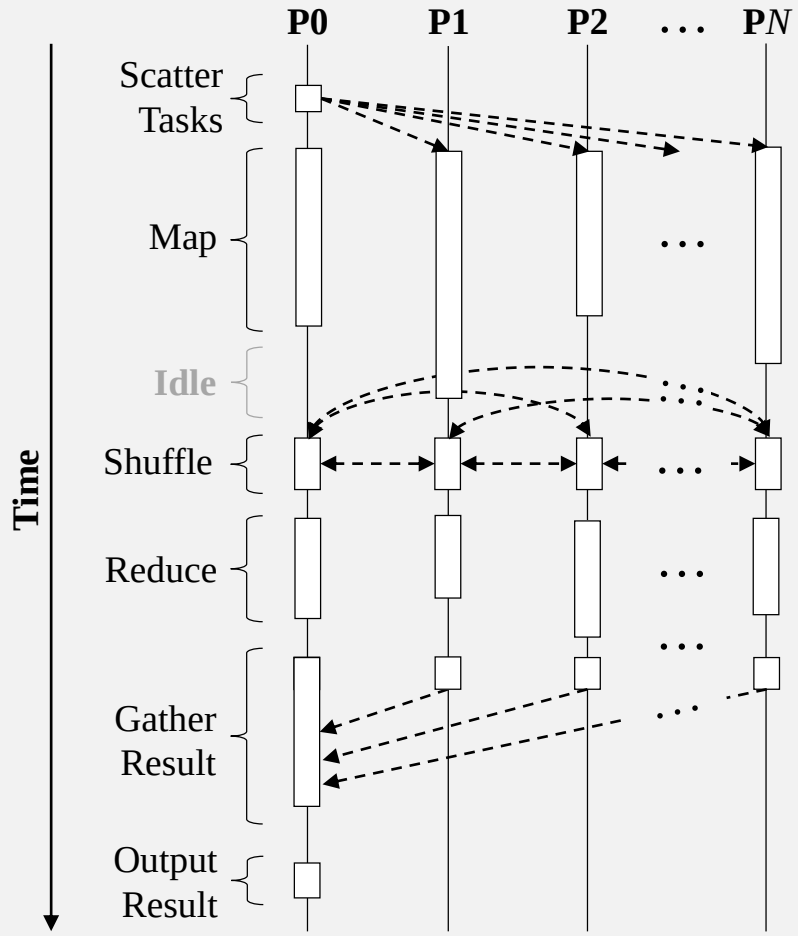

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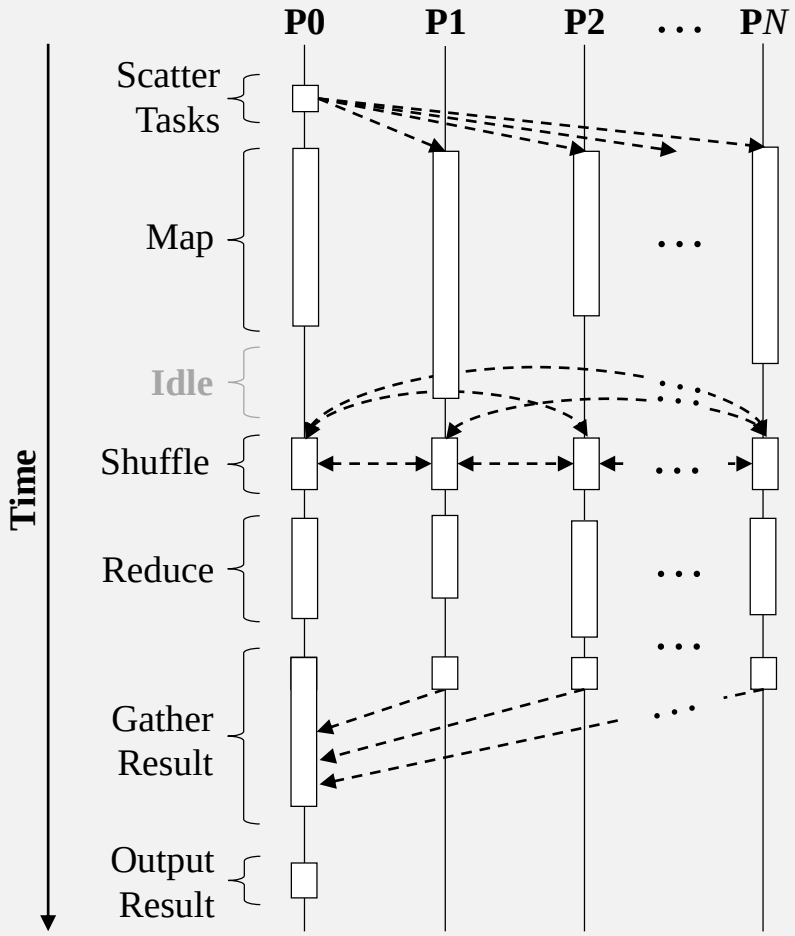

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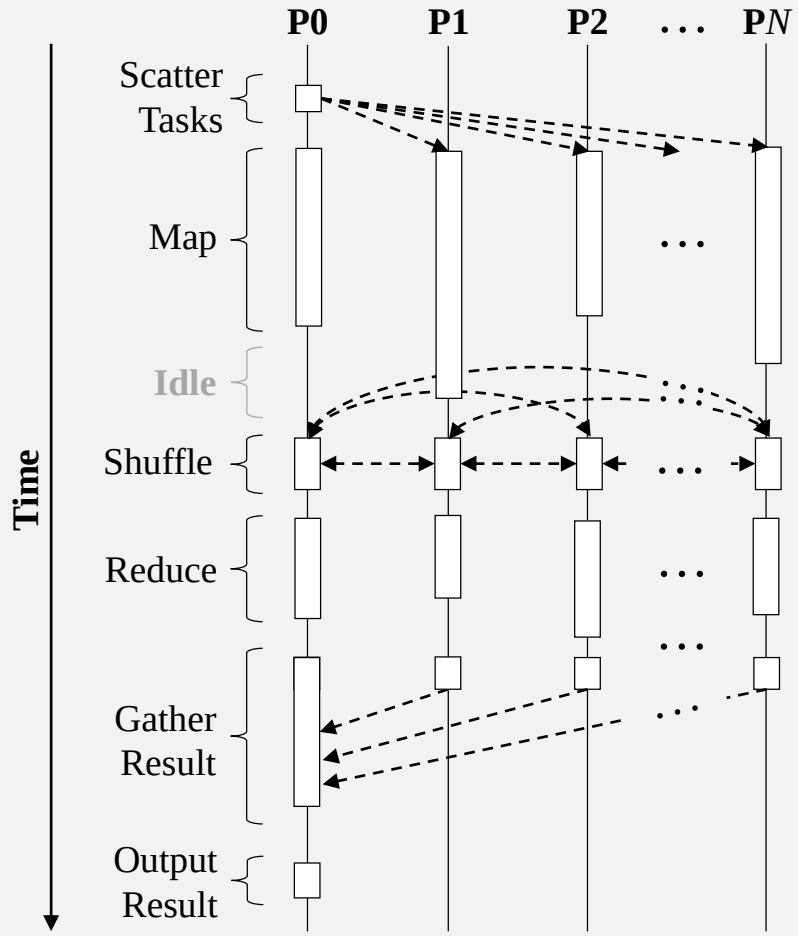

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Idle periods can appear if the workload per process becomes unbalanced

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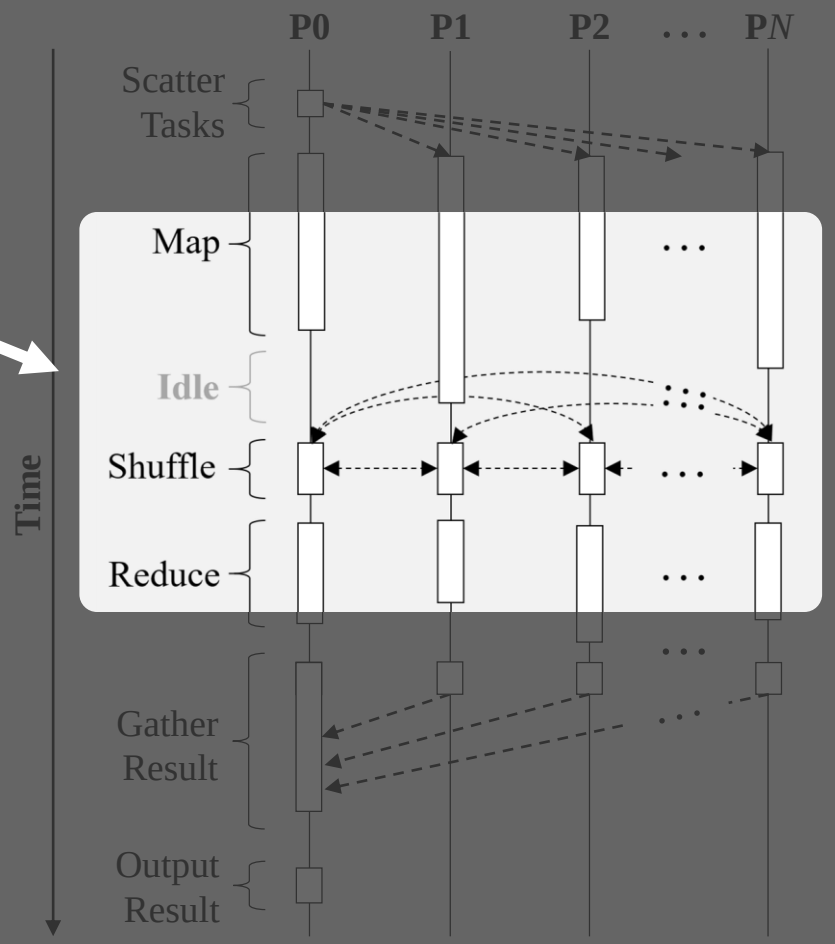

Problem Statement

The inherent coupling between the Map and Reduce phases, can introduce constraints on highly-parallel jobs that become unexpectedly unbalanced

Introduction > Solving the challenges of MapReduce

As the concurrency of upcoming HPC clusters is expected to increase, **several limitations arise from the use of master-slave or the inherent coupling between the Map and Reduce phases of MapReduce frameworks**. These design considerations pose performance restrictions when the workload per process becomes unbalanced:

Objective #1

Decentralized Algorithm

+

Objective #2

MPI One-Sided

+

Objective #3

Non-Blocking I/O

=

MapReduce-1S

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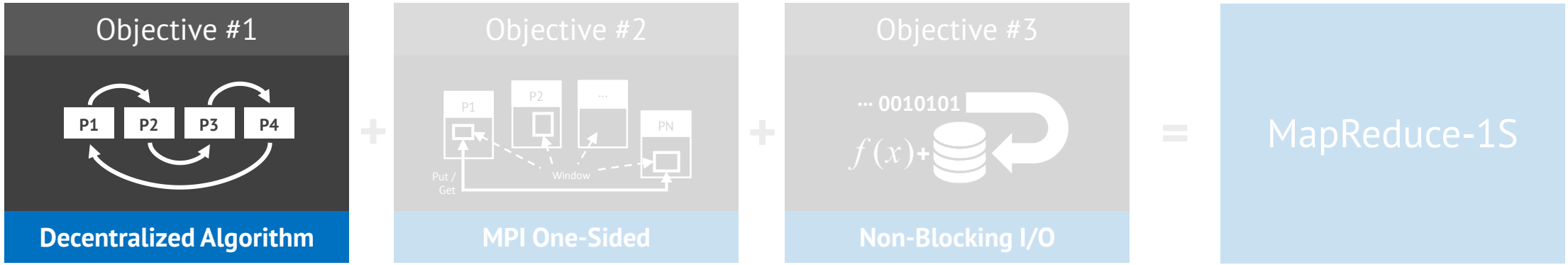

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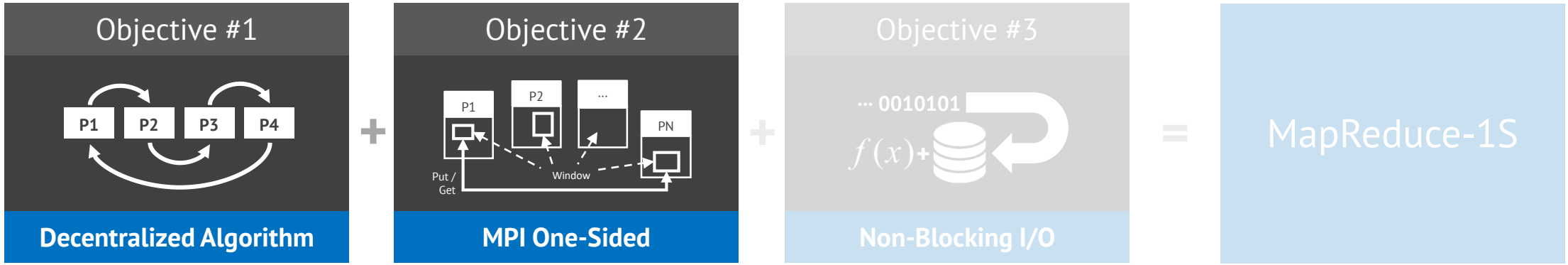

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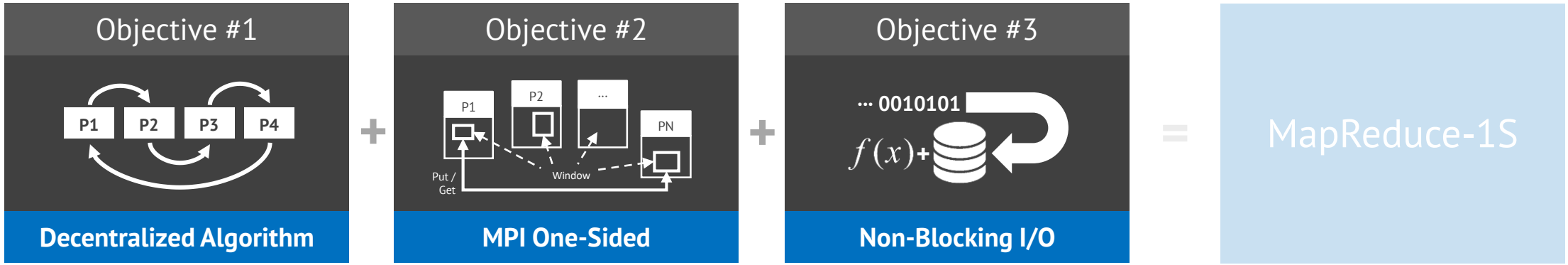

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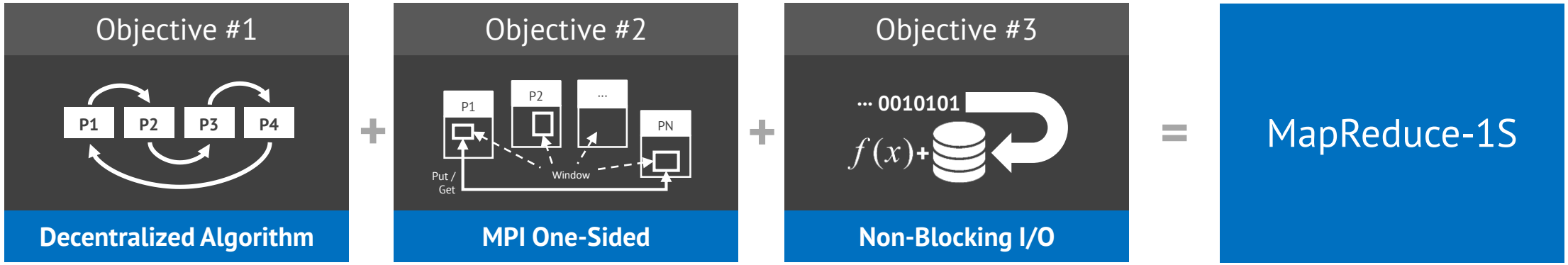

MapReduce-1S / MapReduce "One-Sided"

Integrating the MPI one-sided communication model and non-blocking I/O to reduce the overhead on imbalanced workloads

Methodology > Phases

MapReduce-1S inherits the core principles of traditional MapReduce frameworks, such as Hadoop MapReduce.

We divide the execution into four different isolated phases:

I. **Map**. Transforms a given input into multiple key-value pairs. Each key-value is assigned to a process (hash).
II. **Local Reduce**. Aggregates certain key-value pairs locally, whenever possible, to reduce constraints.
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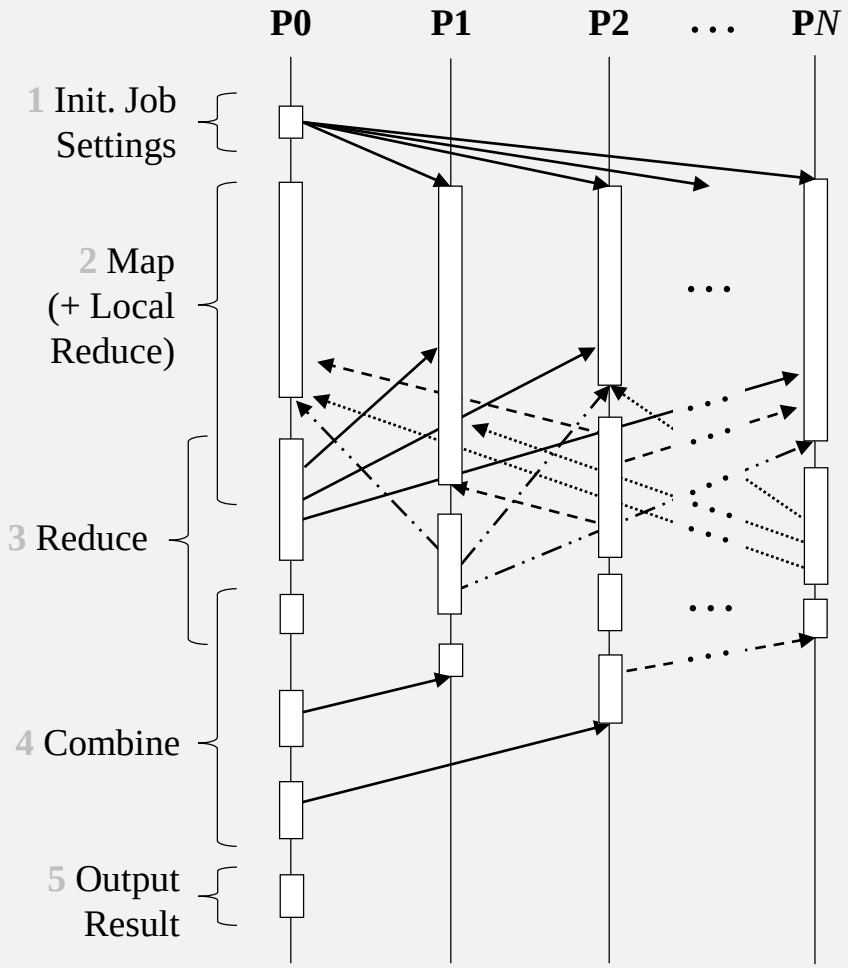

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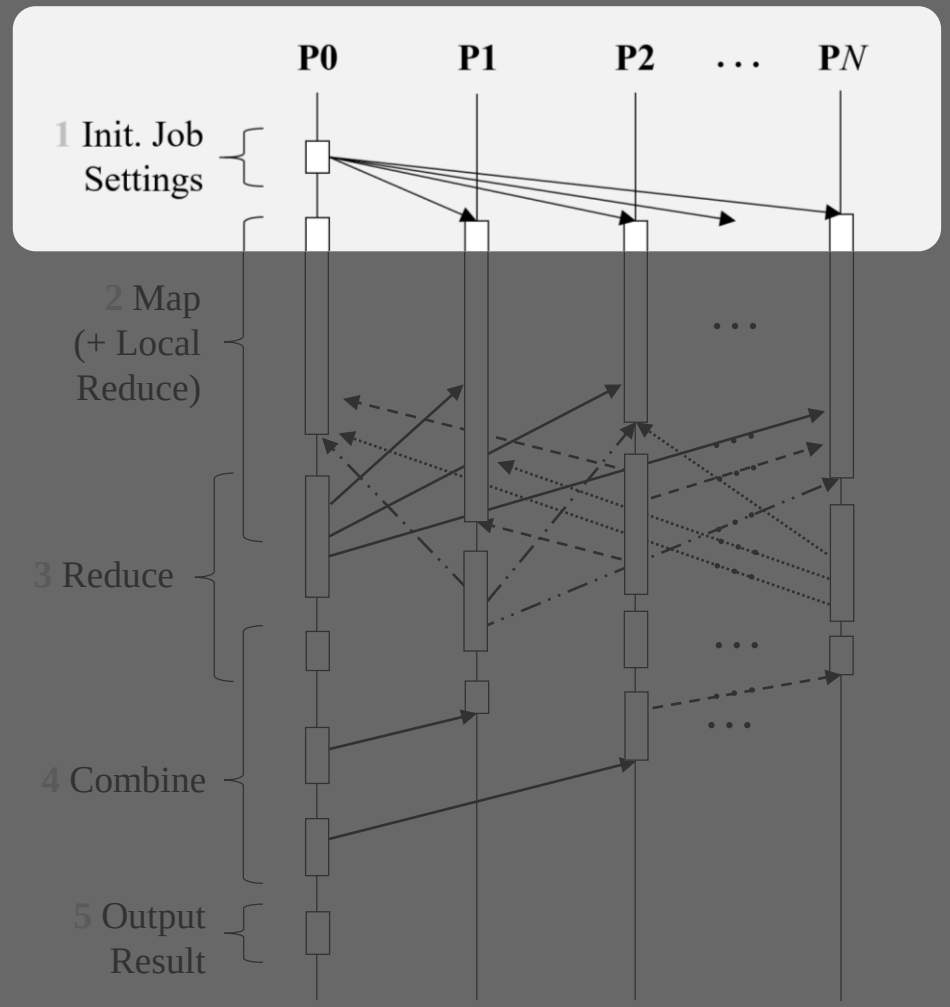

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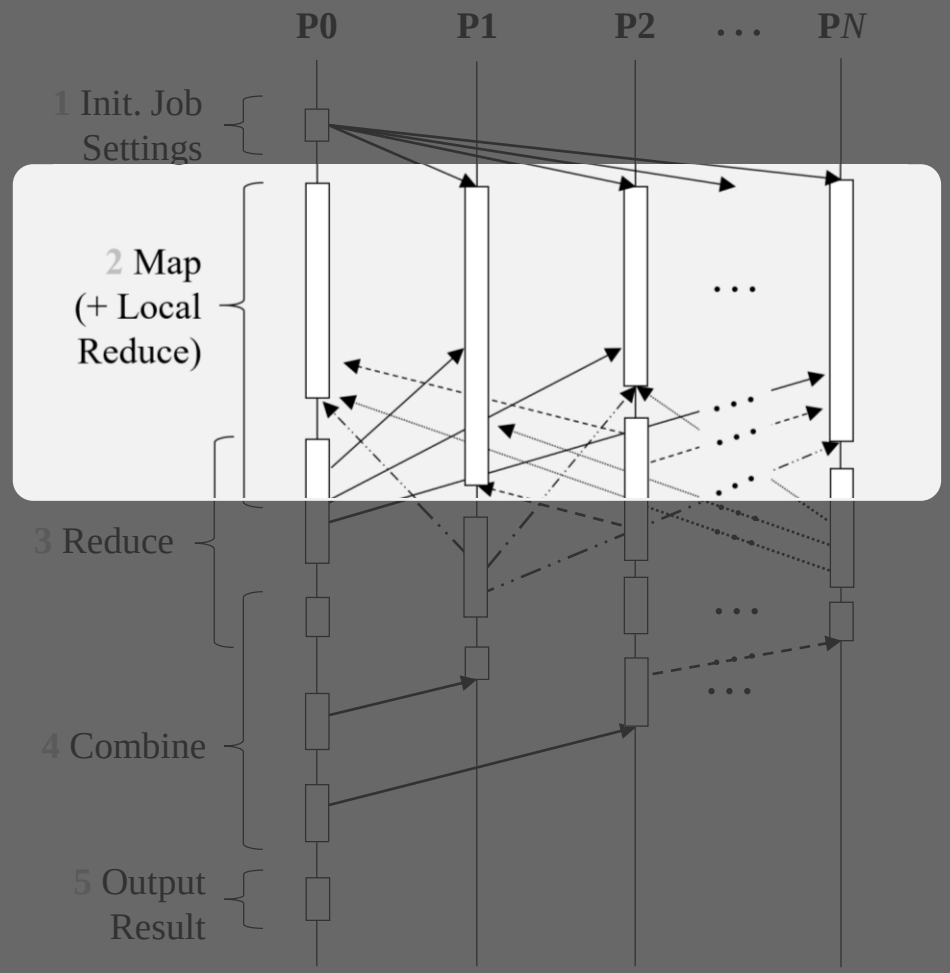

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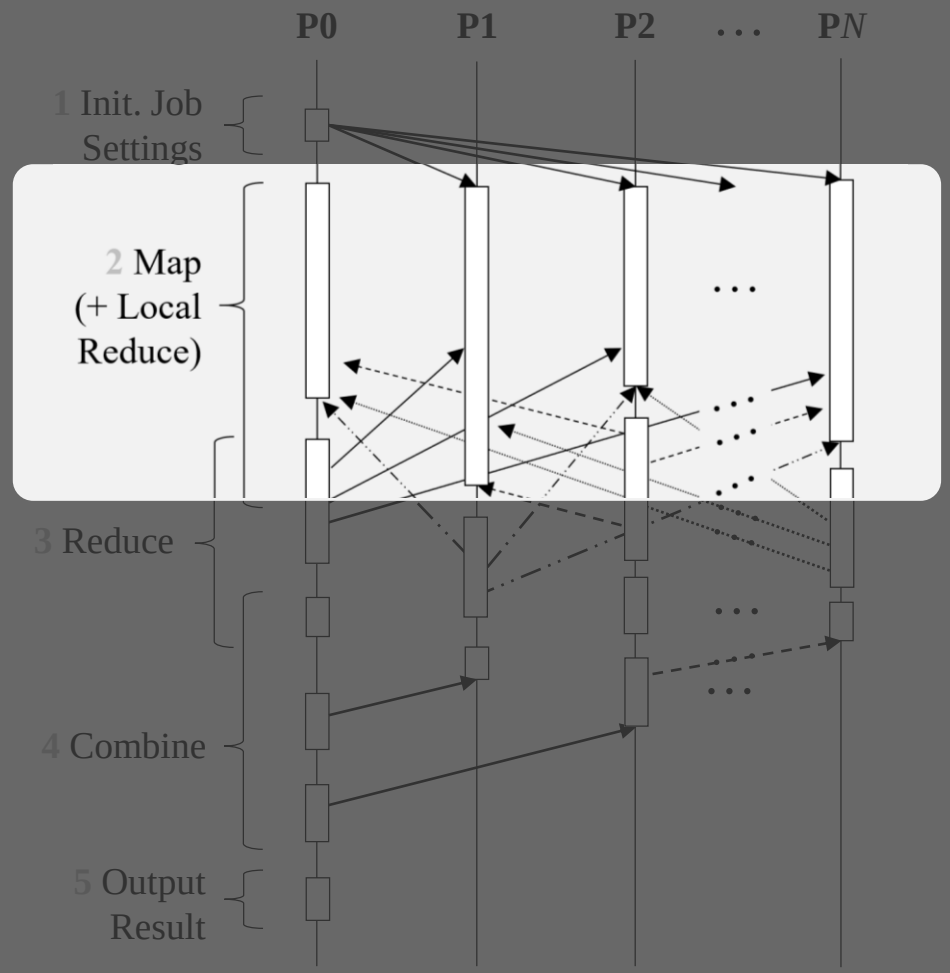

