

# DON'T CRY OVER SPILLED RECORDS

Memory elasticity of data-parallel applications and its  
application to cluster scheduling

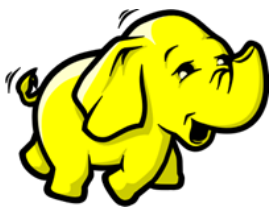
**Călin Iorgulescu** (EPFL), Florin Dinu (EPFL), Aunn Raza (NUST Pakistan),  
Wajih Ul Hassan (UIUC), Willy Zwaenepoel (EPFL)