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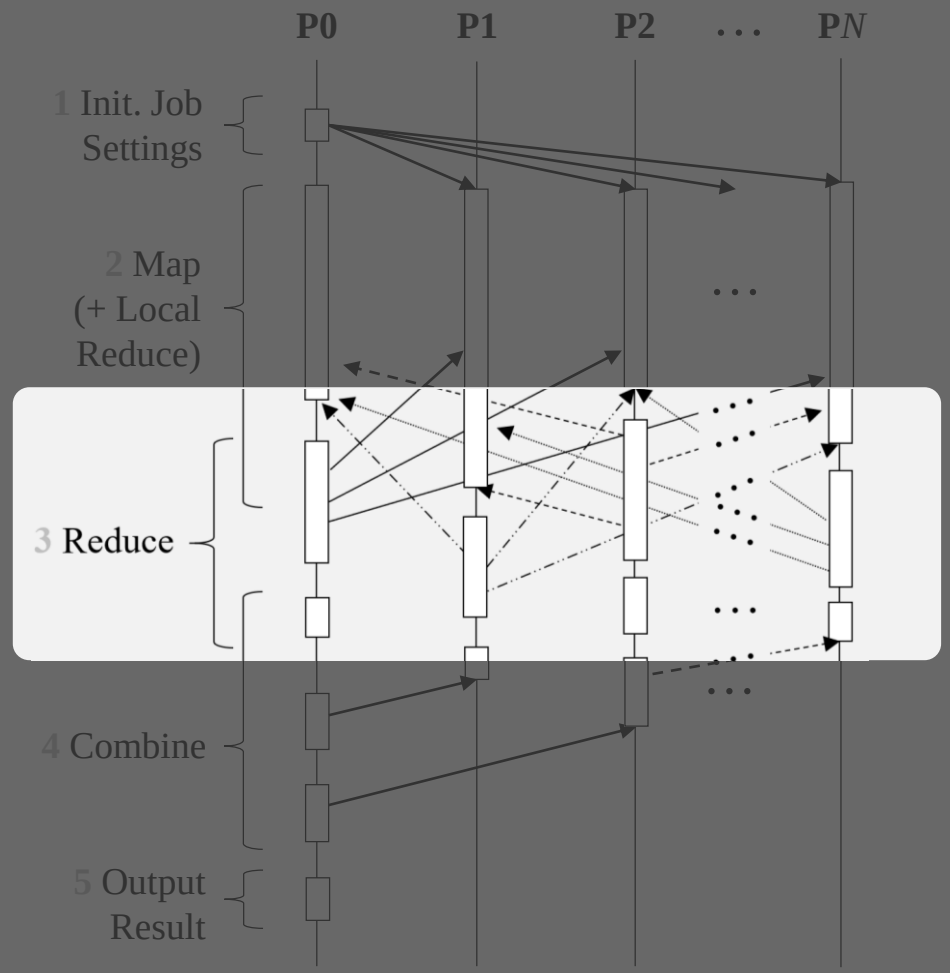

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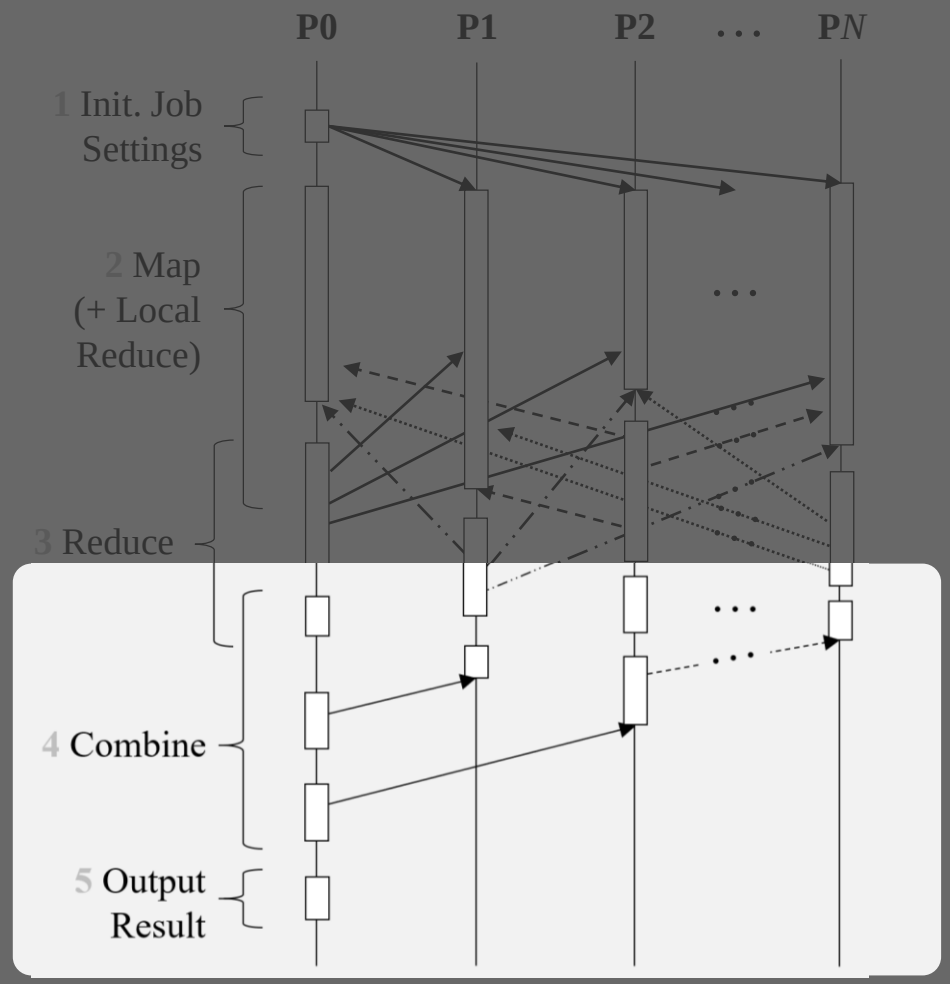

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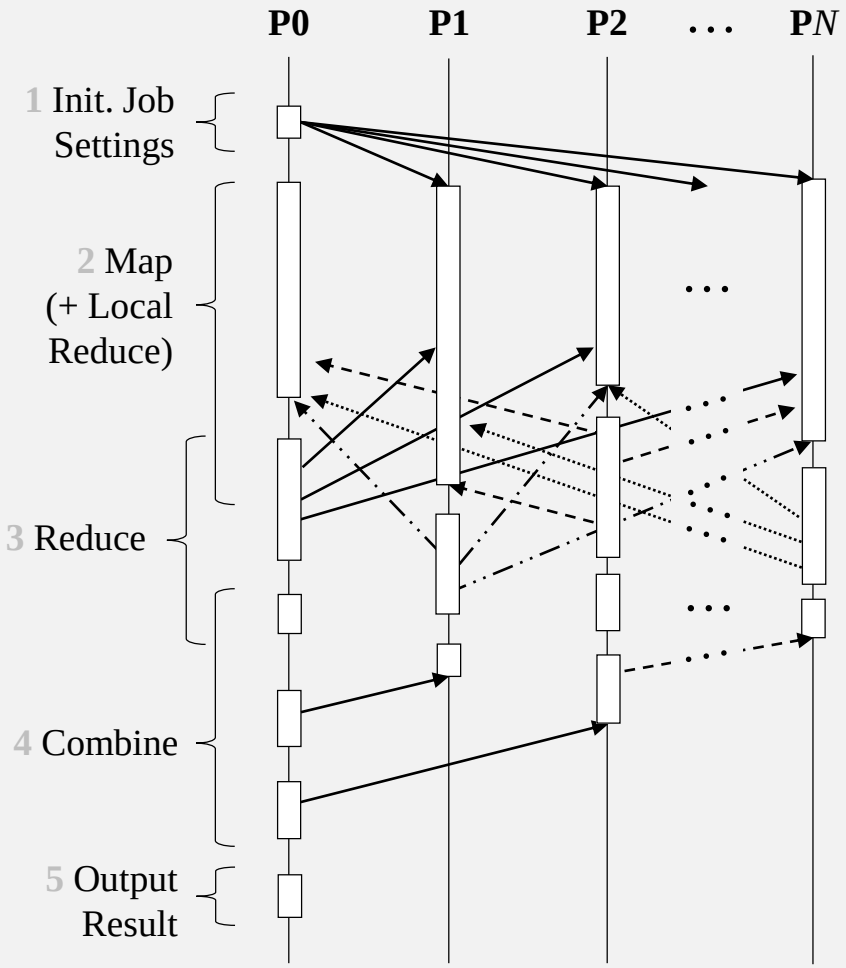

Methodology > Reading Inputs with Non-Blocking I/O

The input datasets are split into equally-sized tasks, that are later handled in parallel by each process. Instead of following a master-slave approach, **each process decide the next task to perform based on the rank, task size, and file offset between tasks**. Thus, we decentralize the MapReduce algorithm:

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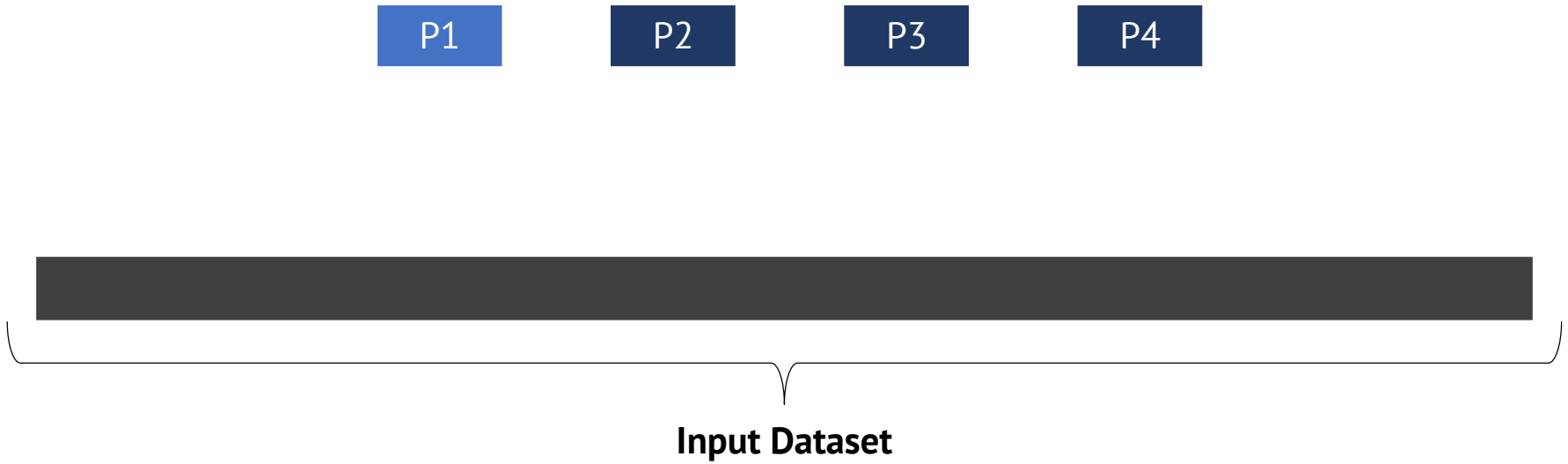

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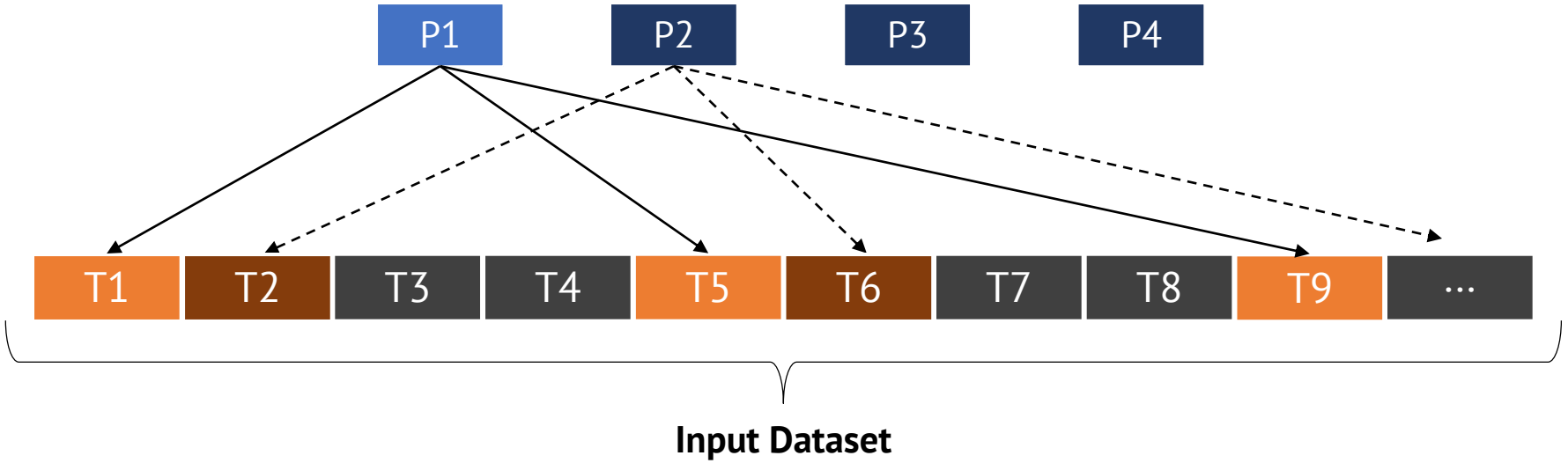

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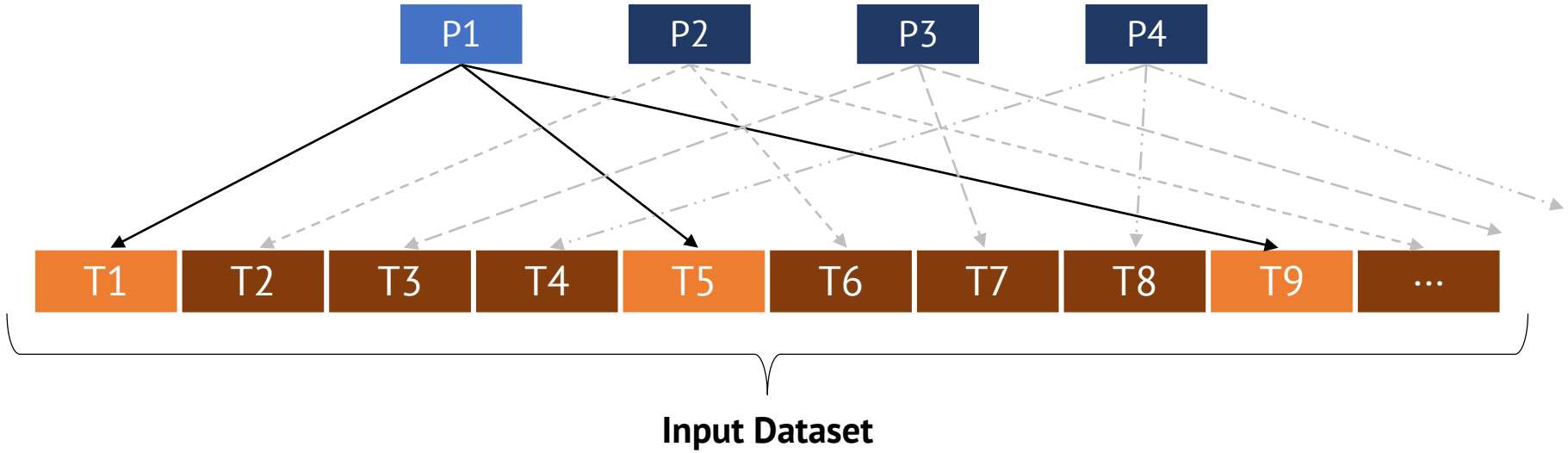

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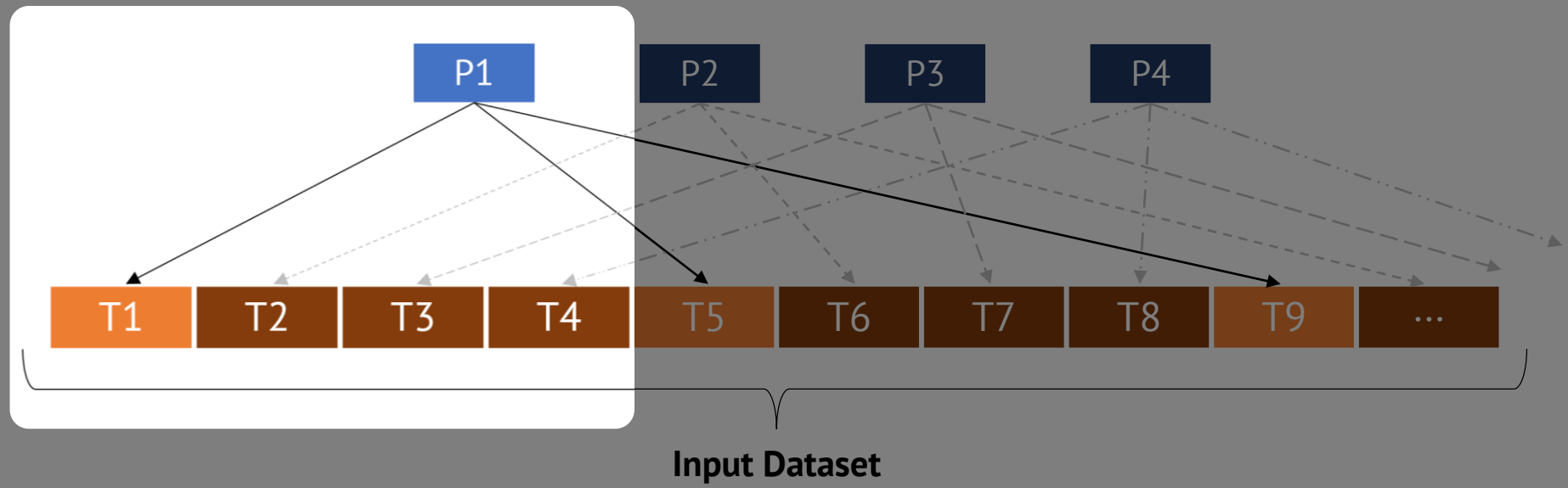
The input datasets are split into equally-sized tasks, that are later handled in parallel by each process. Instead of following a m **d file offset between tasks**. Thus, we decentralize the MapReduce algorithm:

The input portion for the task is retrieved individually using non-blocking MPI I/O



Methodology > MPI Windows

In order to enable remote memory communications during the execution phases, we define a multi-window configuration.

In particular, **four different windows per process are required**:

- **"Status" Window**. Defines the current status for each individual process. The status is updated remotely.
- **"Key-Value" Window.** This multi-dimensional, dynamic window contains buckets to store the key-value pairs, indexed by the target rank.
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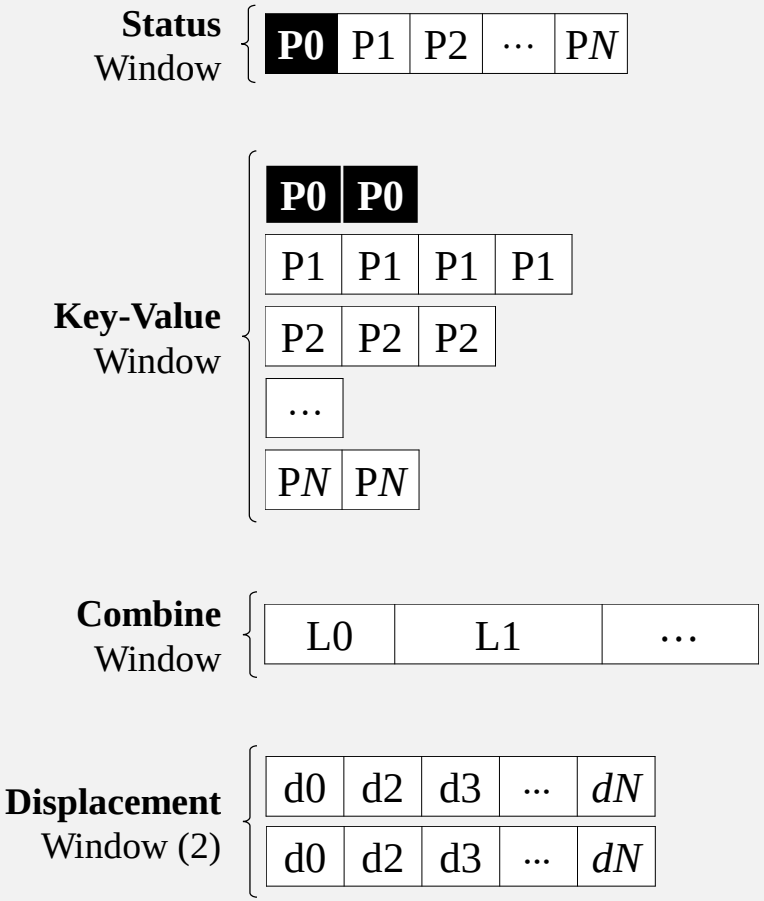

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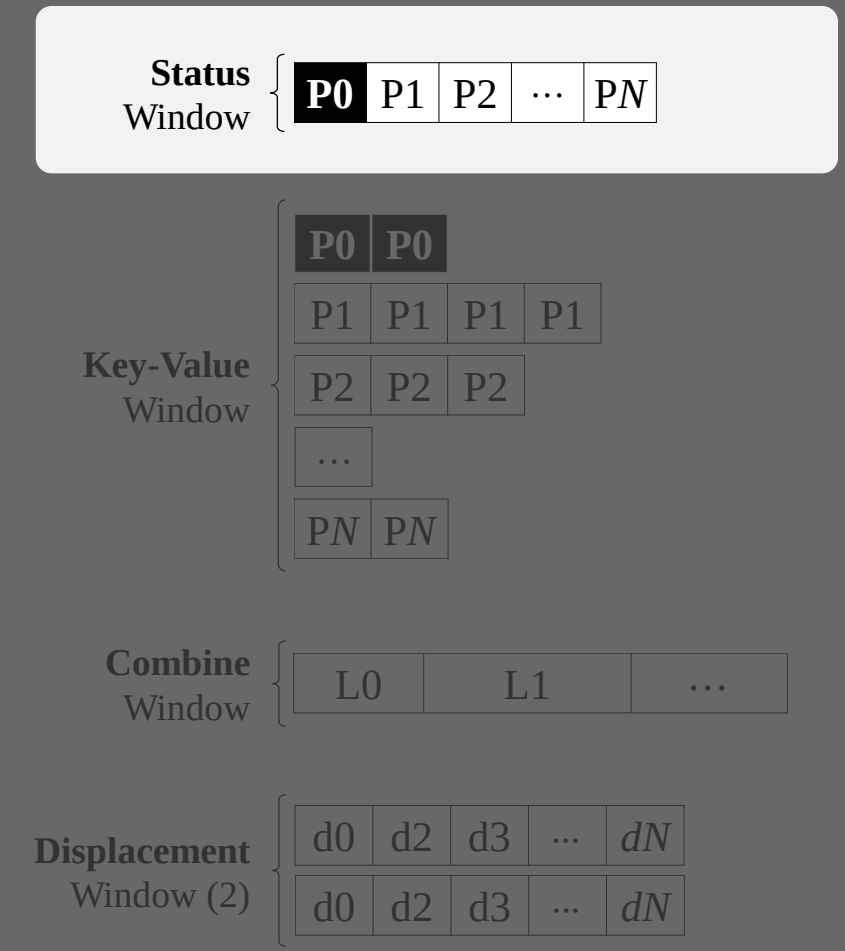

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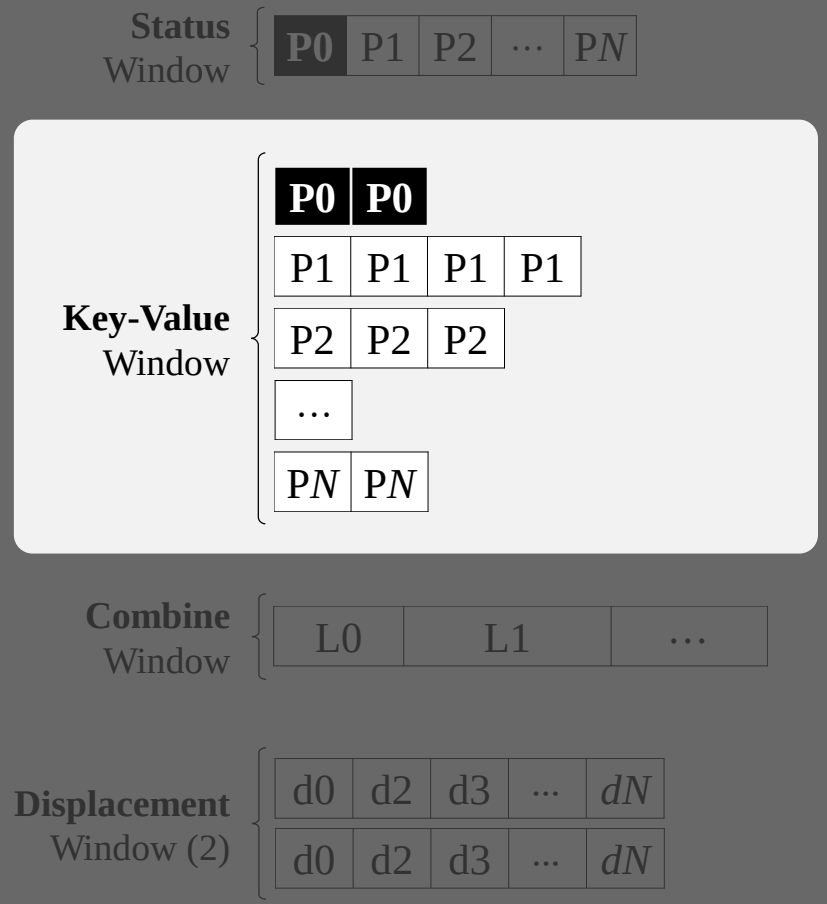

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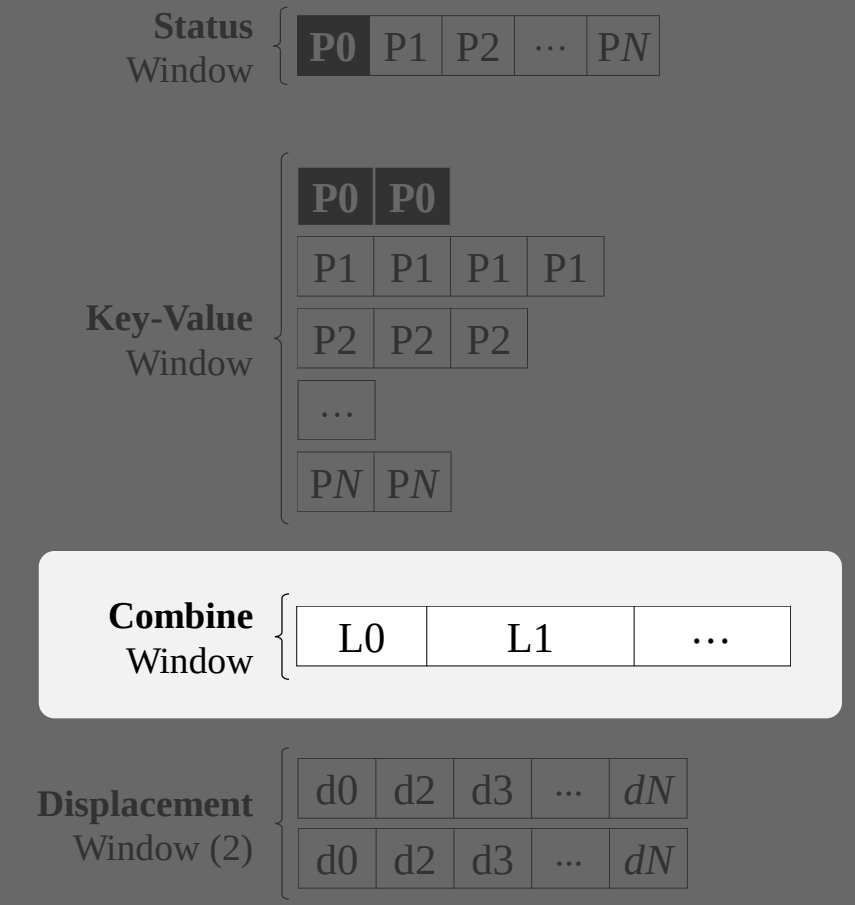

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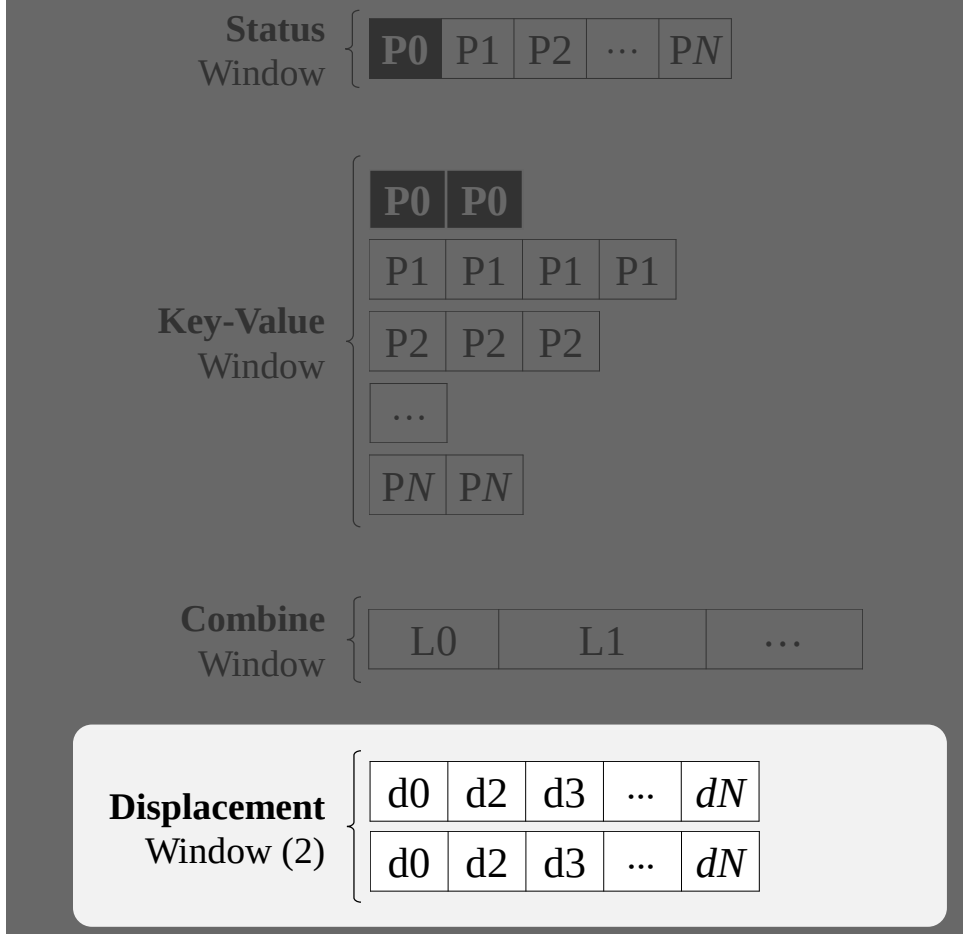

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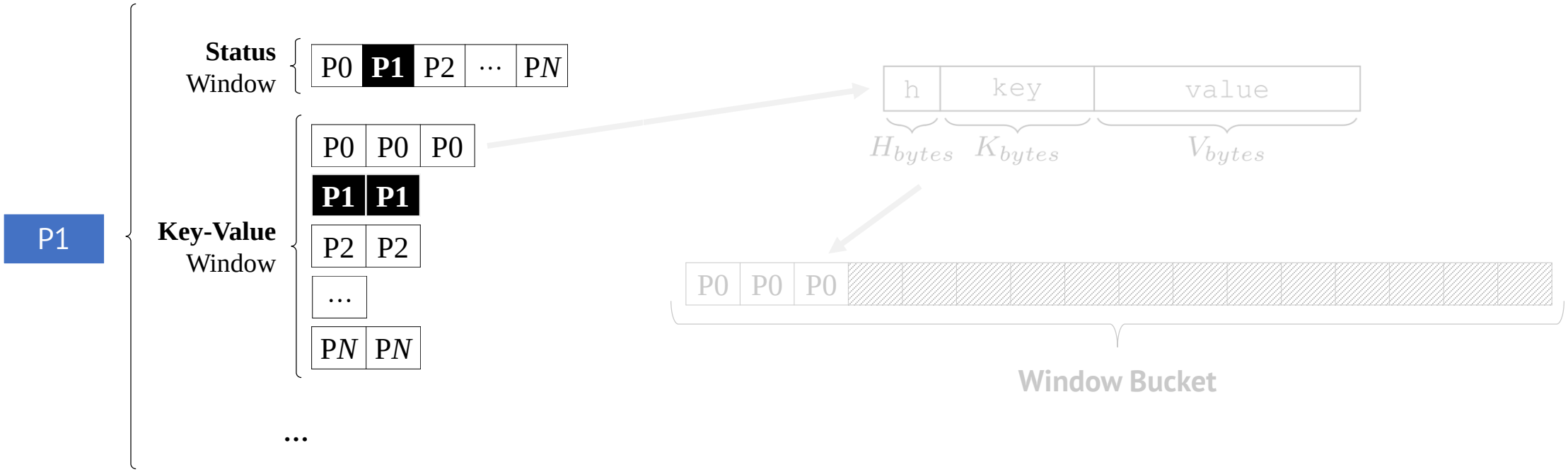

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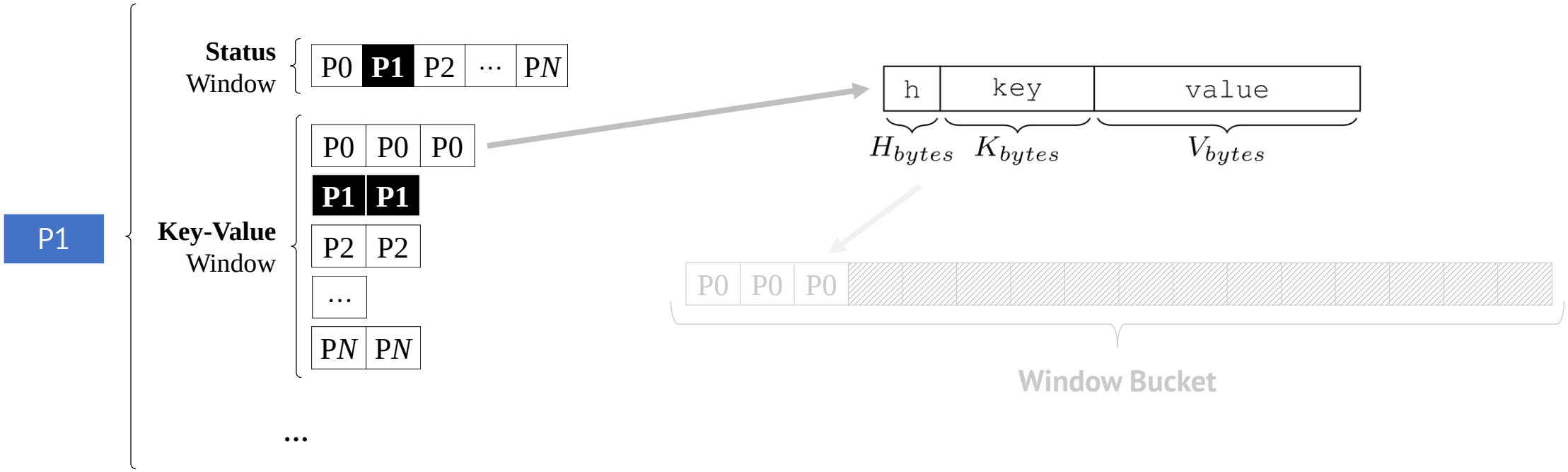

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Support for variable-length **<key,value>** tuples, of arbitrary K and V bytes

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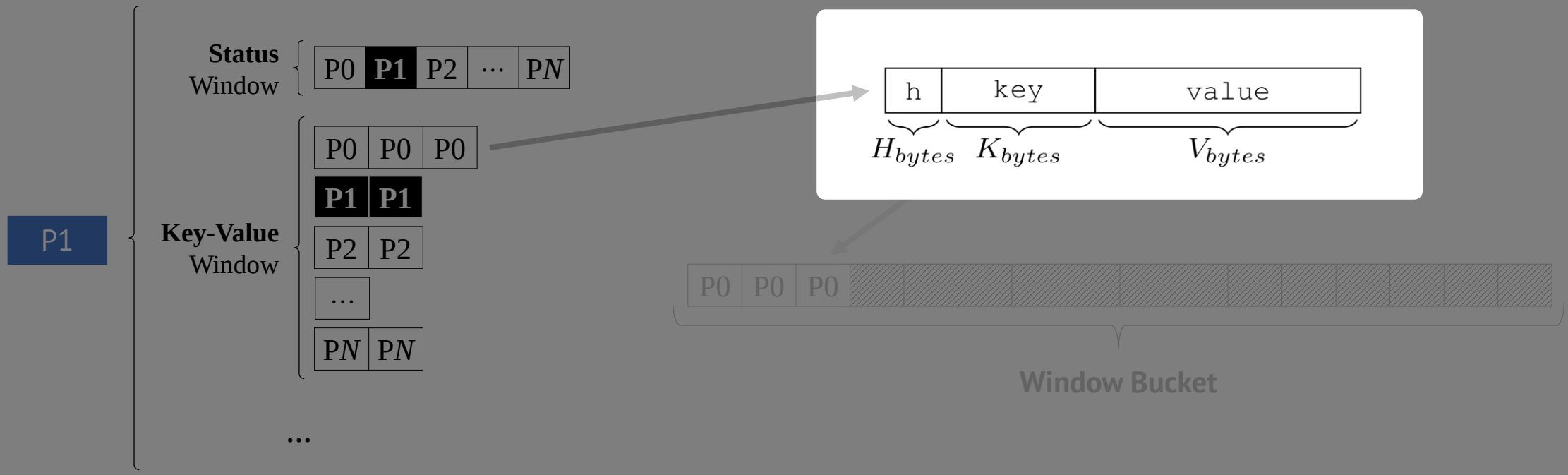

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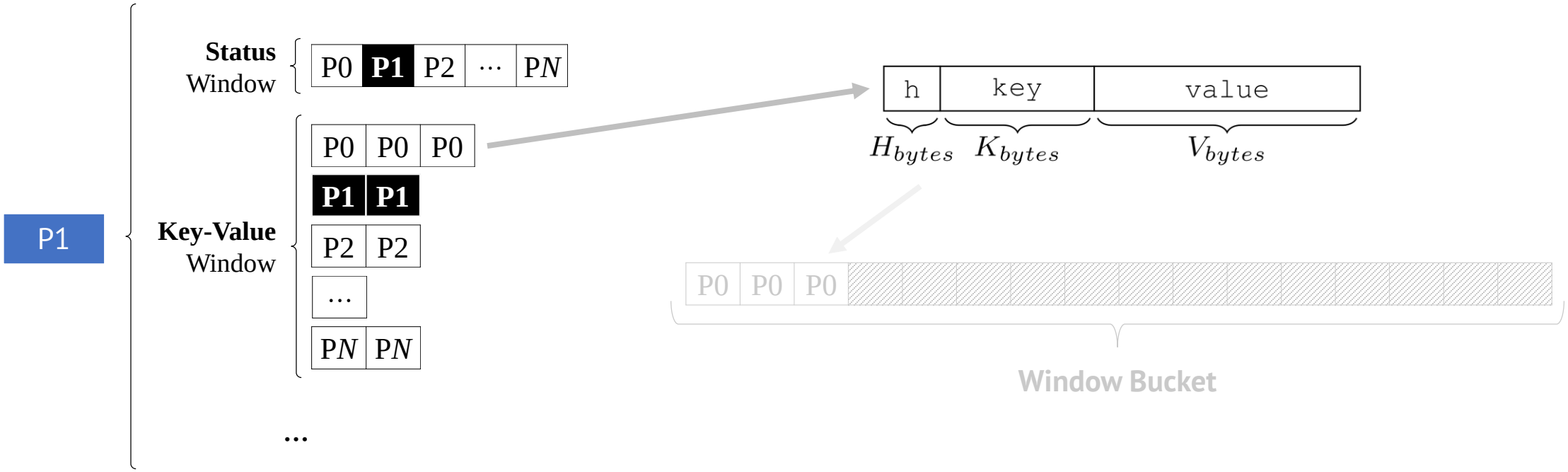

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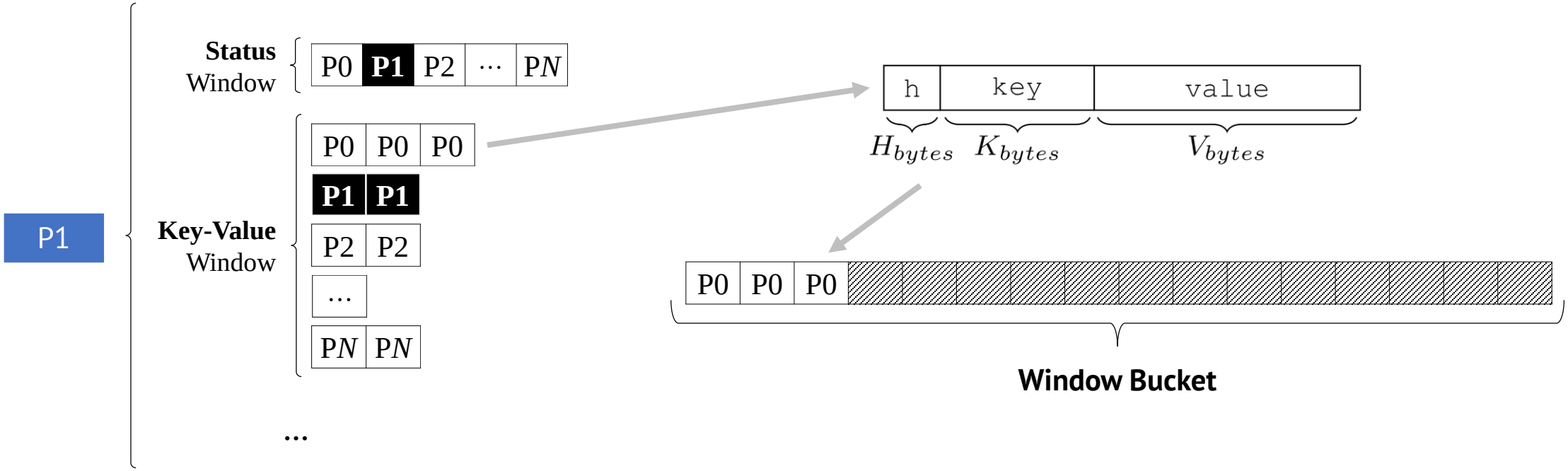

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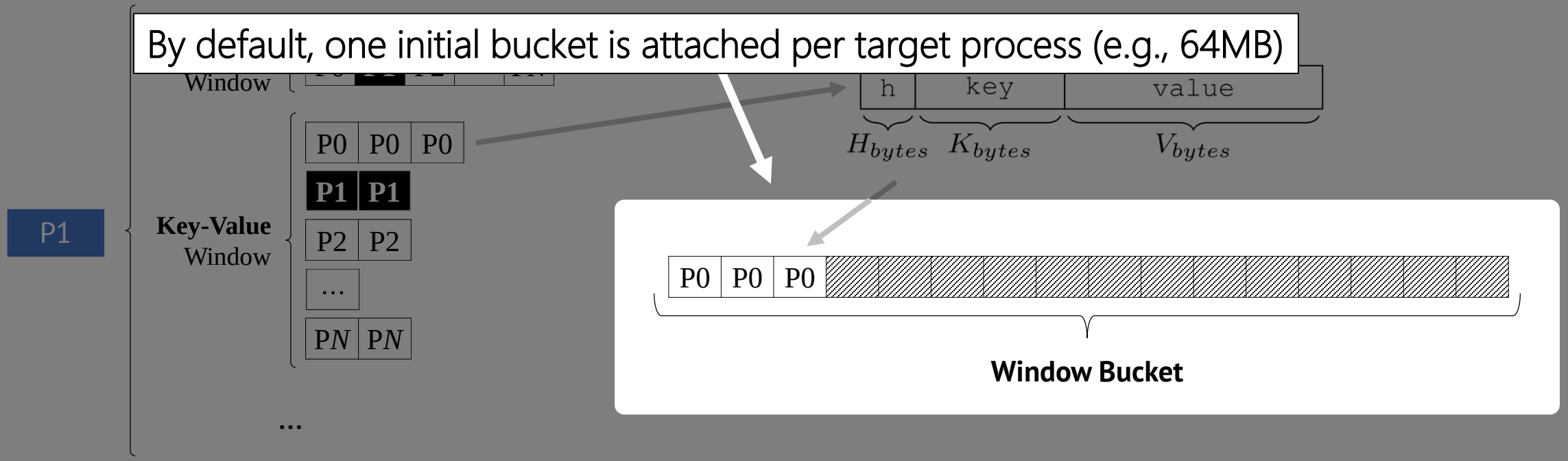

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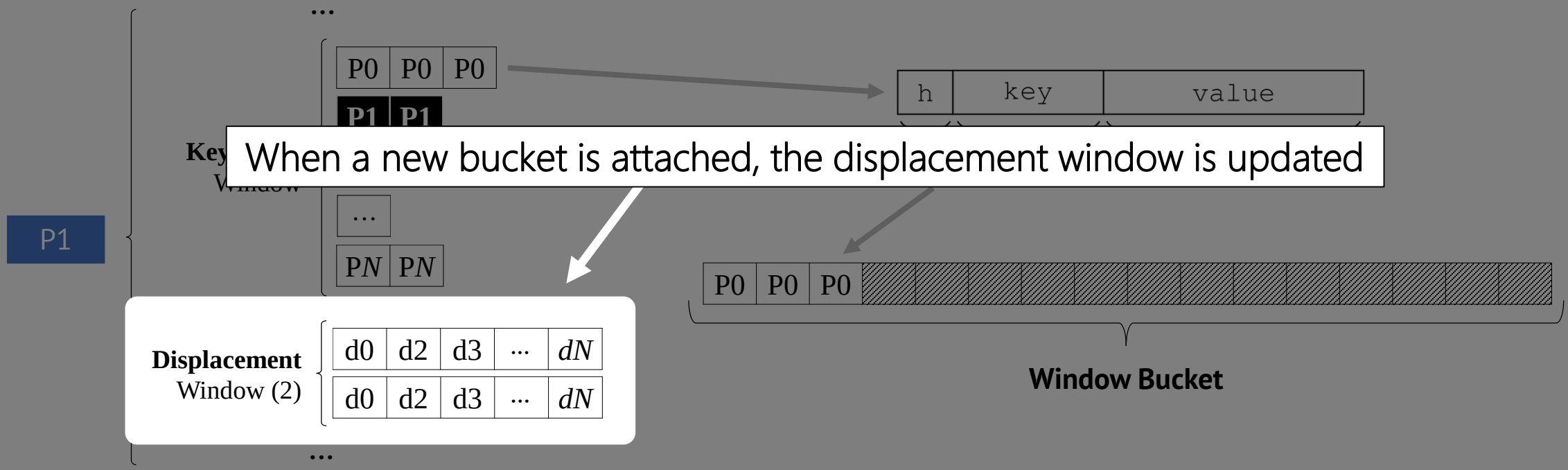

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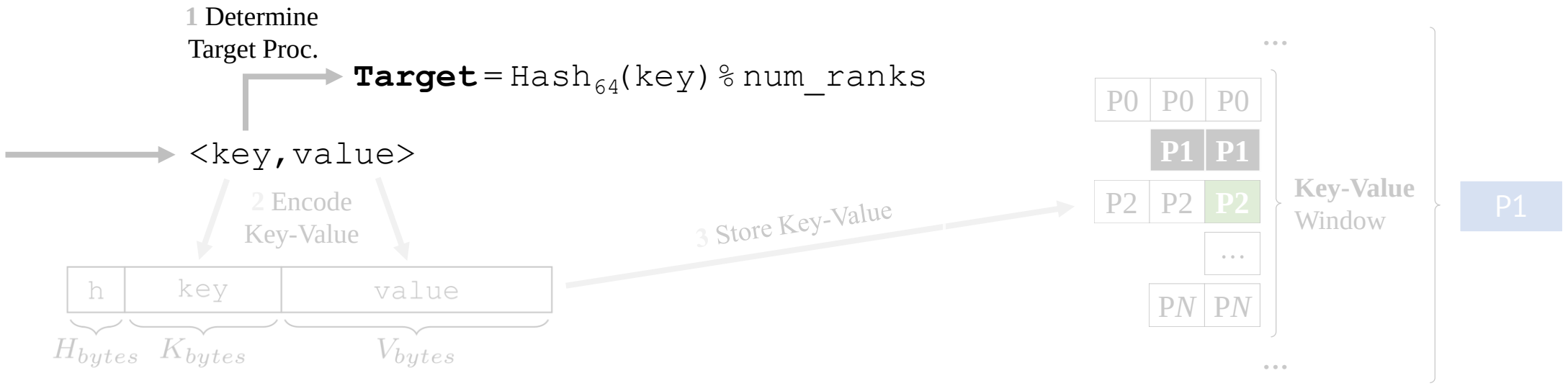

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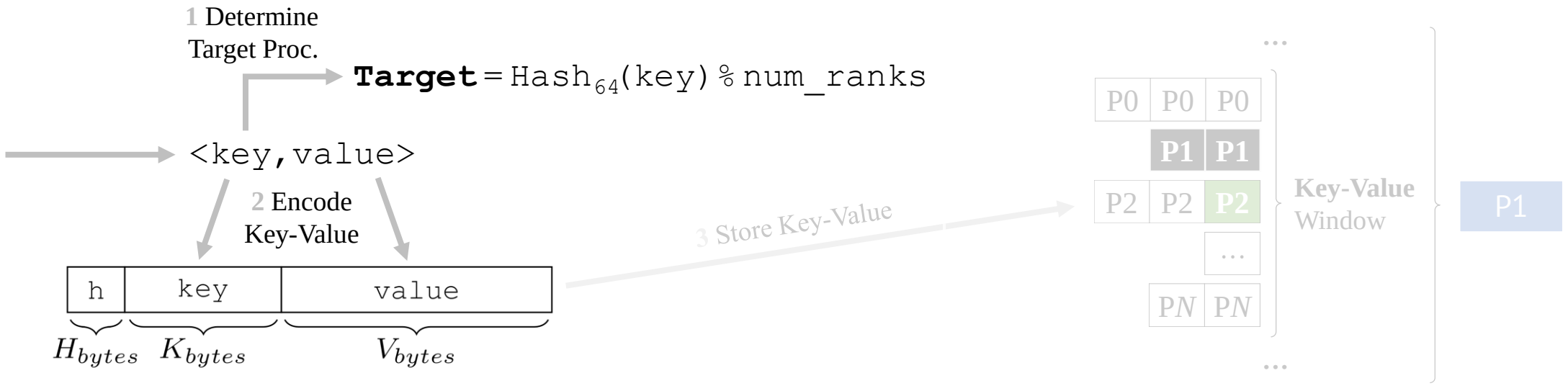

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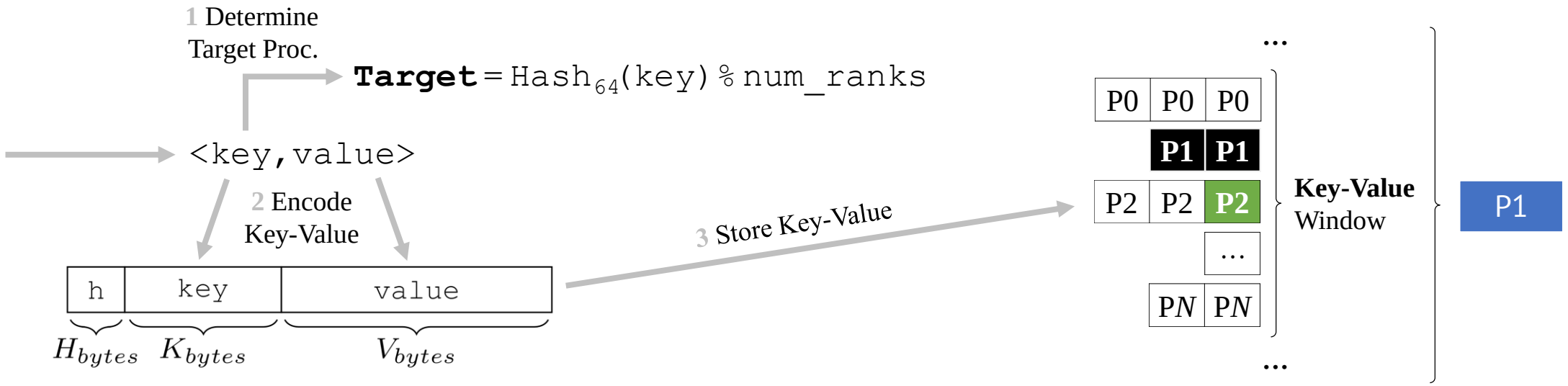

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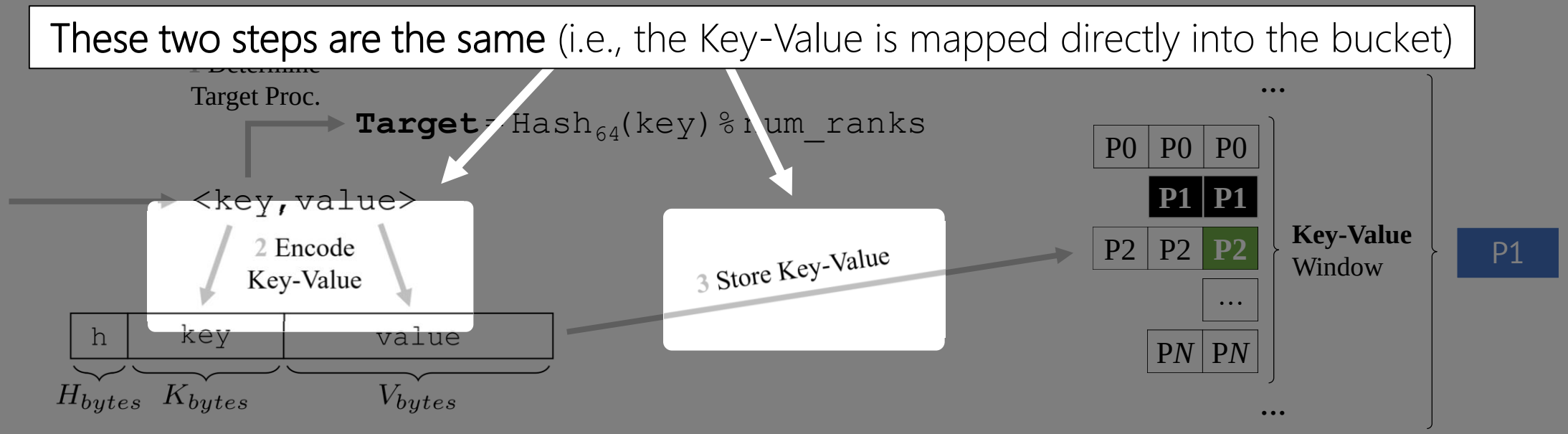

Methodology > Defining the Target Process

The mechanism allows remote processes to directly reference specific key-values, without affecting surrounding buckets

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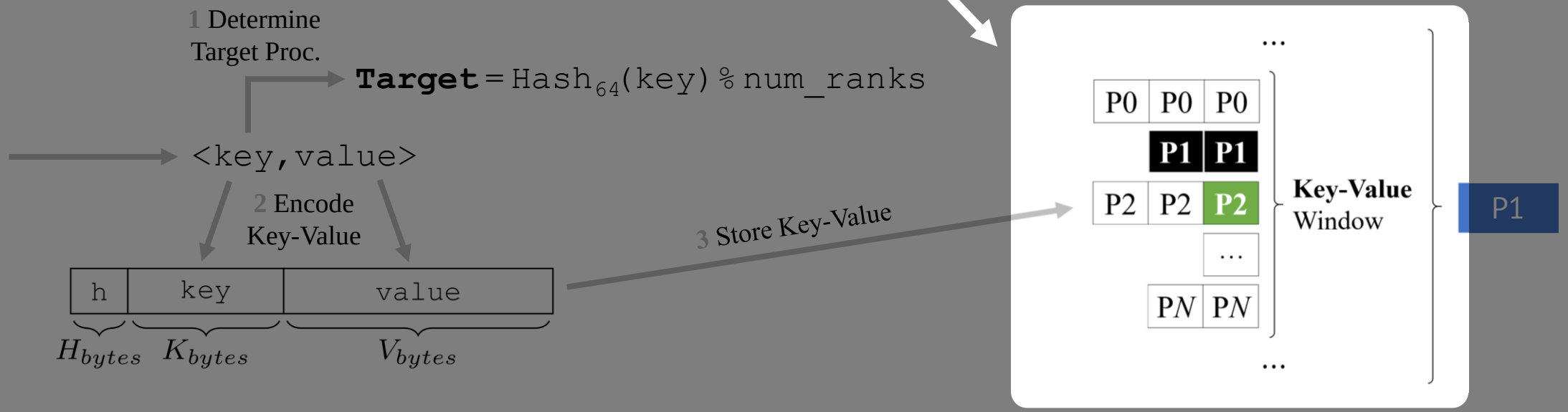

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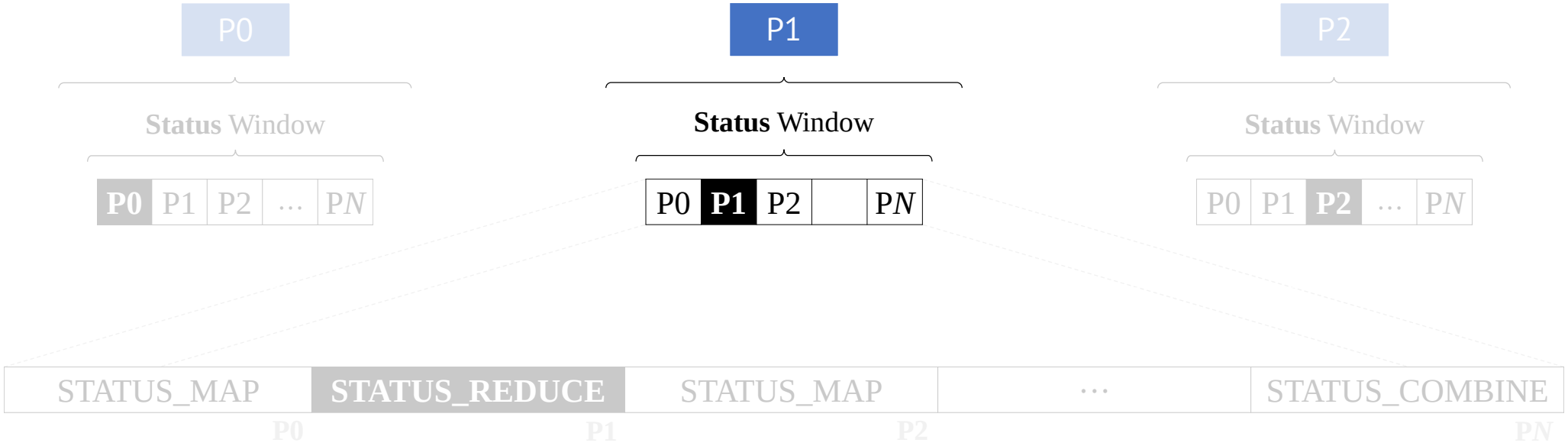

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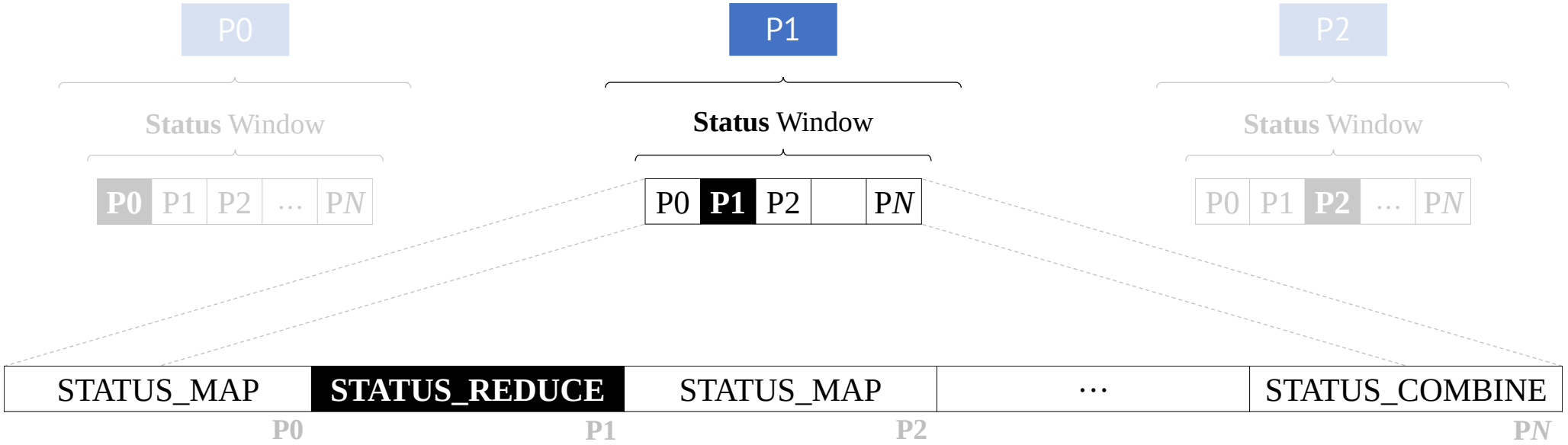

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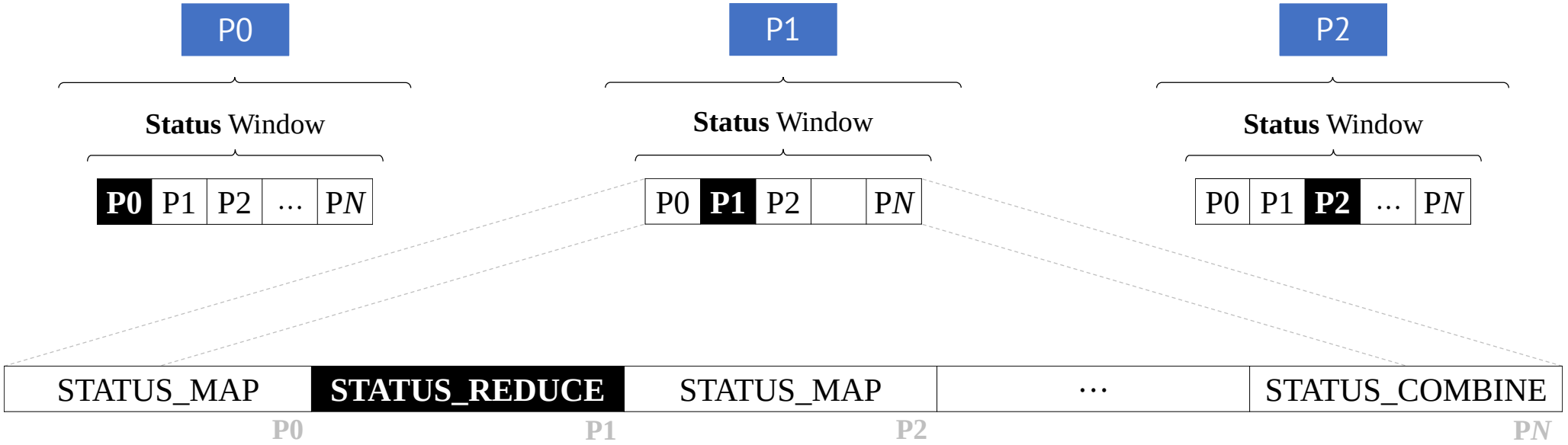

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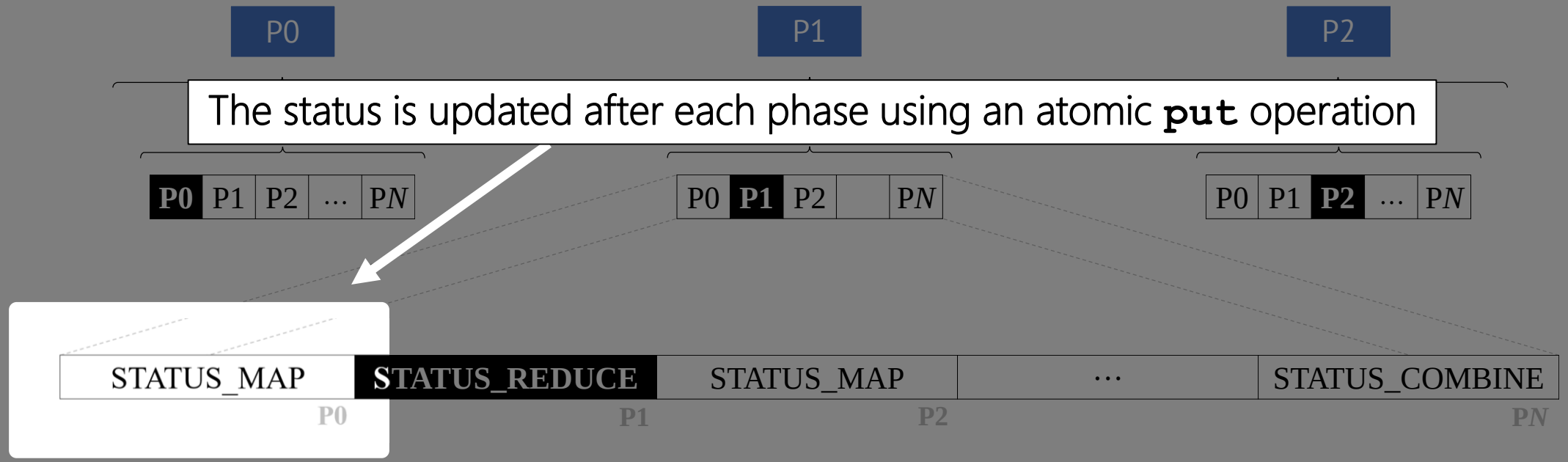

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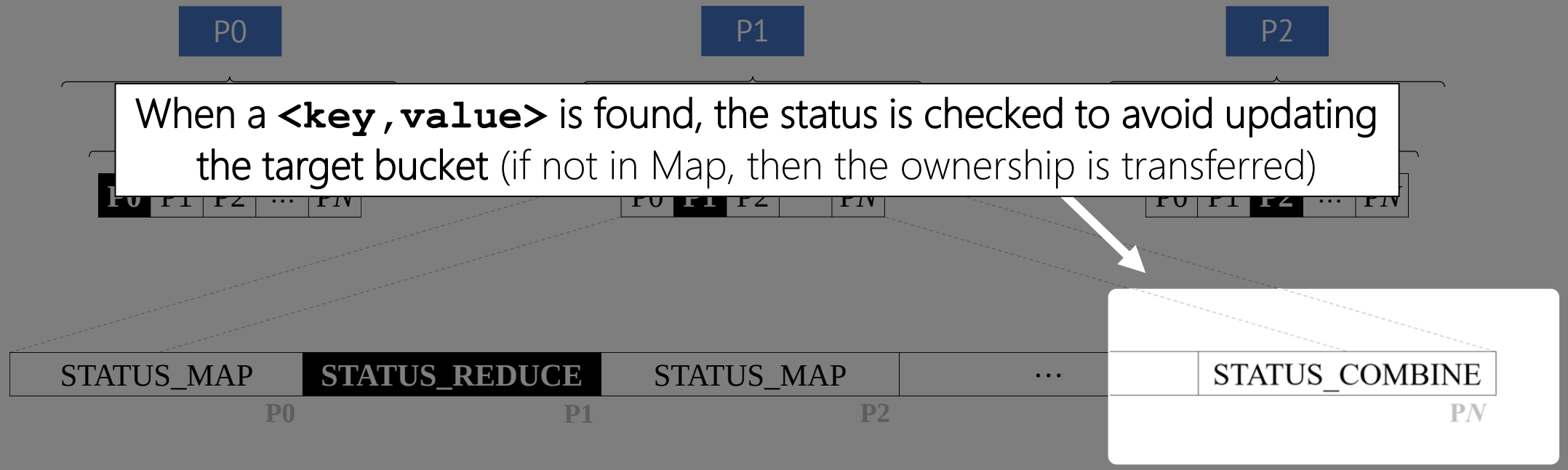

Methodology > Reducing Key-Values

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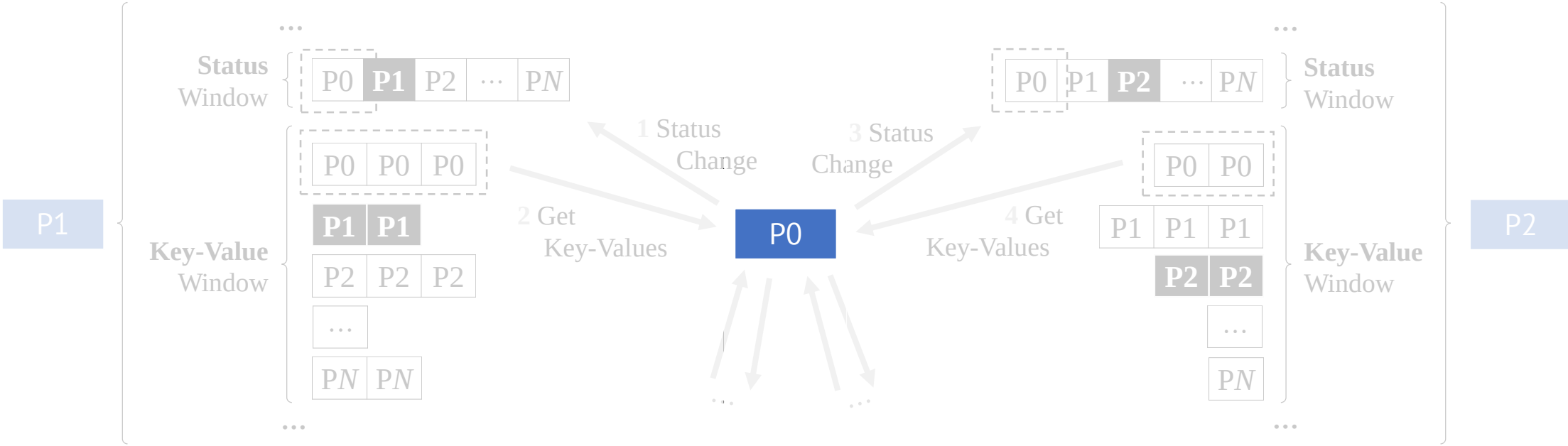

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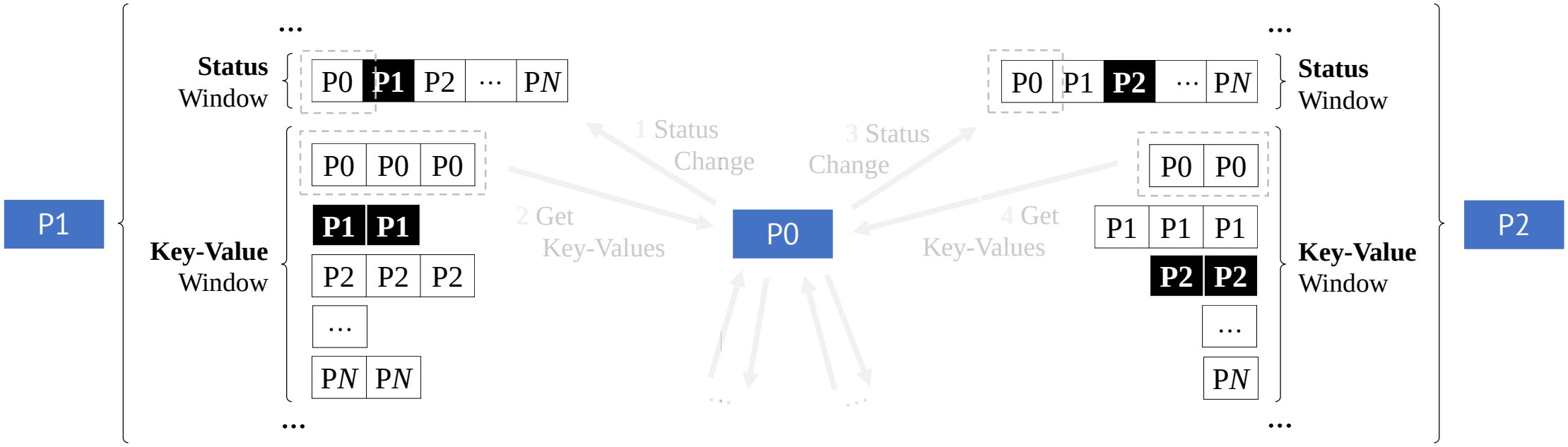

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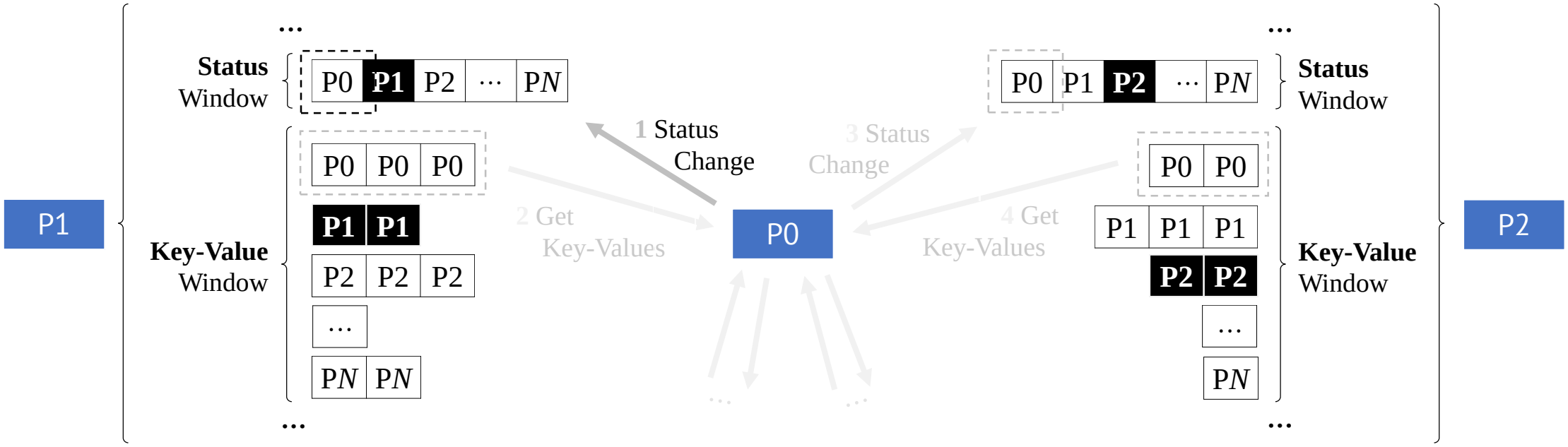

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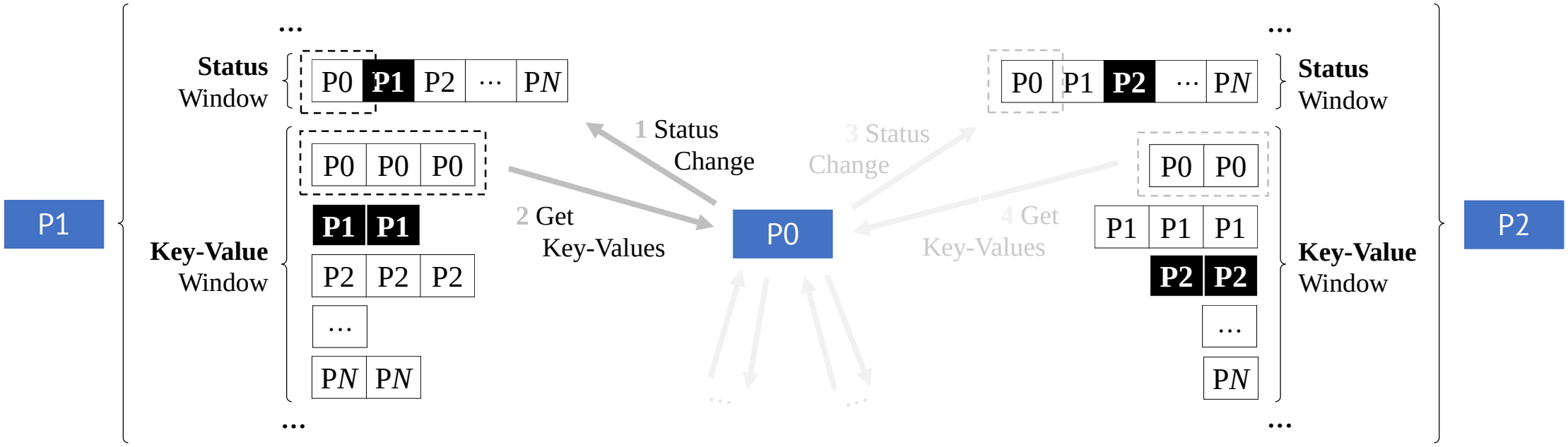

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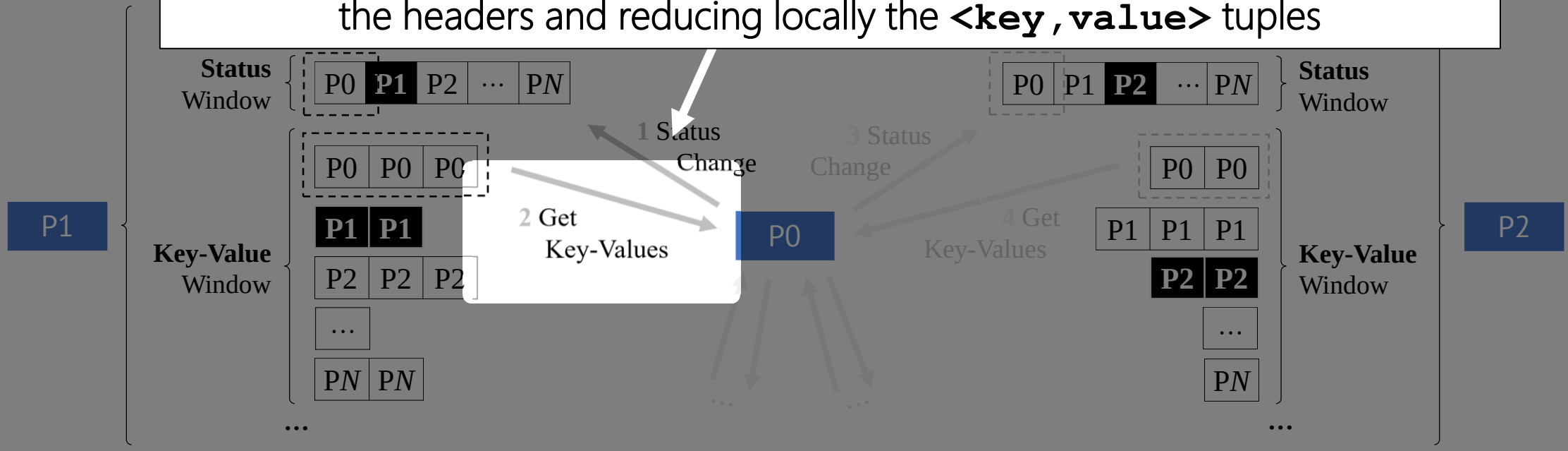

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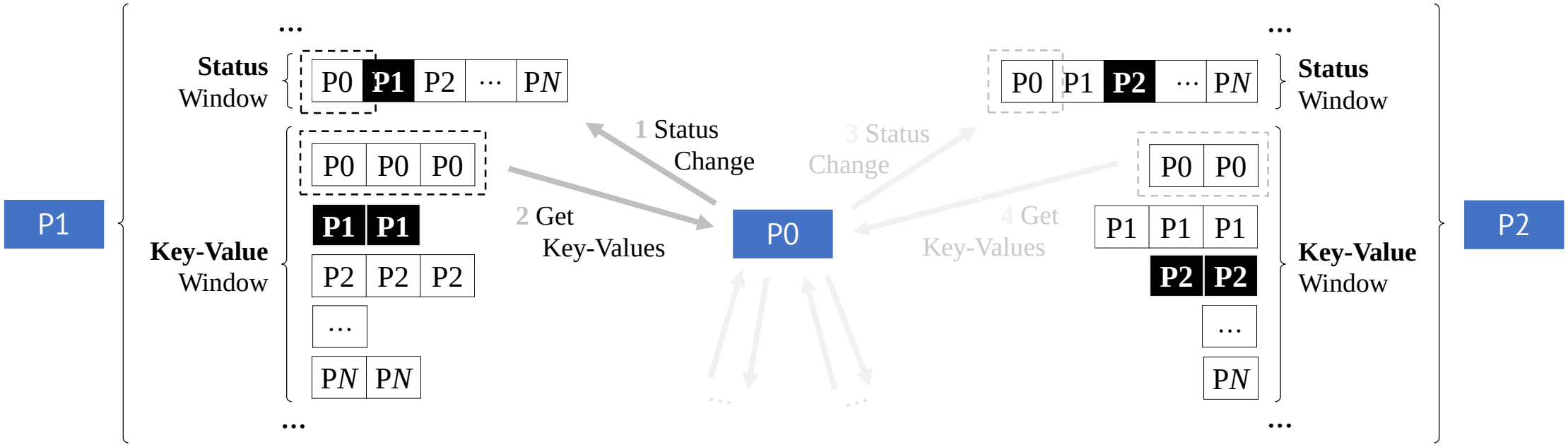

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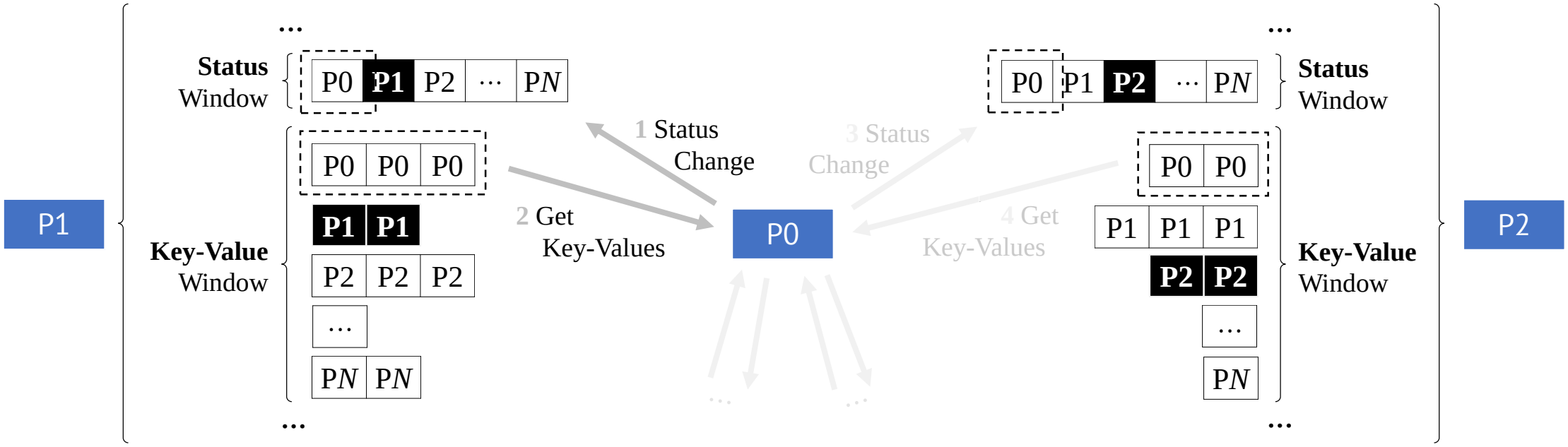

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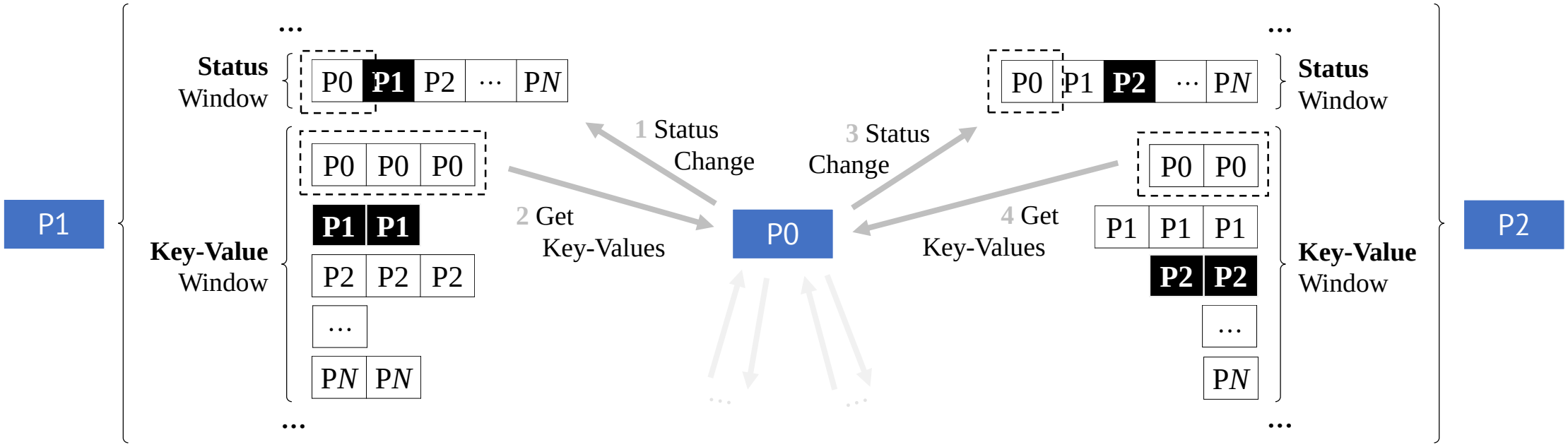
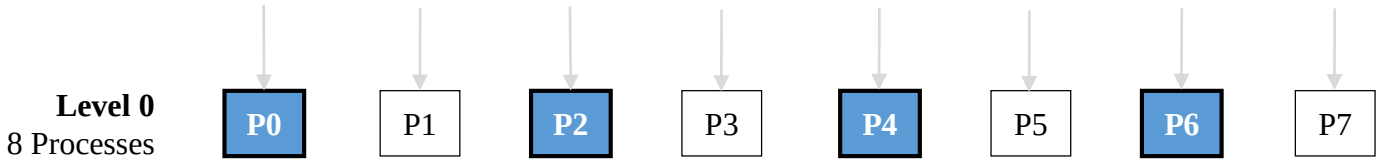


Methodology > Generating the Result

After Map and Reduce are completed, **Combine sets up a tree-based sorting algorithm that fetches key-values from each process to generate the result**. The algorithm used is inspired by *merge sort*:

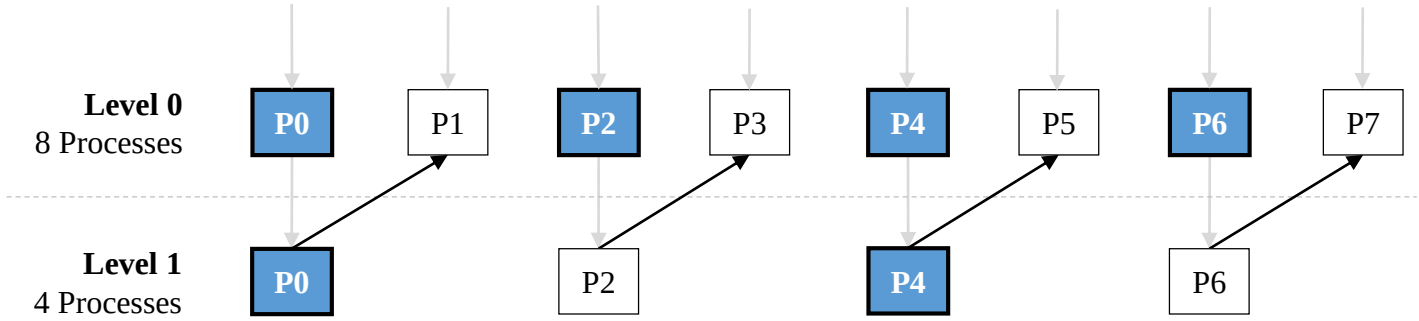
Methodology > Generating the Result

The number of levels in the tree is given by $\lceil \log_2(num\_ranks) \rceil + 1$. **The initial level is common to all the processes and the purpose is to store the local key-value pairs in-order**:



Methodology > Generating the Result

After the initial first step, **the processes retrieve the remote key-values from the previous level using one-sided operations**. This will generate a new level with all the key-value pairs ordered:



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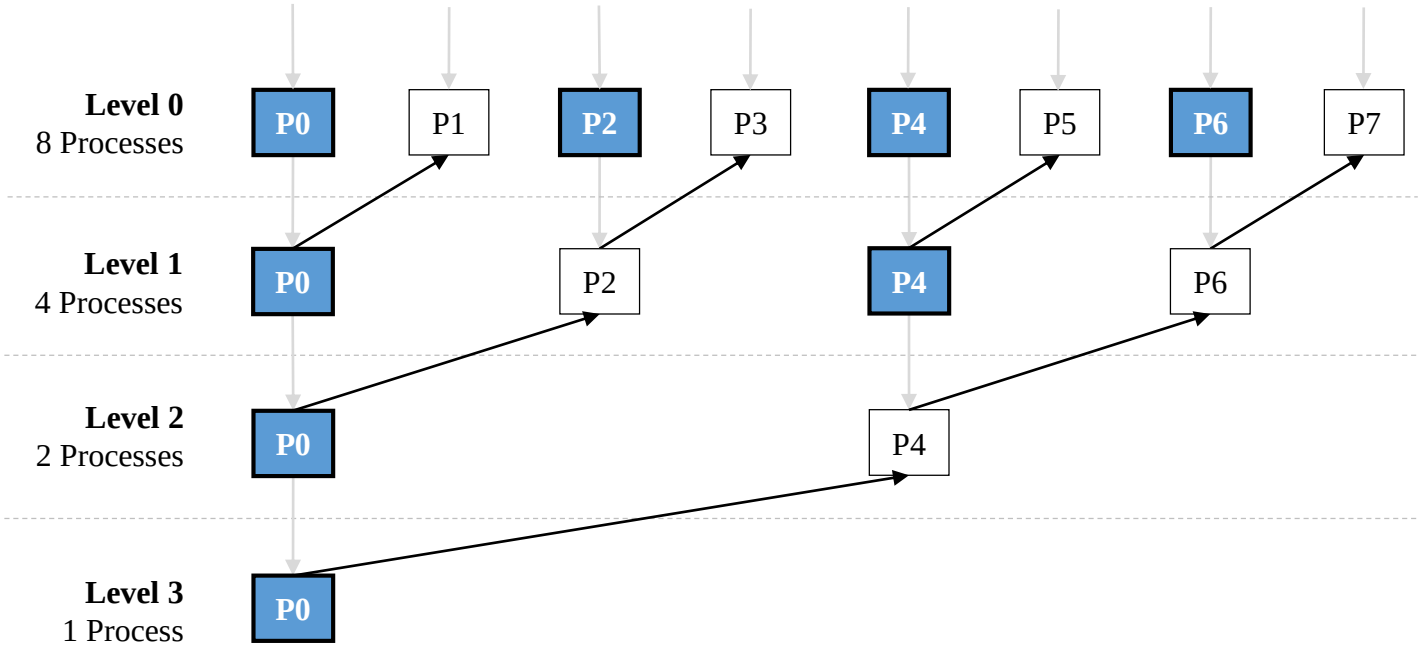

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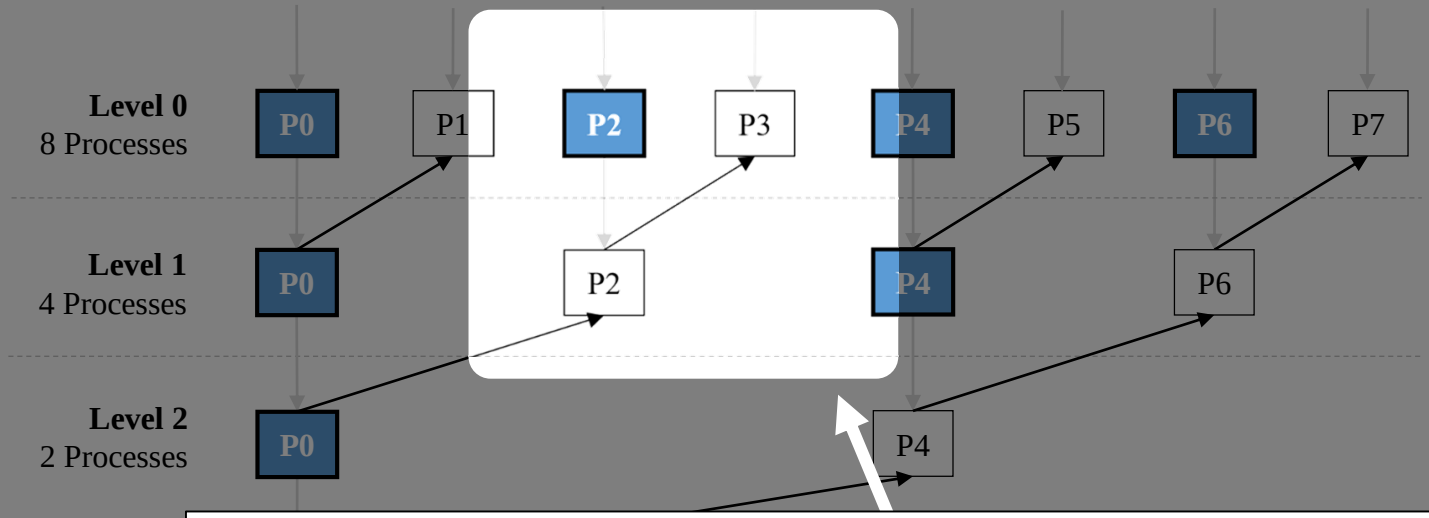

To prevent race conditions over the different levels of the tree, we use an *exclusive* lock (i.e., **`MPI_LOCK_EXCLUSIVE`**) over the Combine window

Methodology > Framework

In order to support our experiments, **we integrate MapReduce-1S as the back-end of a custom MapReduce framework**. The implementation is written in C/C++.

The framework employs a multi-inheritance mechanism by dividing the responsibilities as a hierarchy of classes:

- **Base Class**. Defines the main API to interact with the user, such as initialization or job execution.
- **Back-end Class**. Contains the implementation that performs the phases of the algorithm.
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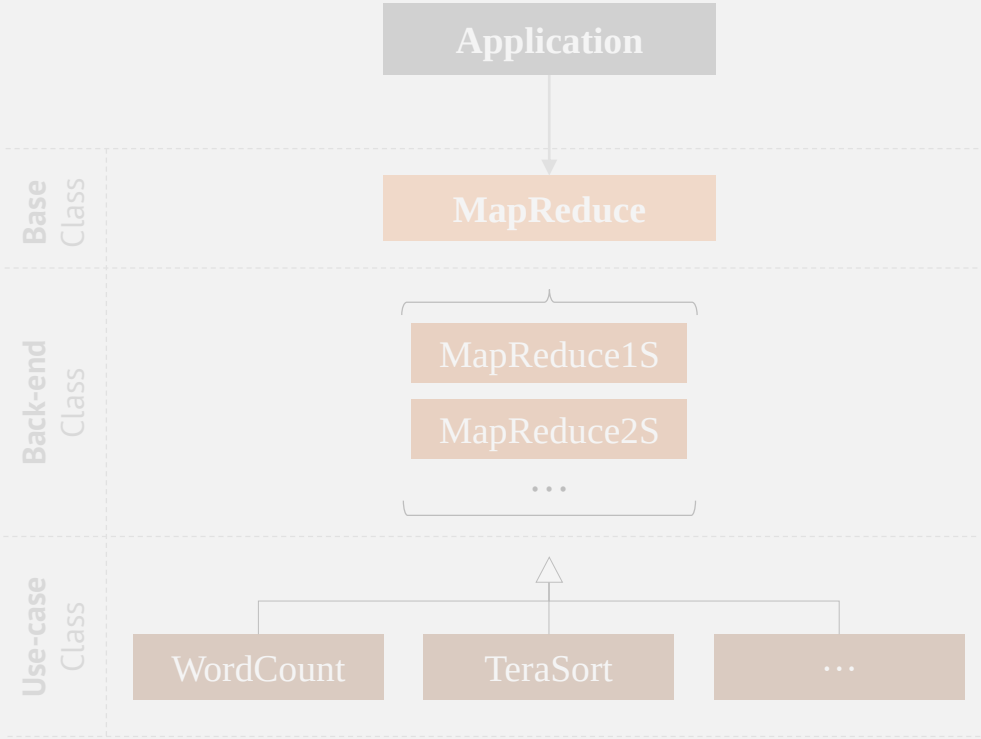

Methodology > Framework

In order to support our experiments, **we integrate MapReduce-1S as the back-end of a custom MapReduce framework**. The implementation is written in C/C++.

The framework employs a multi-inheritance mechanism by dividing the responsibilities as a hierarchy of classes**:**

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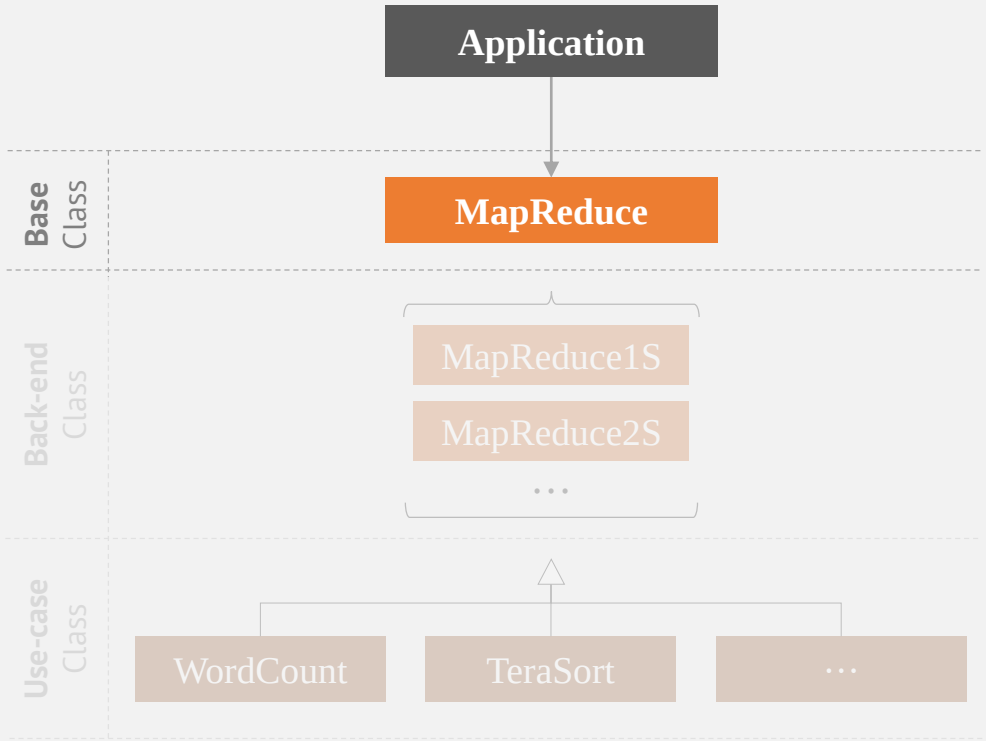

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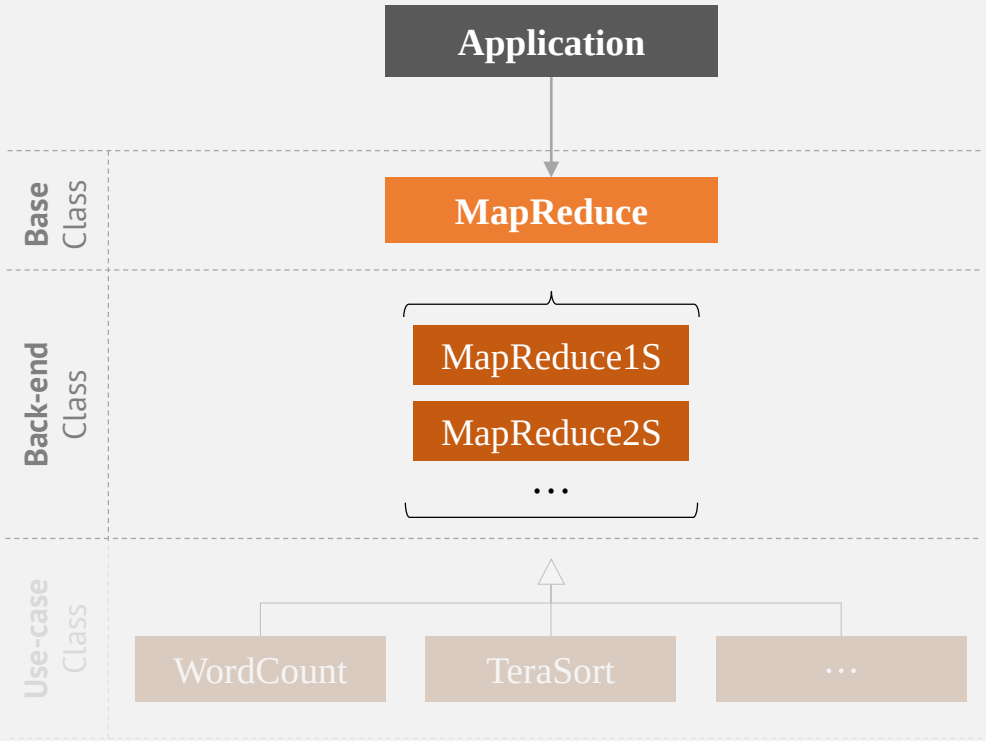

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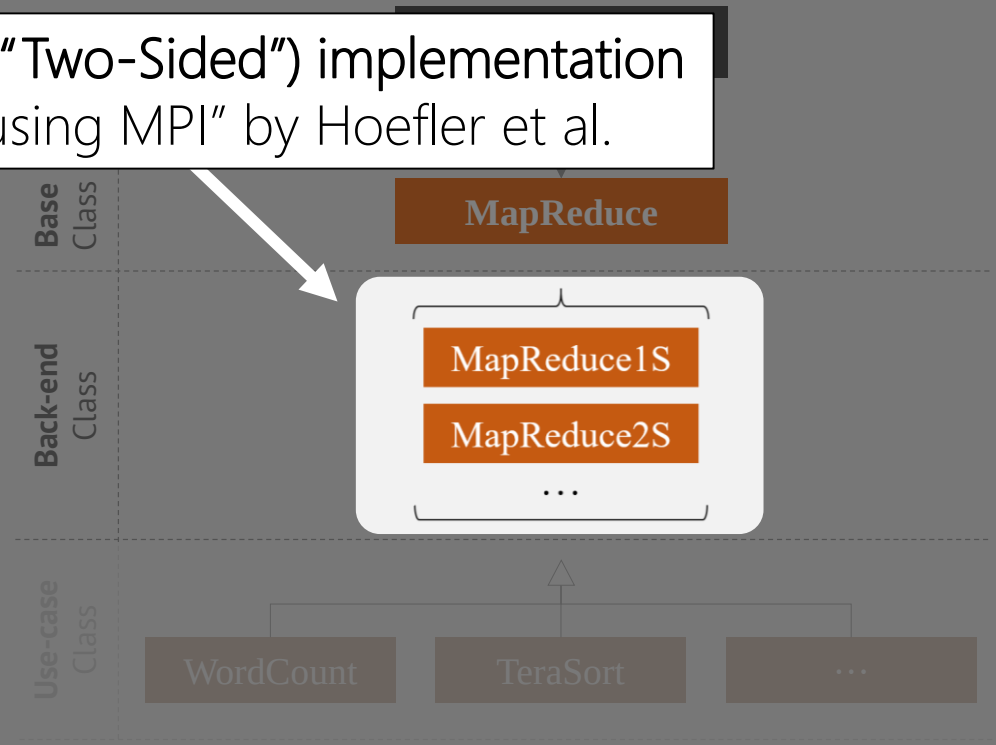

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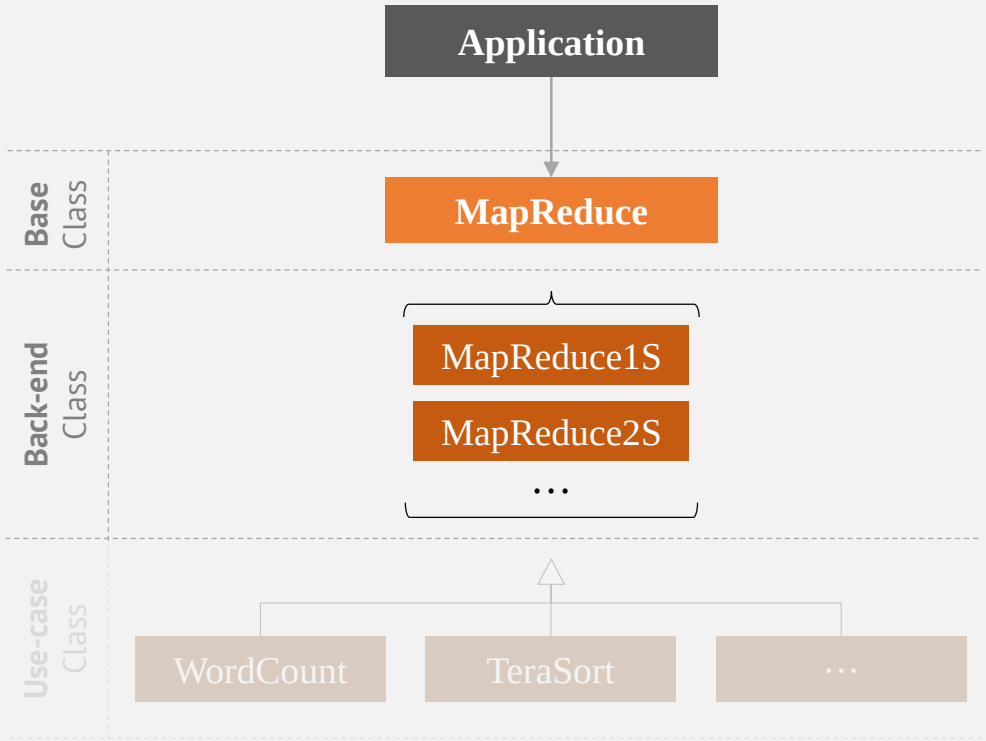

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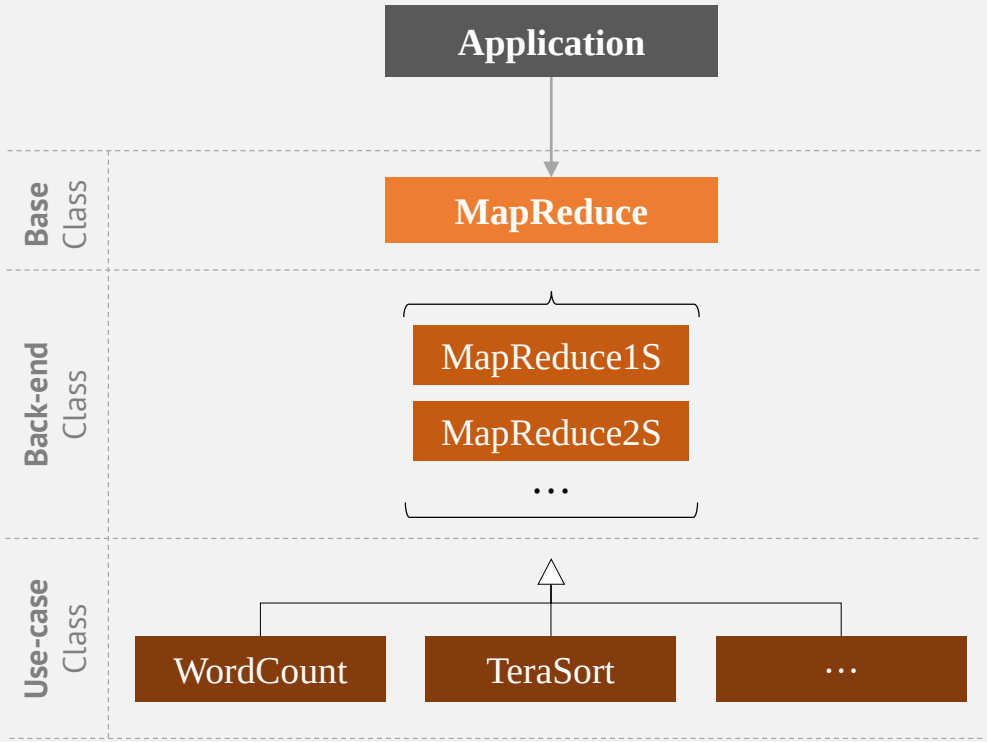

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```
...

// Create the MR object with MR-1S as back-end
MapReduce1S *map_reduce = new WordCount();

// Init the job with the specific settings
map_reduce->Init(input_filename, init_win_size,
                 max_chunk_size, max_task_size,
                 storage_enabled, hash_enabled,
                 input_api, sfactor, sunit);

// Launch the execution and output the result
map_reduce->Run();
map_reduce->Print();

// Close the job and release the object
map_reduce->Finalize();
delete map_reduce;

...
```

Experimental Results

We estimate the overall performance of MapReduce-1S compared to MapReduce-2S. We aim to understand how our approach could fit in existing MapReduce frameworks:

Specifications of Supercomputer "Tegner"	
Nodes	46 × Haswell-based compute nodes
Processor	2 × 12-core Haswell E5-2690v3 @ 2.6GHz
Memory	512GB DRAM per node
Storage	5PB Lustre PFS (Client v2.5.2) with 165 × OST Servers
Software	CentOS v7.4.1708 / Intel ICC and Intel MPI v18.0.1

All the figures reflect the standard deviation of the samples as error bars. **The terms "MR-1S" and "MR-2S" are used to refer to MapReduce-1S and MapReduce-2S**.

HPC System for Visualization and Big Data

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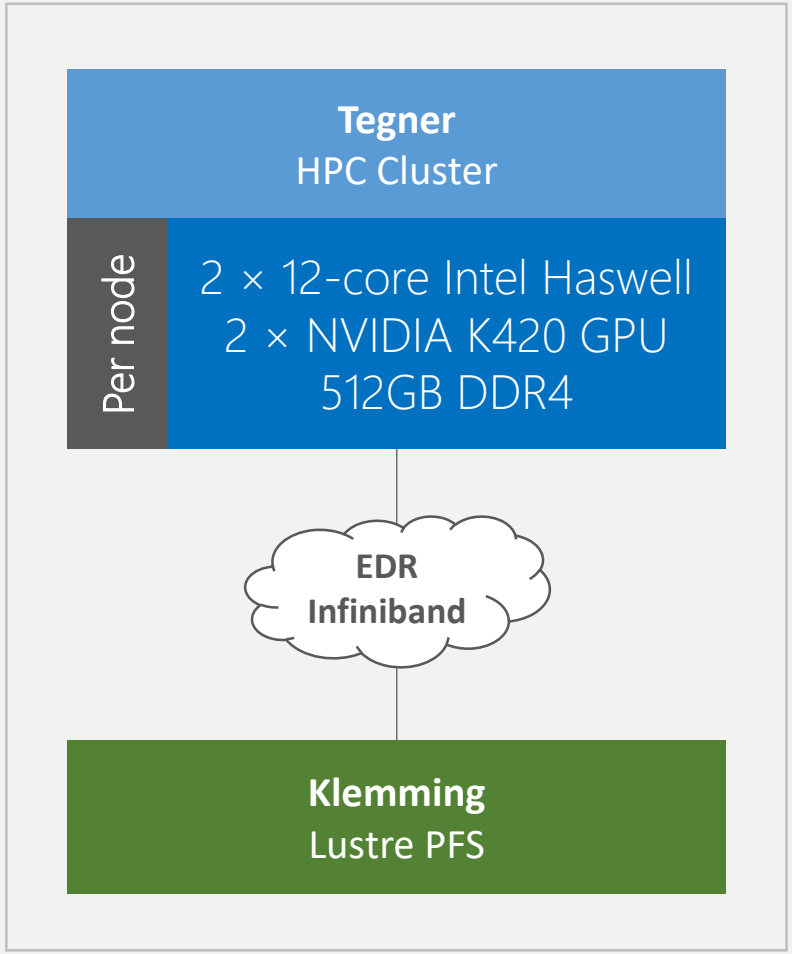

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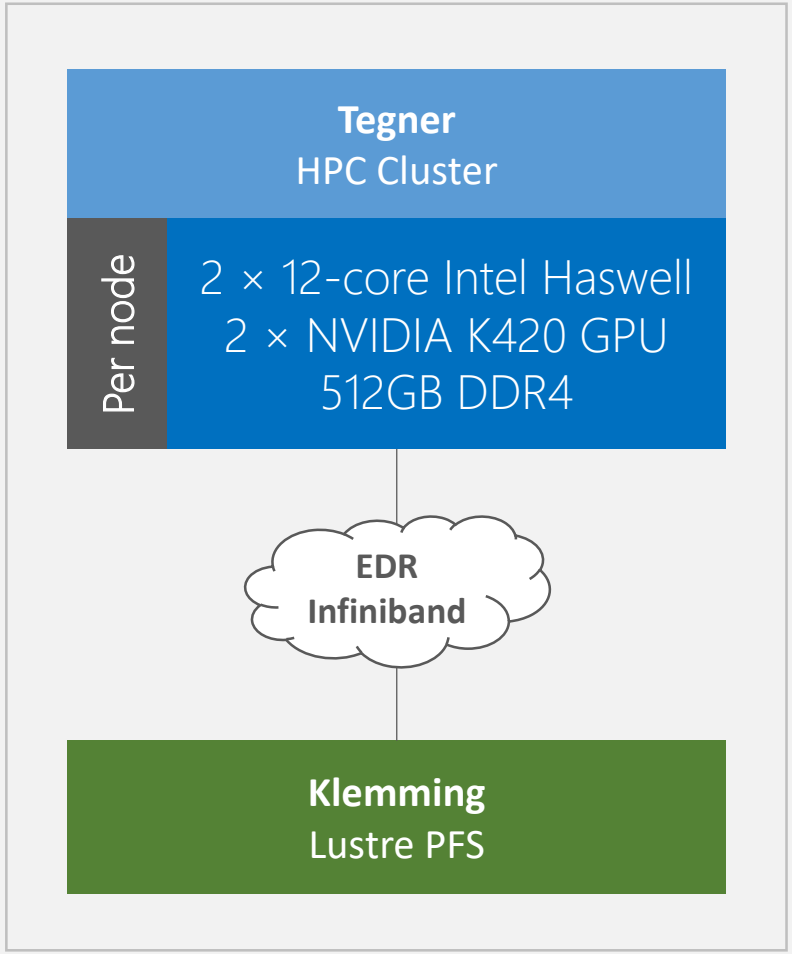

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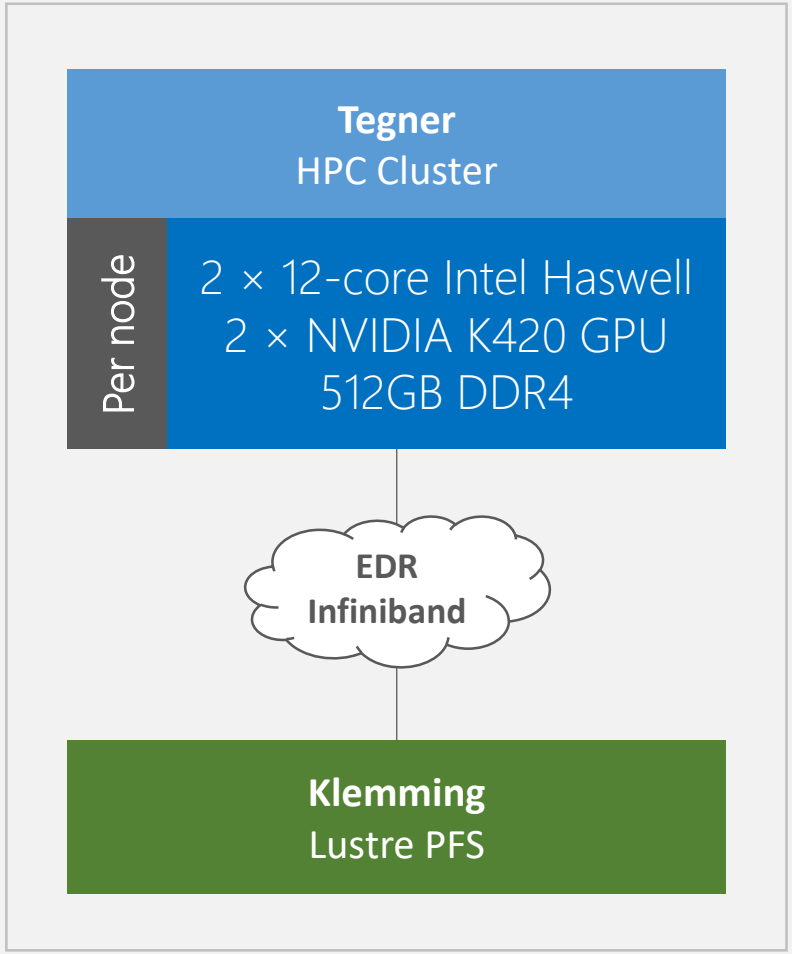

HPC System for Visualization and Big Data

Experimental Results > Word-Count

We evaluate the scalability of MapReduce-1S using Word-Count, a technique that has major relevance in Big Data analytics.

The basic principle of Word-Count is to compute the occurrences of individual words over large collections of documents:

- The Map phase emits `<word,1>` key-value pairs, where `word` represents the key and `1` the occurrence found.
- The Reduce phase aggregates the occurrences for a given `word` to generate its final `<word,count>`.
- Finally, the Combine phase aggregates all the key-values to produce the result.

We use the PUMA-Wikipedia datasets from PURDUE University
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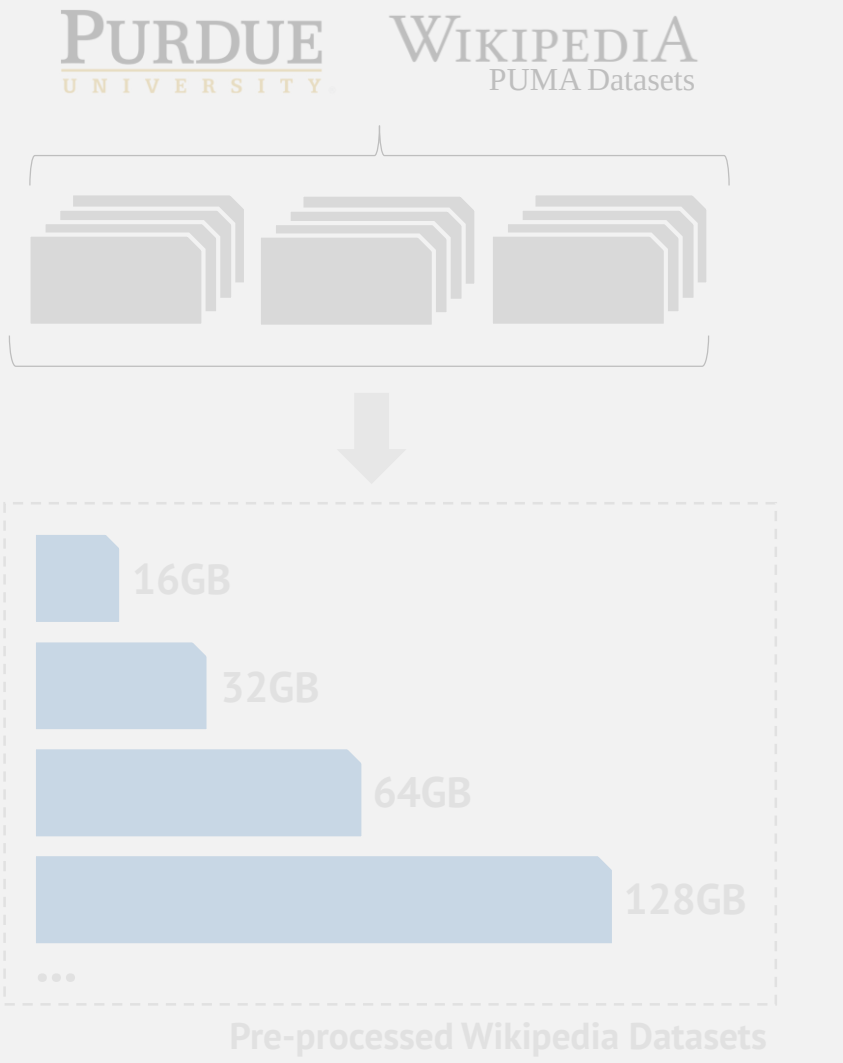

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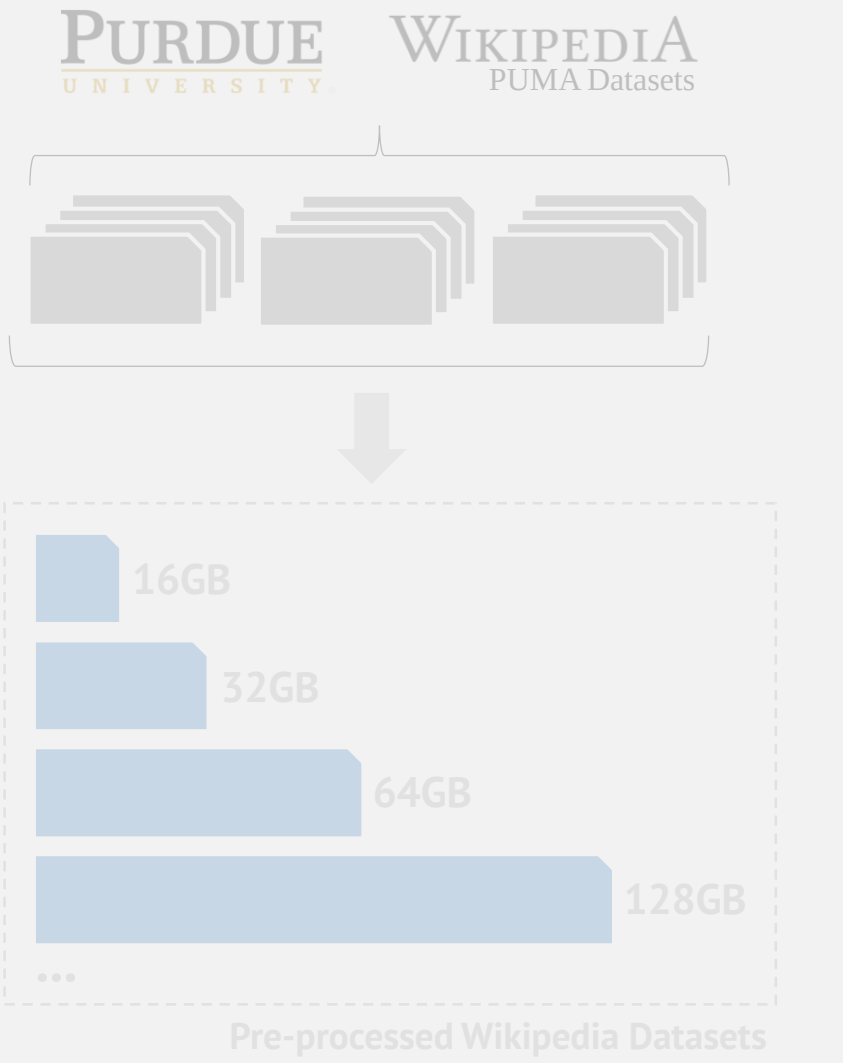

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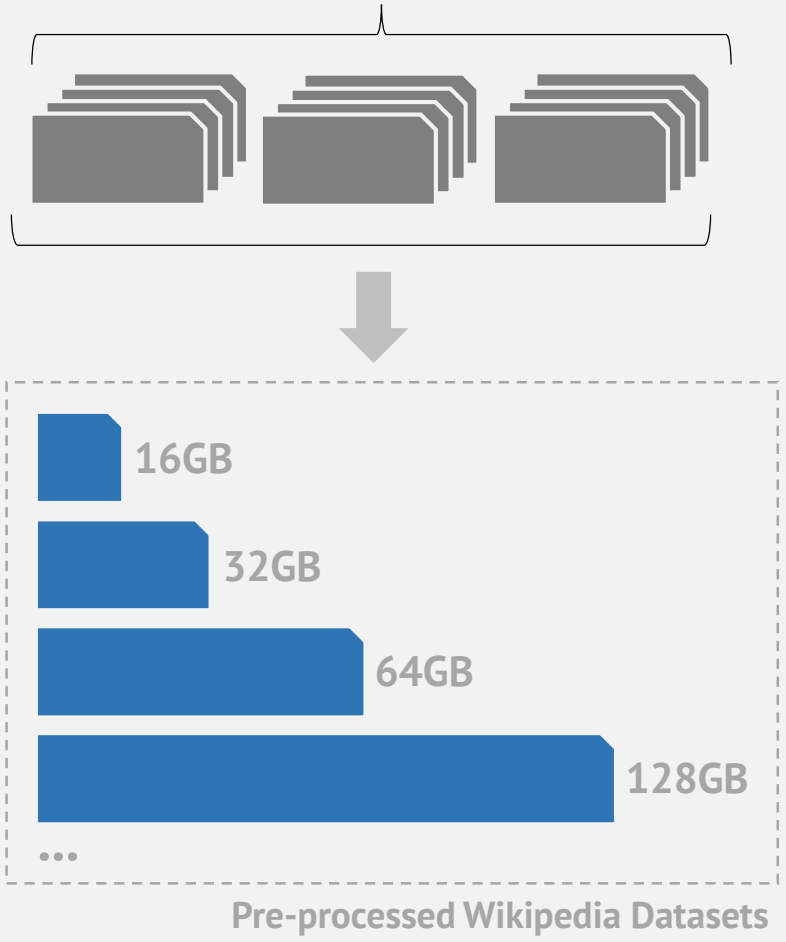
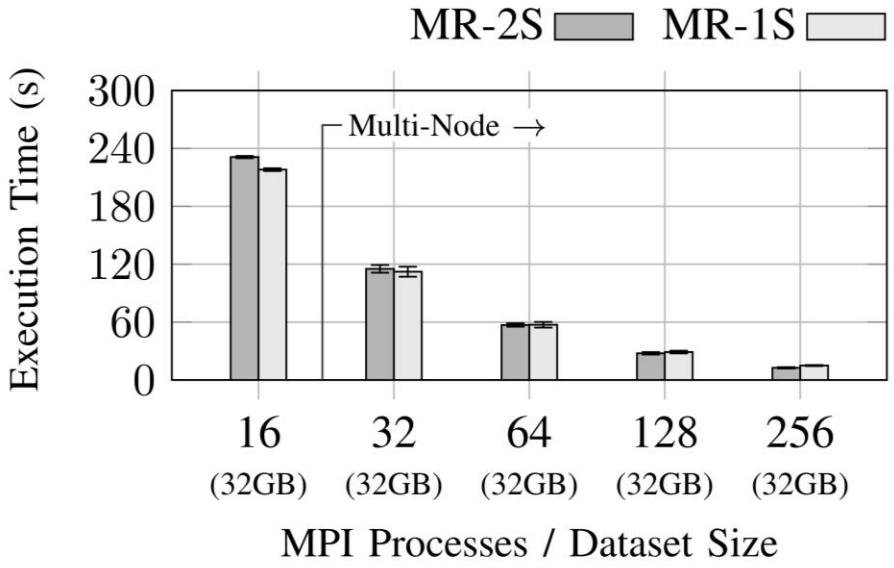


Experimental Results > Performance Evaluation

The following figure illustrates the performance of each approach by varying the number of MPI processes on Tegner for a fixed-size and variable-size input datasets (i.e., strong / weak scaling), **under balanced workload**:



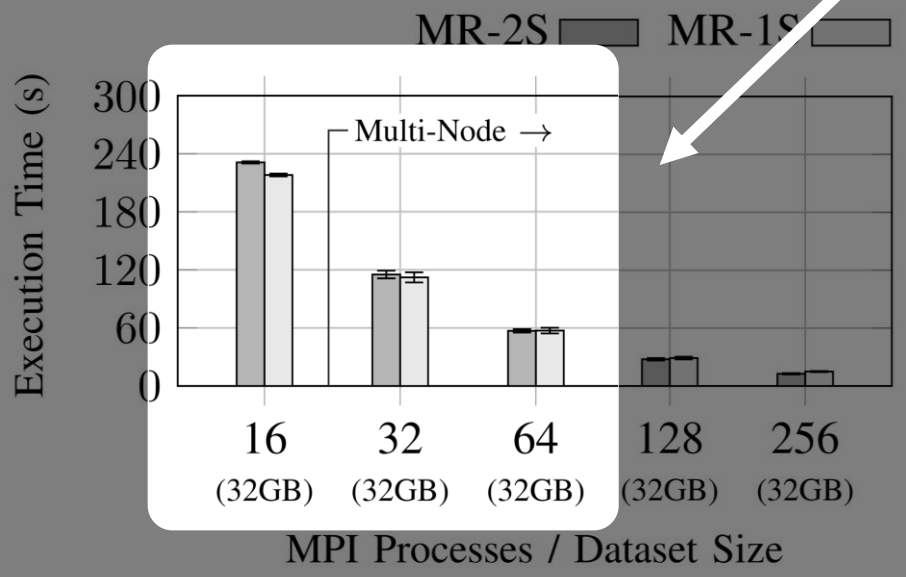
(a) **Strong Scaling Evaluation** under Balanced Workload

(b) **Weak Scaling Evaluation** under Balanced Workload

Experimental Results > Performance Evaluation

The following figure illustr processes on Tegner for a fixed-size and rkload:

MapReduce-1S provides approximately 4.8% improvement on average for lower process counts (up to 64 processes)



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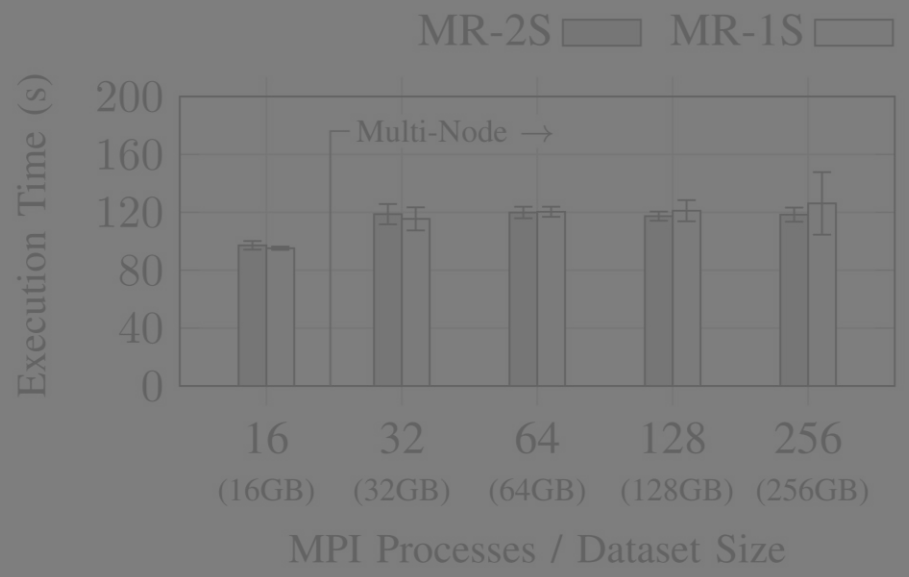

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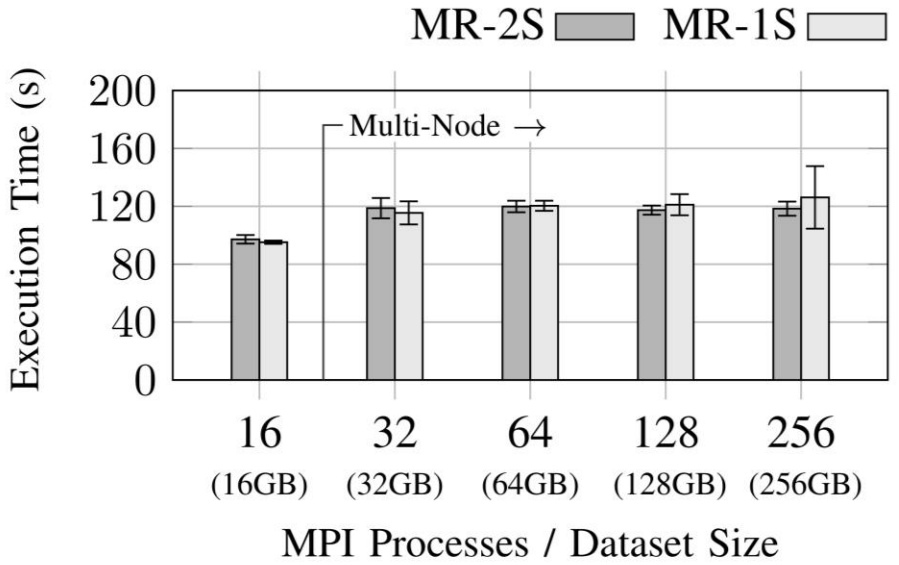
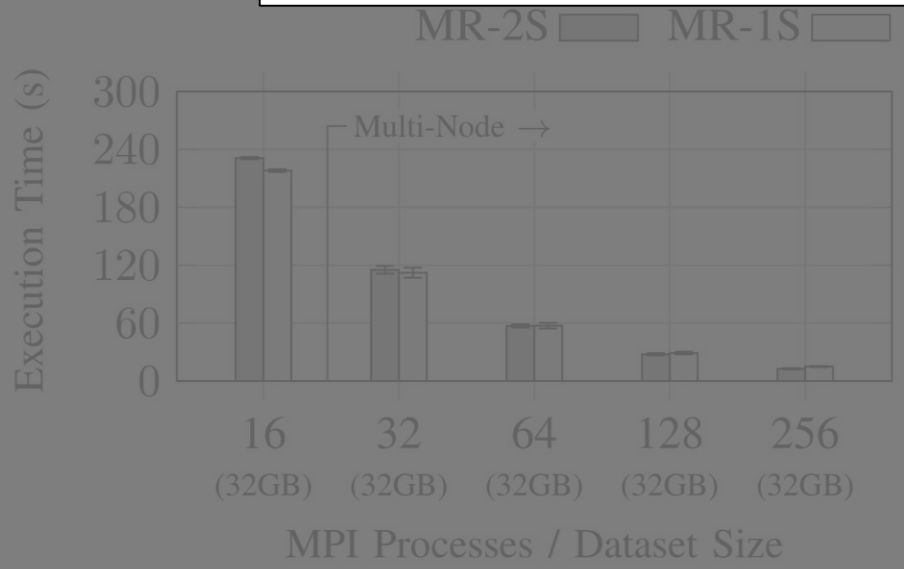


(b) **Weak Scaling Evaluation** under Balanced Workload

Experimental Results > Performance Evaluation

The following figure illustrates the performance of each approach by varying the number of MPI processes on Tegner for a fixe **der balanced workload**:

The average execution time is 111.3 seconds for MapReduce-2S, and 111.8 seconds for MapReduce-1S (0.5% difference)



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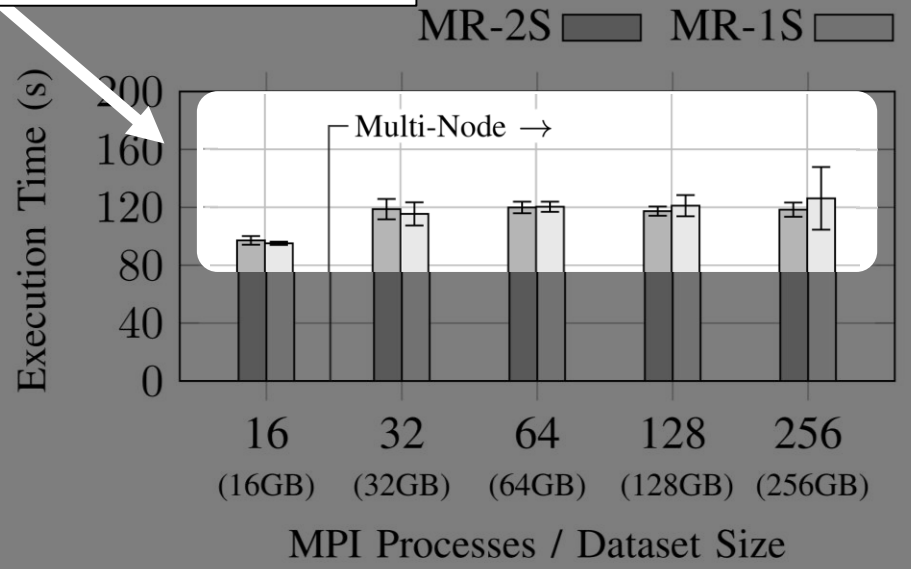
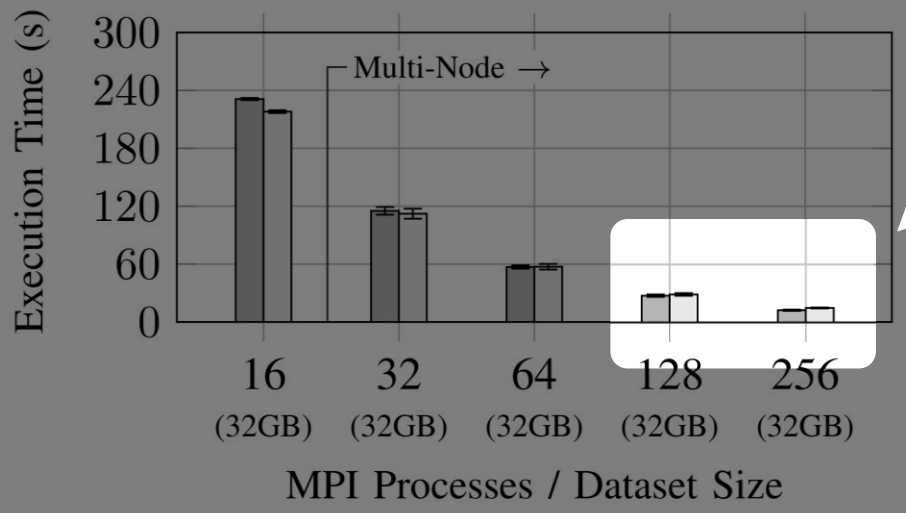


(b) **Weak Scaling Evaluation** under Balanced Workload

Experimental Results > Performance Evaluation

The following figure illustrates the performance of each approach by varying the number of MPI processes on Tegner for a fix

The performance of MapReduce-1S is clearly affected as the process counts increases
Hence, collective communication and collective I/O results in better performance



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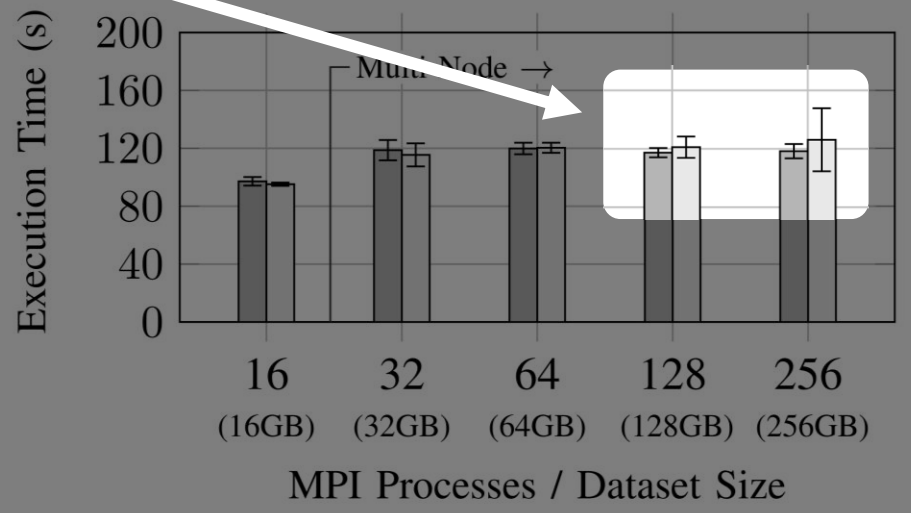

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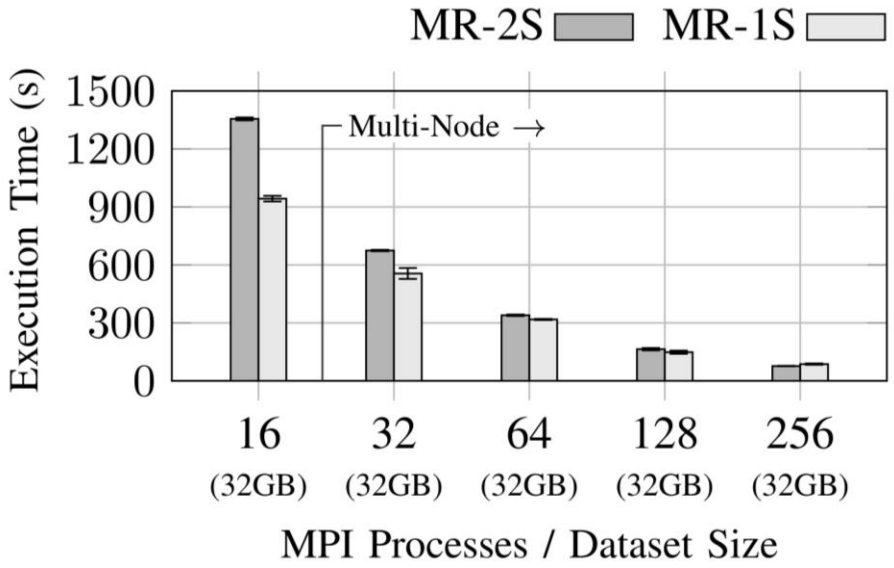
The following figure illustrates the performance of each approach by varying the number of MPI processes on Tegner for a fixed-size and variable-size input datasets (i.e., strong / weak scaling), **under unbalanced workload**:



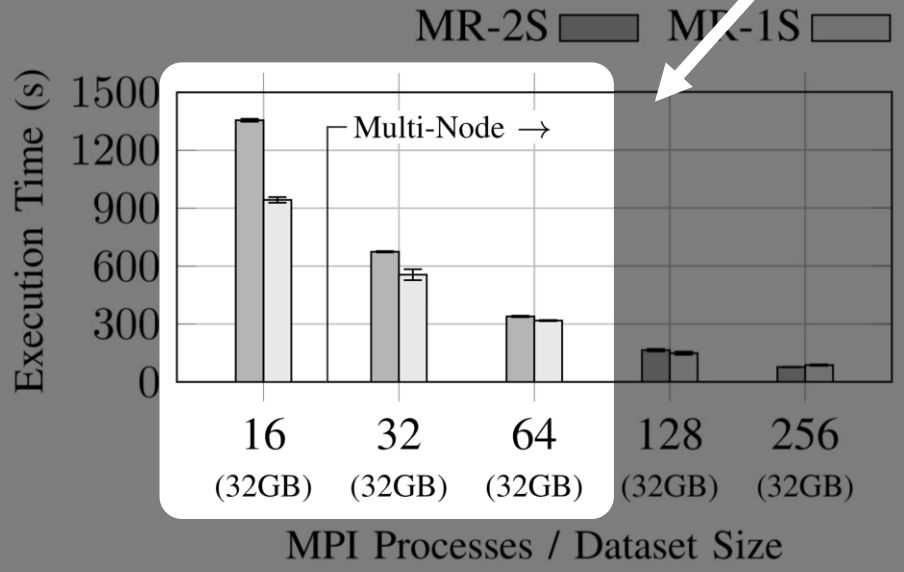
(c) **Strong Scaling Evaluation** under Unbalanced Workload

(d) **Weak Scaling Evaluation** under Unbalanced Workload

Experimental Results > Performance Evaluation

The following fig… MPI processes on Tegner for a fixed … **nced workload**:

If the workload is unbalanced, the average improvement is approximately 20.4% on average compared to MapReduce-2S



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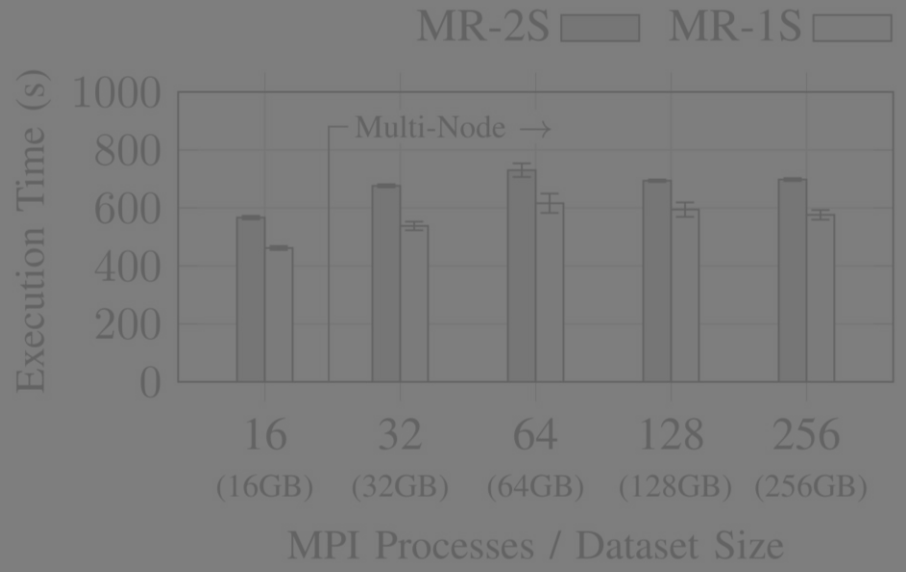

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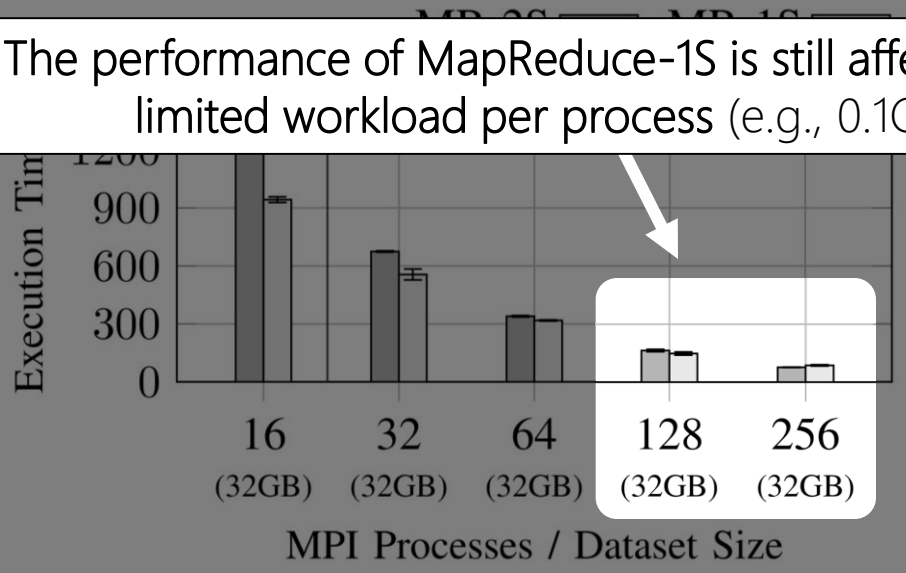
Experimental Results > Performance Evaluation

The following figure illustrates the performance of each approach by varying the number of MPI processes on Tegner for a fixed-size and variable-size input datasets (i.e., strong / weak scaling), **under unbalanced workload**:

The performance of MapReduce-1S is still affected, mainly due to the limited workload per process (e.g., 0.1GB on the last test)



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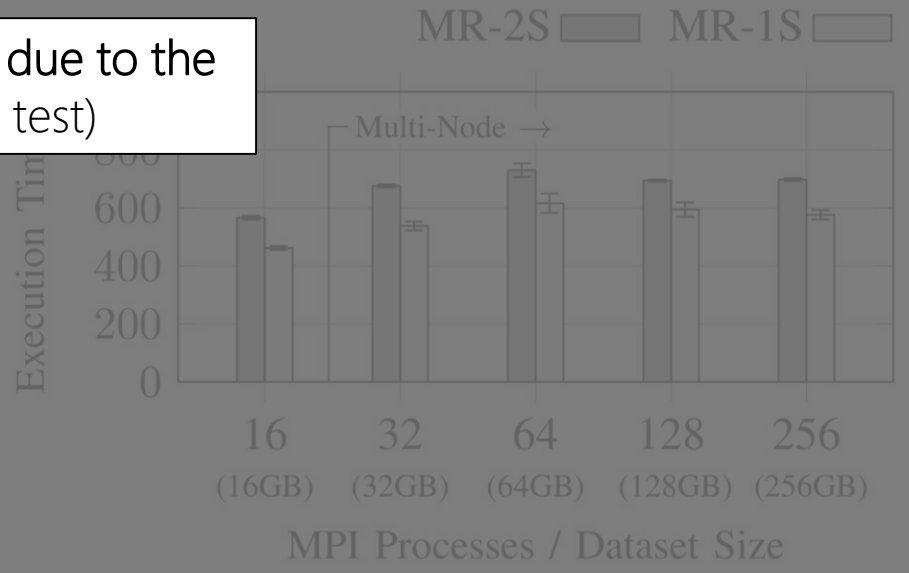

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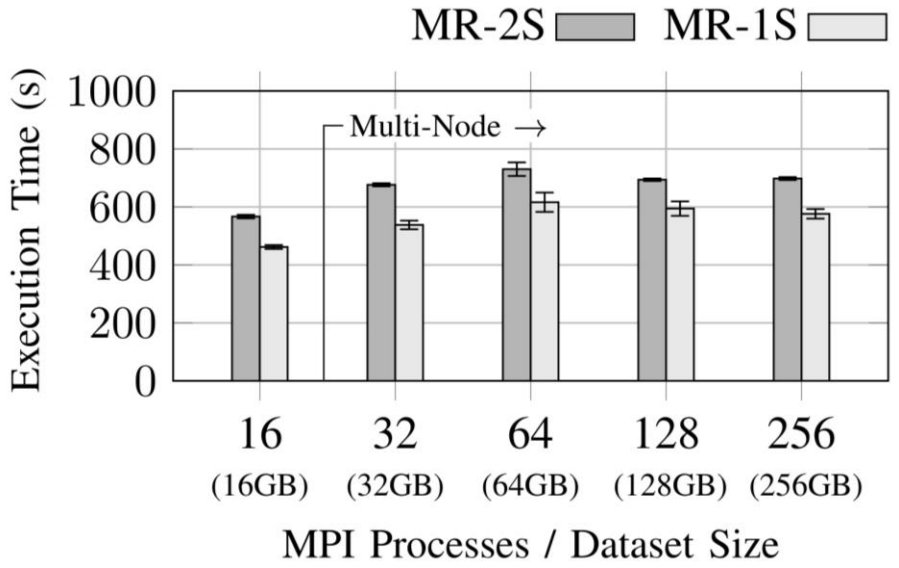
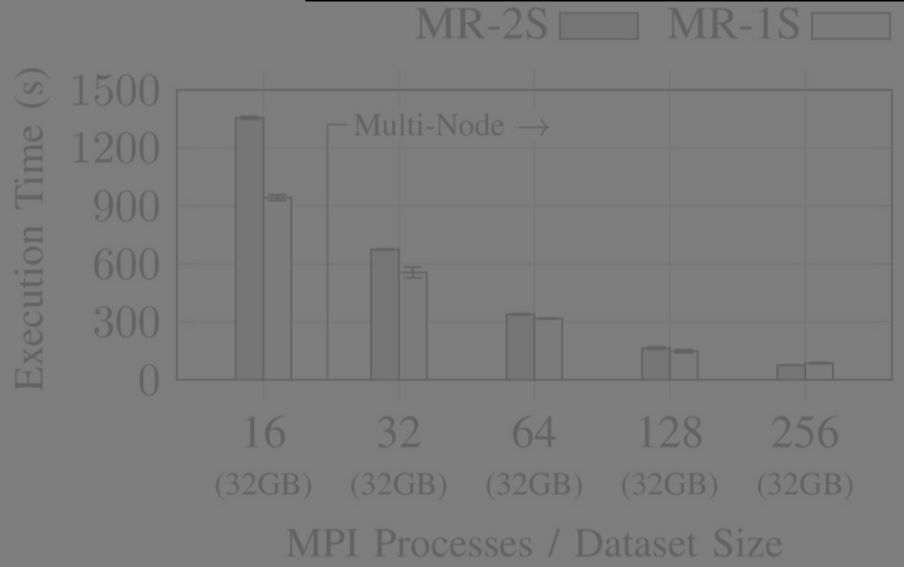


(d) **Weak Scaling Evaluation** under Unbalanced Workload

Experimental Results > Performance Evaluation

The following figure illustrates the performance of each approach by varying the number of MPI processes on Tegner for a fixed-s **unbalanced workload**:

The improvement on unbalanced workloads is 23.1% on average for MapReduce-1S (with a peak of 33.9%)



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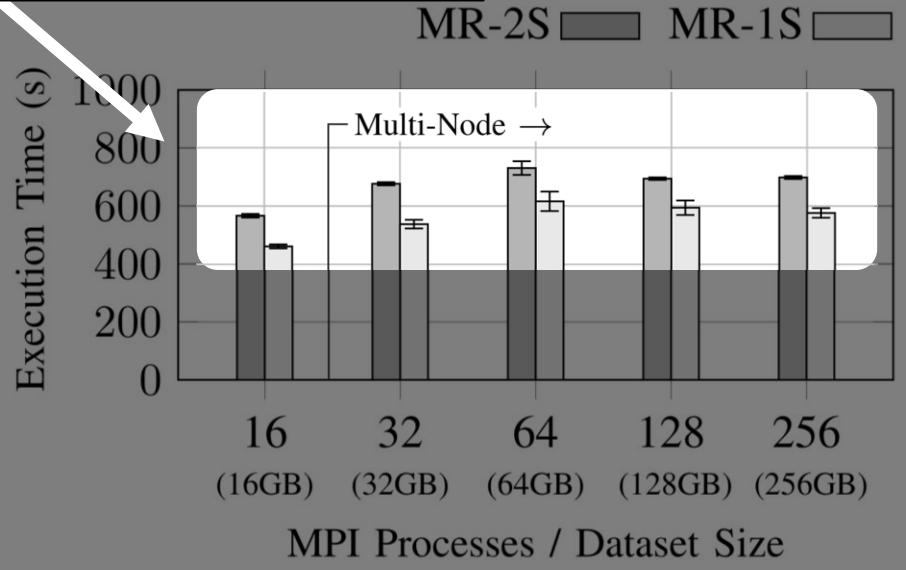
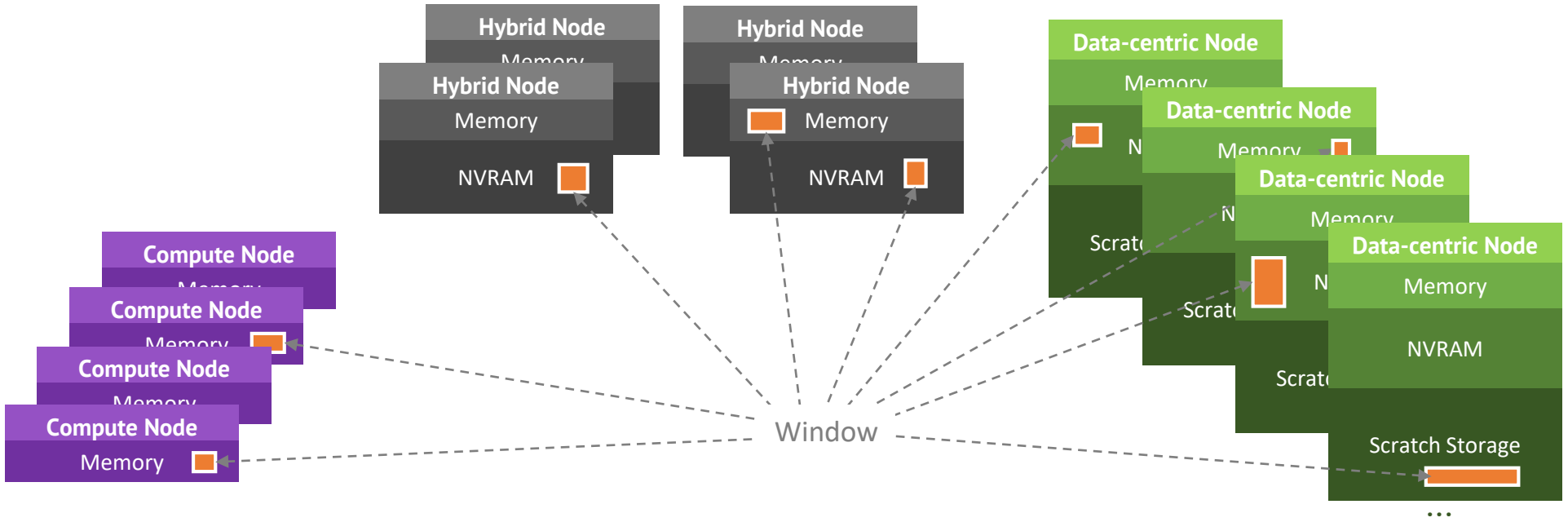


(d) **Weak Scaling Evaluation** under Unbalanced Workload

Background > MPI windows on storage

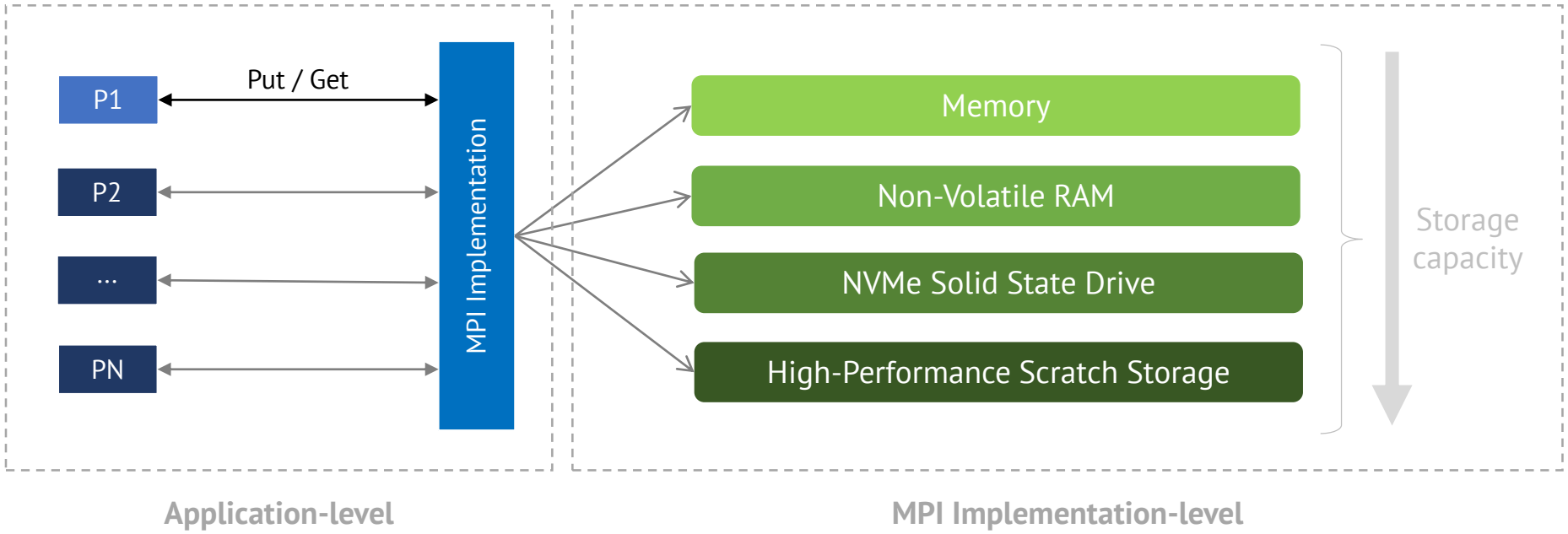
This on-going effort proposes to extend the concept of MPI window to storage. Hence, allowing programmers to map MPI windows to a wide-range of persistent storage devices:



S. Rivas-Gomez, R. Gioiosa, I. B. Peng, G. Kestor, S. Narasimhamurthy, E. Laure, and S. Markidis, "**MPI Windows on Storage for HPC Applications**," in Proceedings of the 24th European MPI Users' Group Meeting. ACM, 2017, p. 15. **[Best Paper Award]**

Background > Unified interface for conducting I/O

With MPI storage windows, **both memory and storage become accessible through the unified, familiar interface based of the MPI one-sided communication model:**



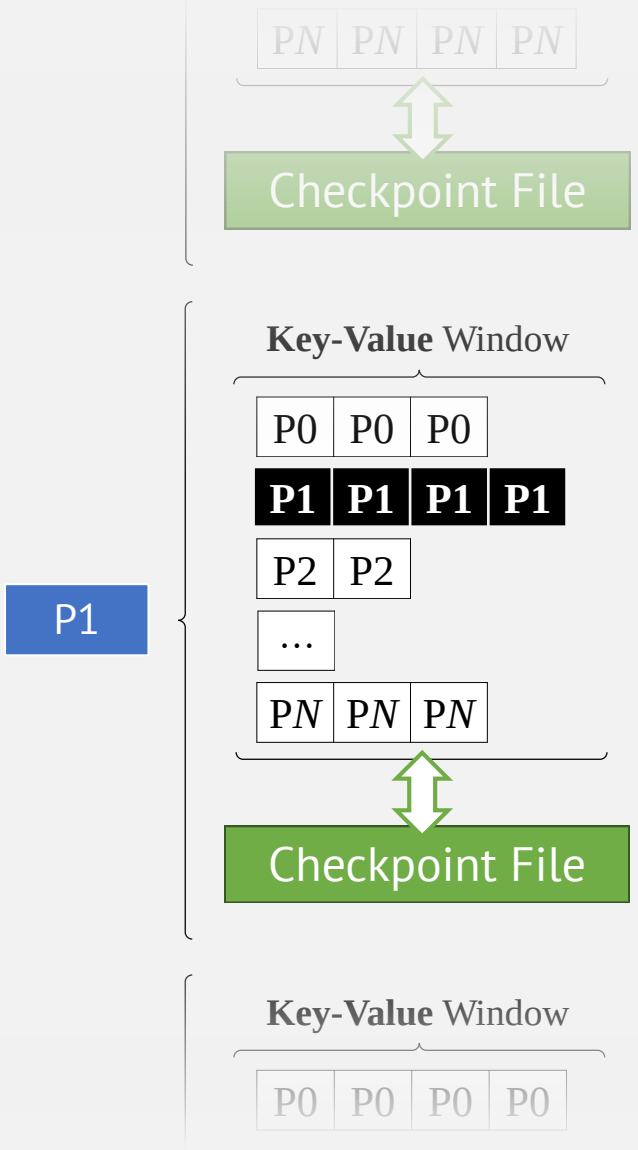
Evaluation > Transparent Checkpoint

With the arrival of the first wave of pre-Exascale machines, the chances for unexpected failures during the execution of parallel applications will considerably increase.

By integrating the concept of MPI storage windows, **we can define a novel checkpoint mechanism inside MapReduce-1S**.

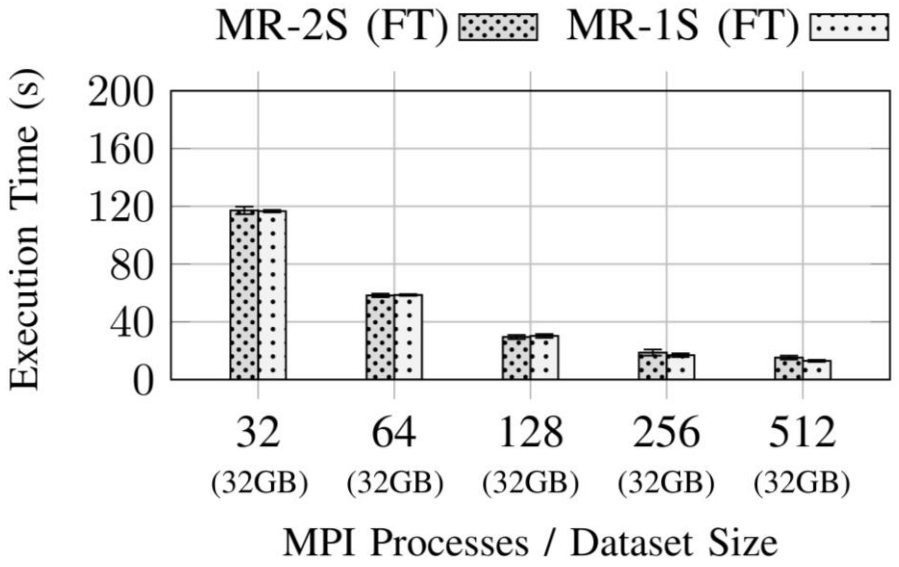
We introduce support for MPI storage windows and extend our approach to perform a window synchronization point after each Map task, as well as after the Reduce phase is completed.

In addition, **we extend MapReduce-2S to perform each checkpoint using MPI collective I/O instead.**



Experimental Results > Performance Evaluation

The following figure illustrates the checkpoint performance of each approach by varying the number of MPI processes on Tegner for a fixed-size input dataset (i.e., strong scaling), **under balanced workload**:



(a) **Strong Scaling Evaluation** with Checkpoint Support

(b) **Checkpoint Performance Overhead** (Strong Scaling)

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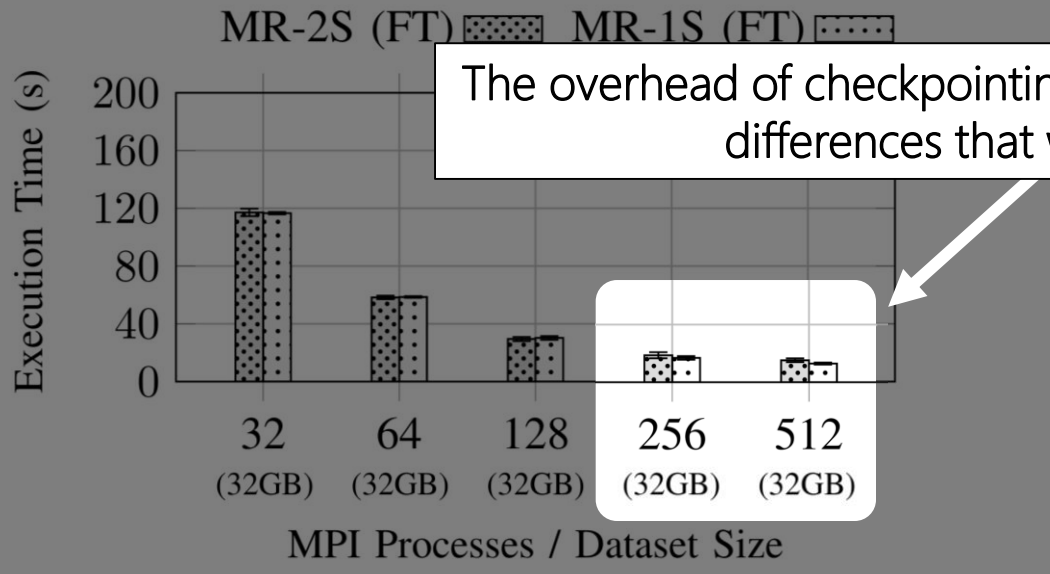
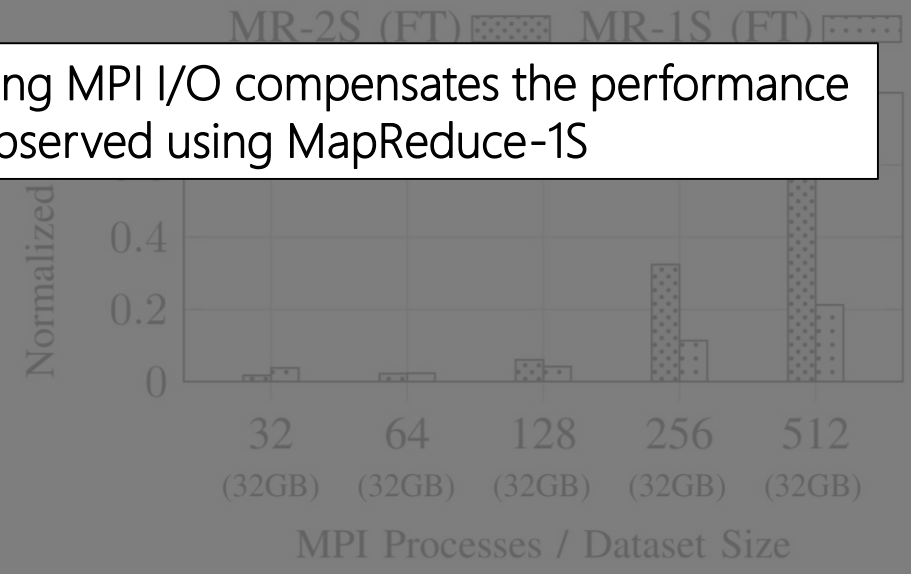


(a) **Strong Scaling Evaluation** with Checkpoint Support

The overhead of checkpointing using MPI I/O compensates the performance differences that we observed using MapReduce-1S

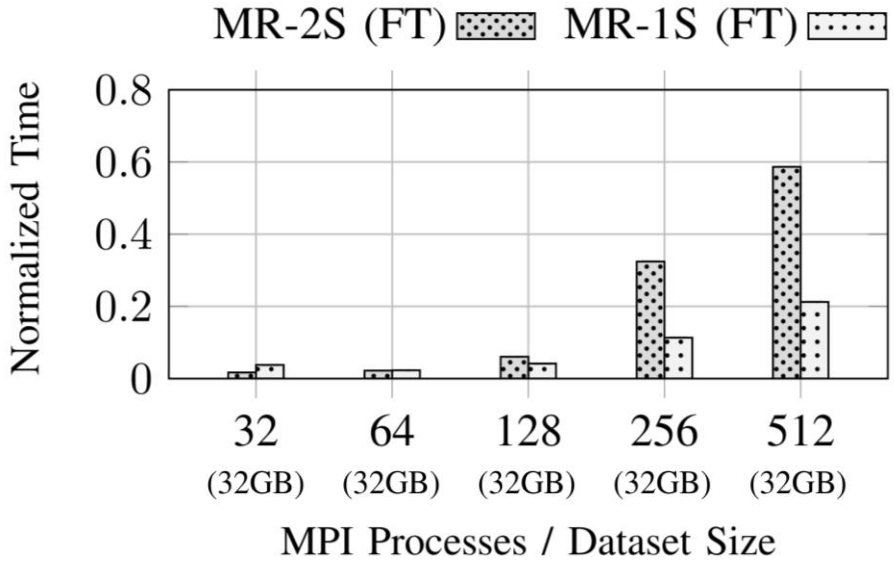


(b) **Checkpoint Performance Overhead** (Strong Scaling)

Experimental Results > Performance Evaluation

Using 512 processes, MapReduce-1S with checkpoint support is 17.6% faster in comparison with MapReduce-2S. In this particular case, **the checkpoint overhead is 21.2% for MapReduce-1S and 58.6% for MapReduce-2S**:

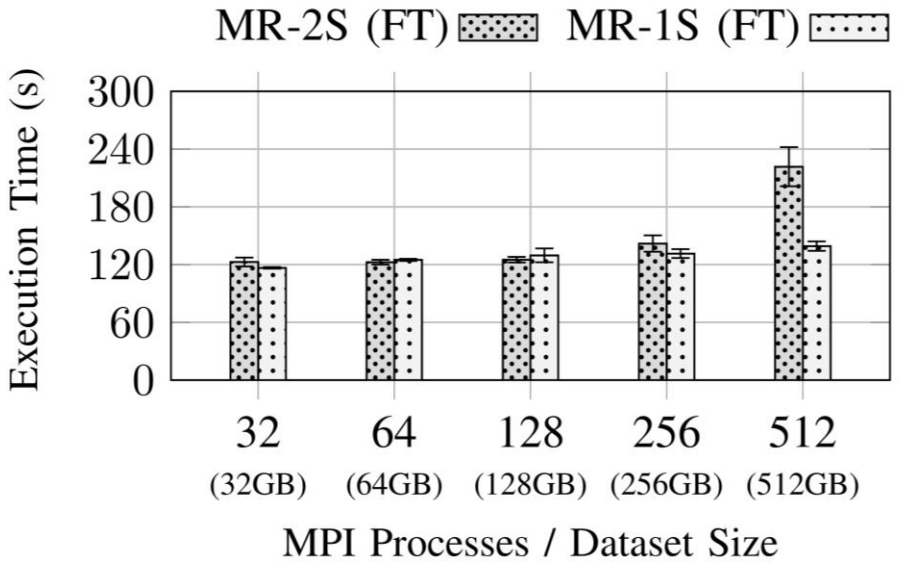
(a) **Strong Scaling Evaluation** with Checkpoint Support



(b) **Checkpoint Performance Overhead** (Strong Scaling)

Experimental Results > Performance Evaluation

The following figure illustrates the checkpoint performance of each approach by varying the number of MPI processes on Tegner for a variable-size input datasets (i.e., weak scaling), **under balanced workload**:



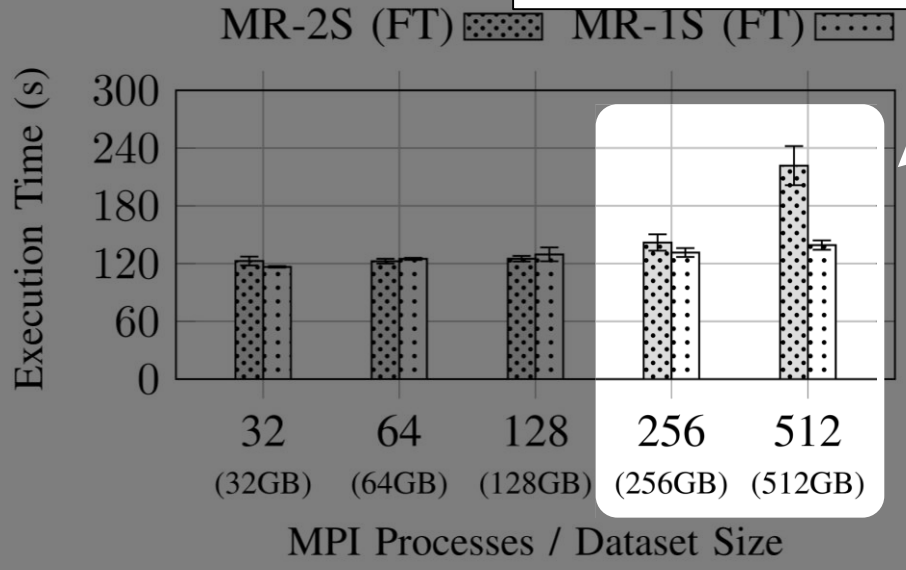
(c) **Weak Scaling Evaluation** with Checkpoint Support

(d) **Checkpoint Performance Overhead** (Weak Scaling)

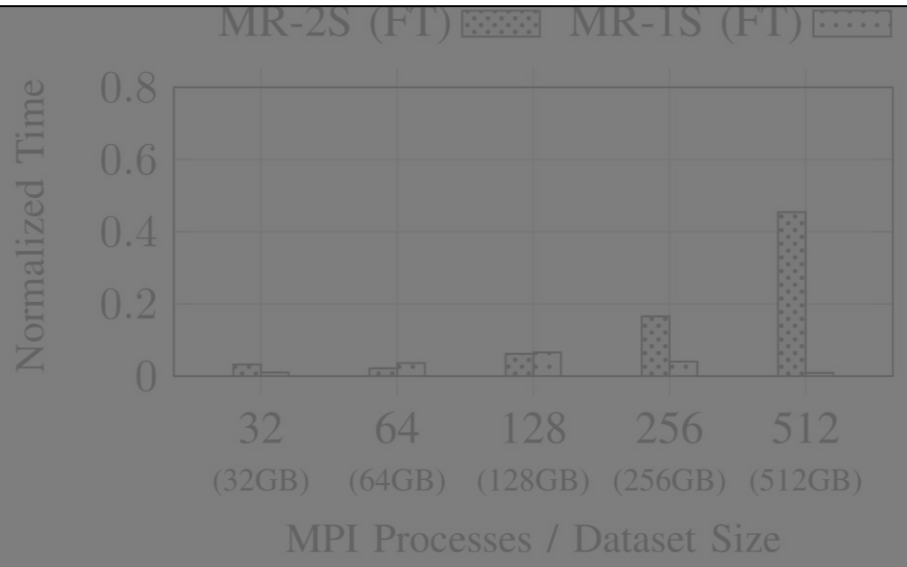
Experimental Results > Performance Evaluation

The following figure illustrates the checkpoint performance of each approach by varying the number of MPI processes on Tegner for a var

The overhead of checkpointing using MPI I/O is, once again, affected as the process count increases, making our approach more suitable



(c) **Weak Scaling Evaluation** with Checkpoint Support

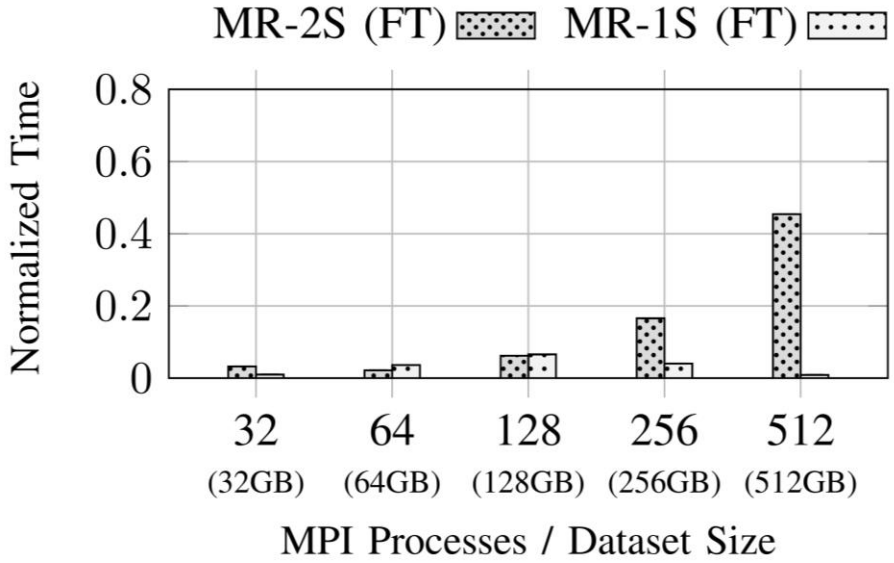


(d) **Checkpoint Performance Overhead** (Weak Scaling)

Experimental Results > Performance Evaluation

The performance of MapReduce-1S with checkpoint support is 59.3% faster in the last case of 512 processes, in comparison with MapReduce-2S. **The checkpoint overhead using MPI storage windows is only 3.8% on average**:

(c) **Weak Scaling Evaluation** with Checkpoint Support



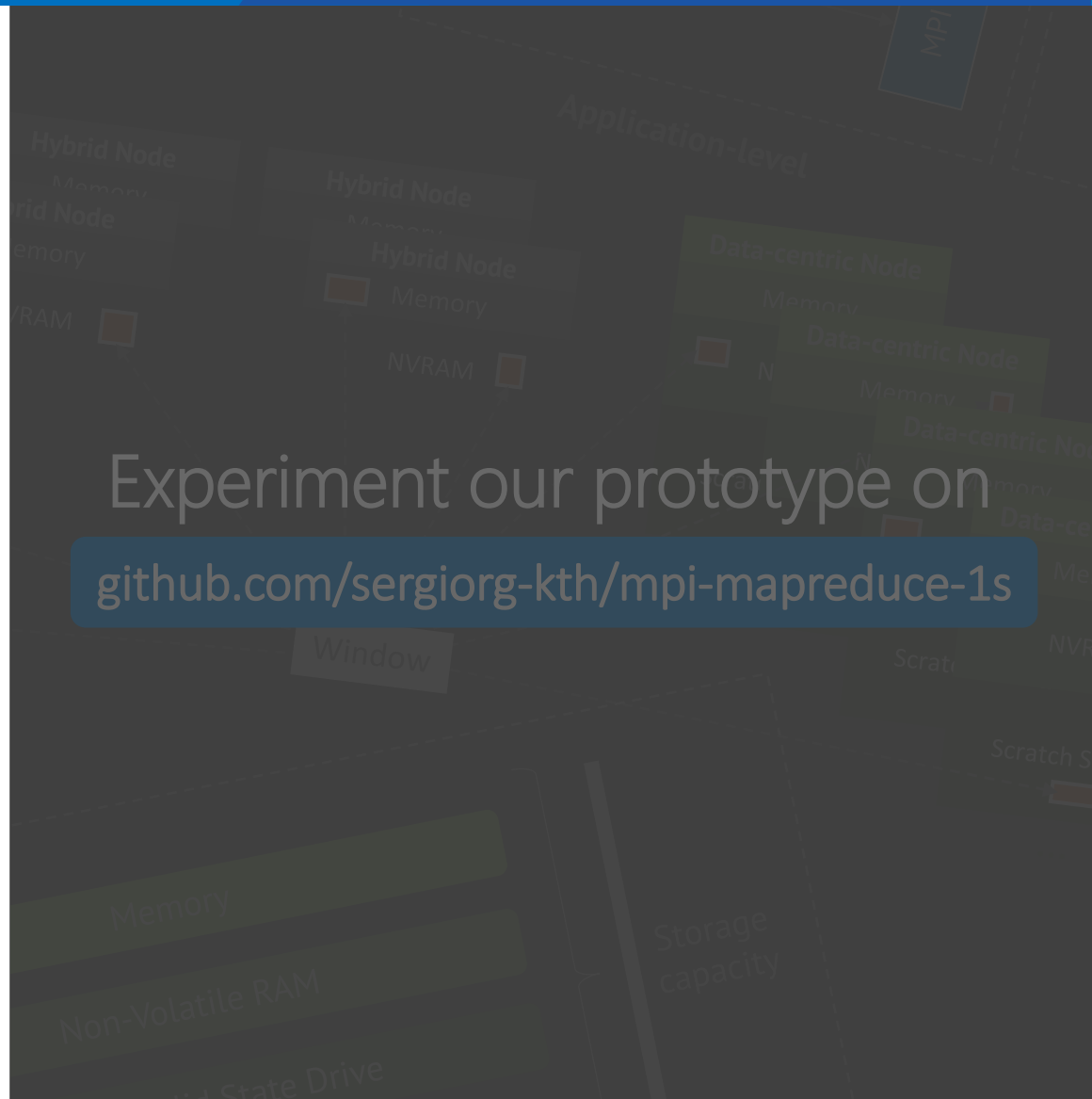
(d) **Checkpoint Performance Overhead** (Weak Scaling)

Conclusions

With the emergence of machine learning and data-centric applications on HPC, MapReduce has become one of the preferred programming models to hide the complexity of process and data parallelism.

We propose decoupled strategy for MapReduce:

- Hide the heterogeneity of upcoming HPC clusters.
- Overlap the Map and Reduce phases of MapReduce using MPI one-sided and non-blocking I/O.
- Benefits are limited on large-process counts and balanced workloads per process, but it does feature performance advantages on unbalanced workloads.
- Negligible performance degradation with checkpoint support using MPI storage windows.



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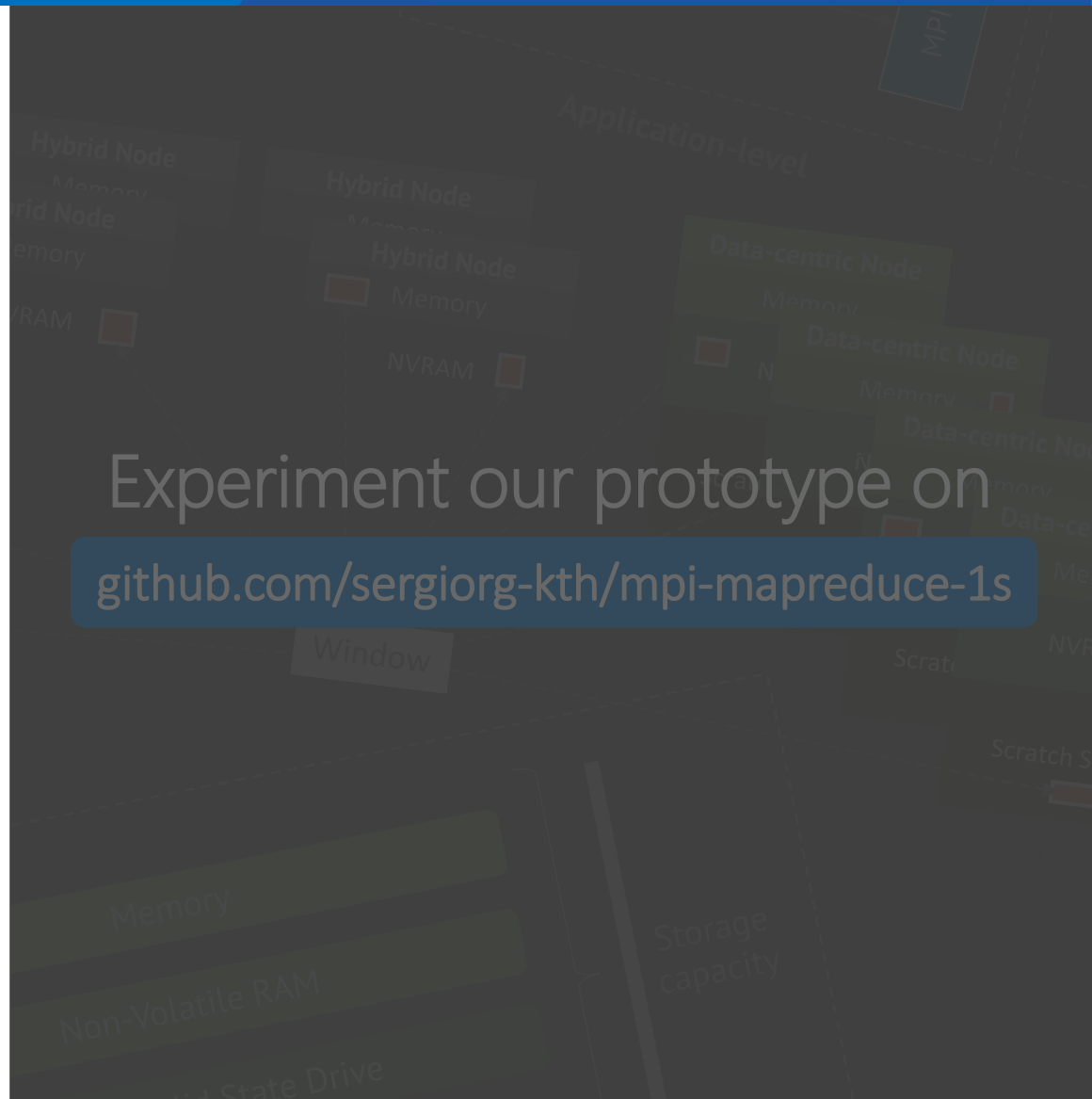

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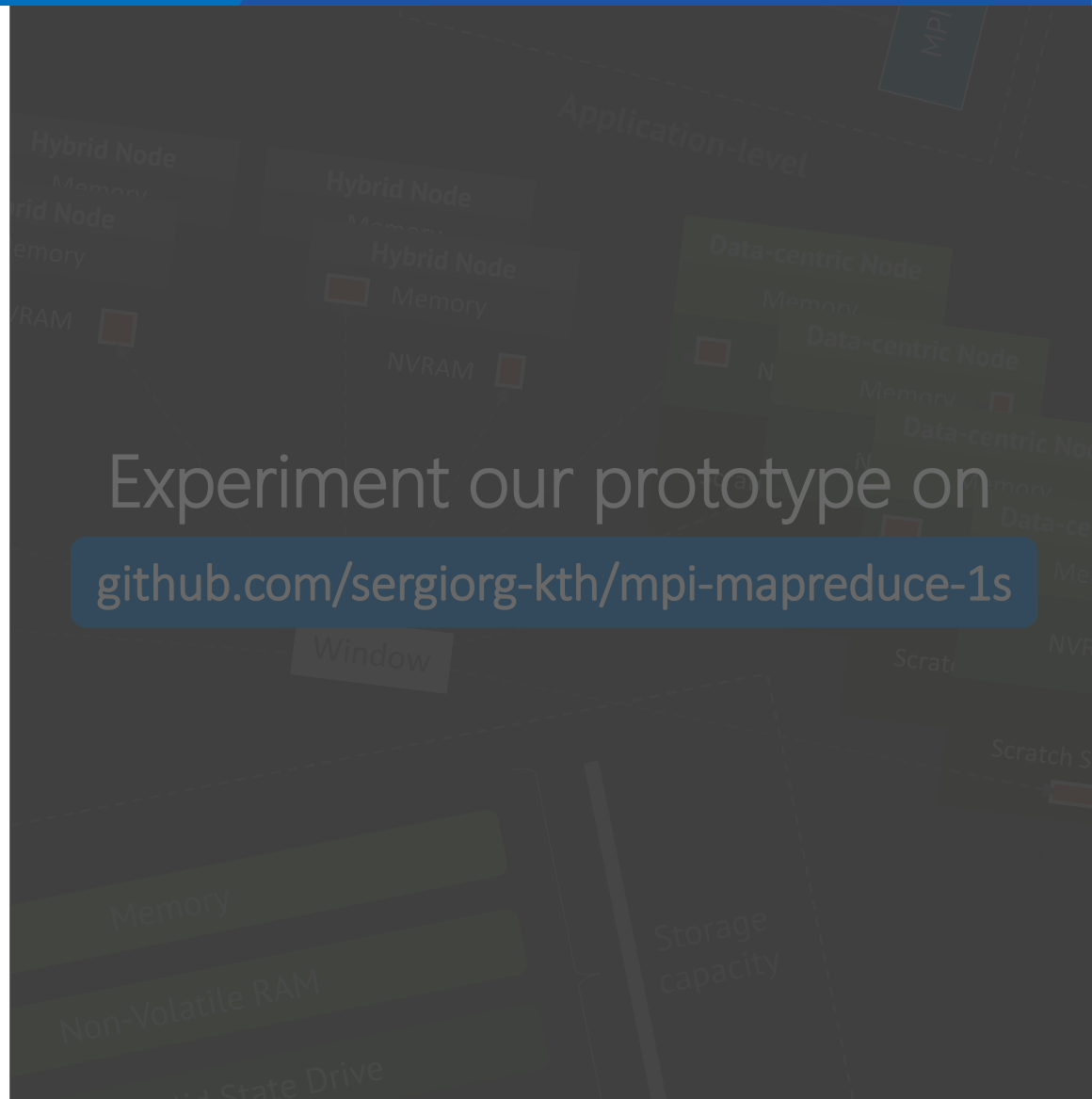

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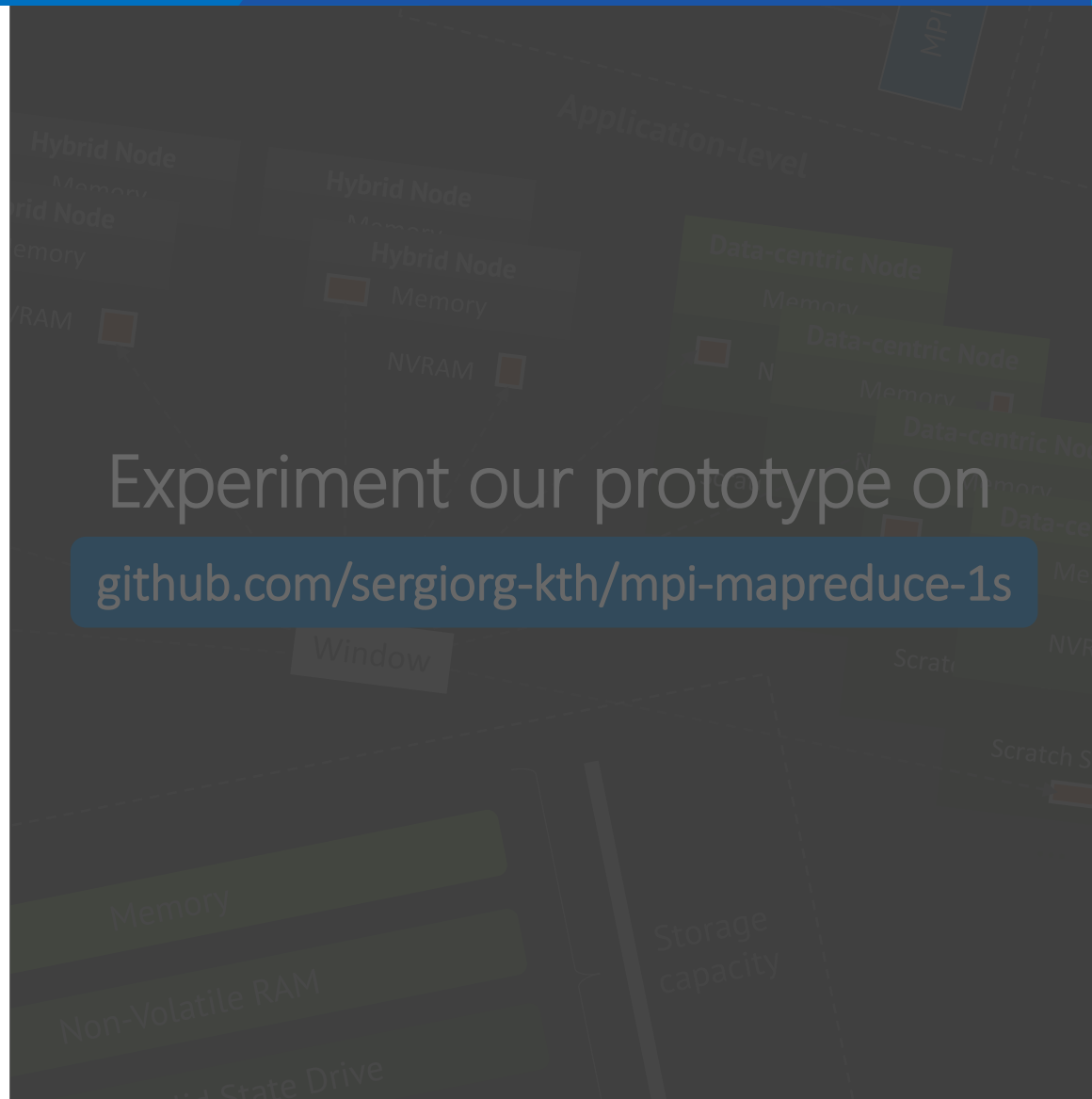

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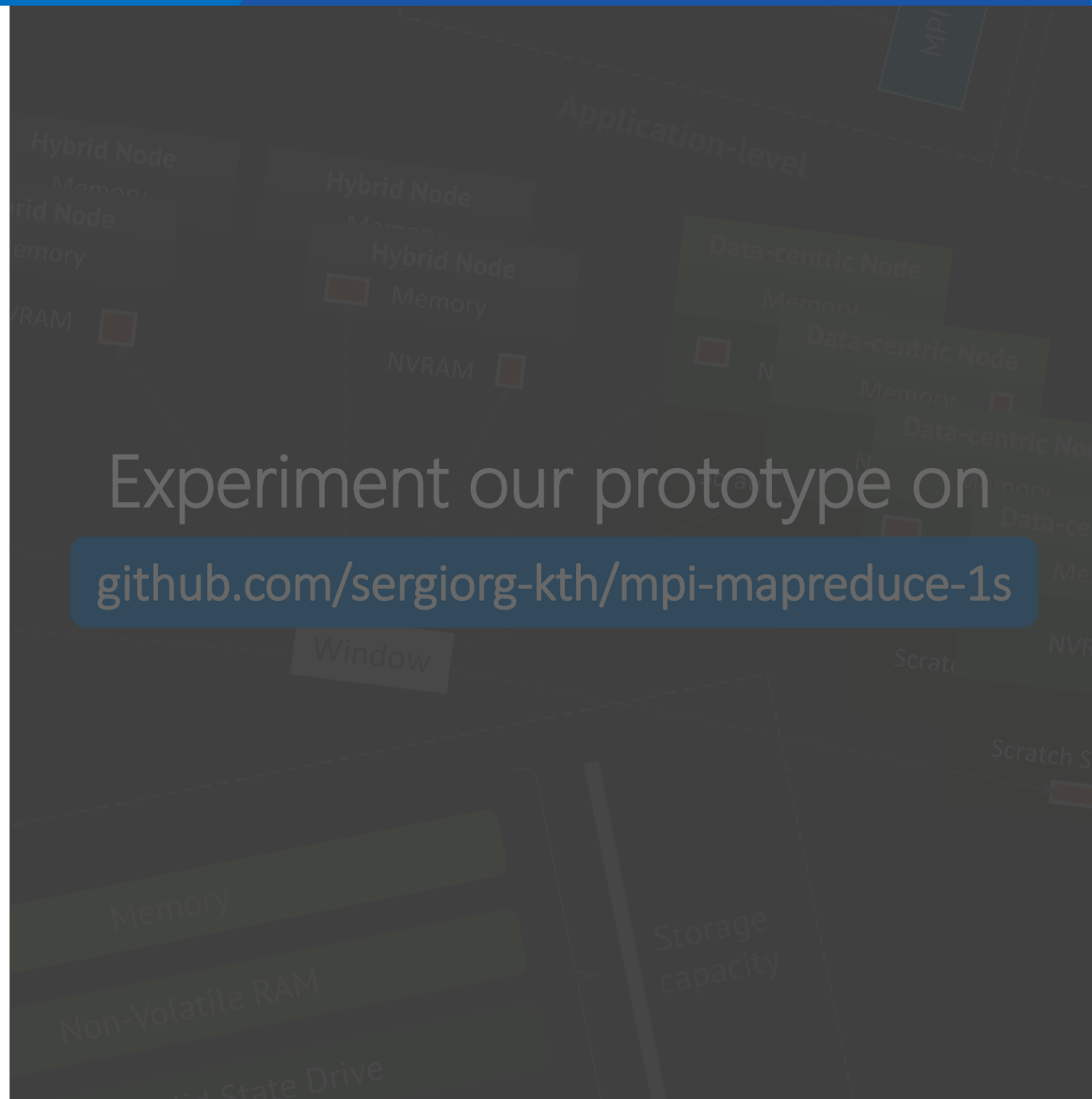

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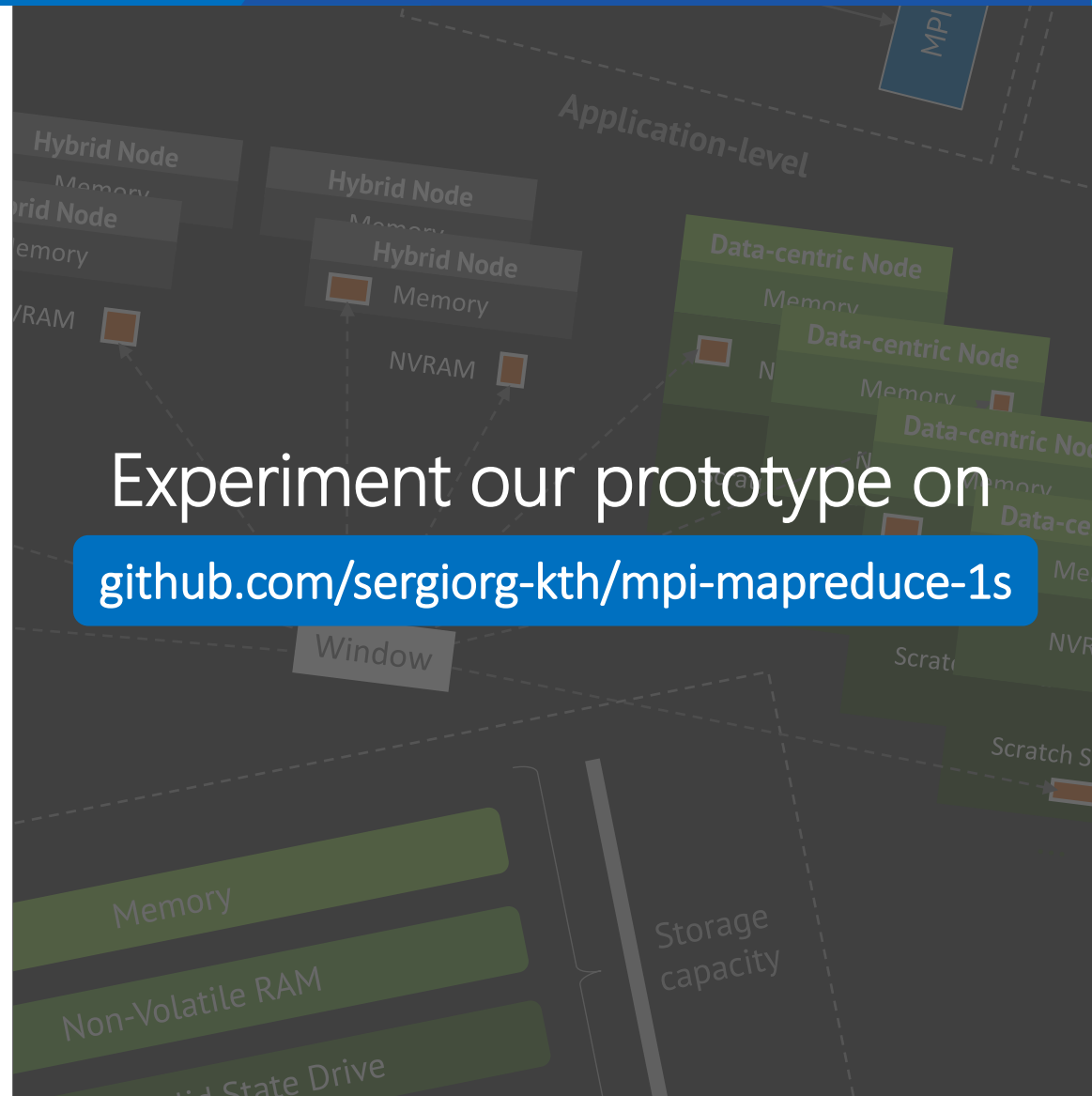

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for Research & Innovation

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[Grant agreement no. 671500 | More information on http://www.sagestorage.eu]

Thank you for coming!

Questions?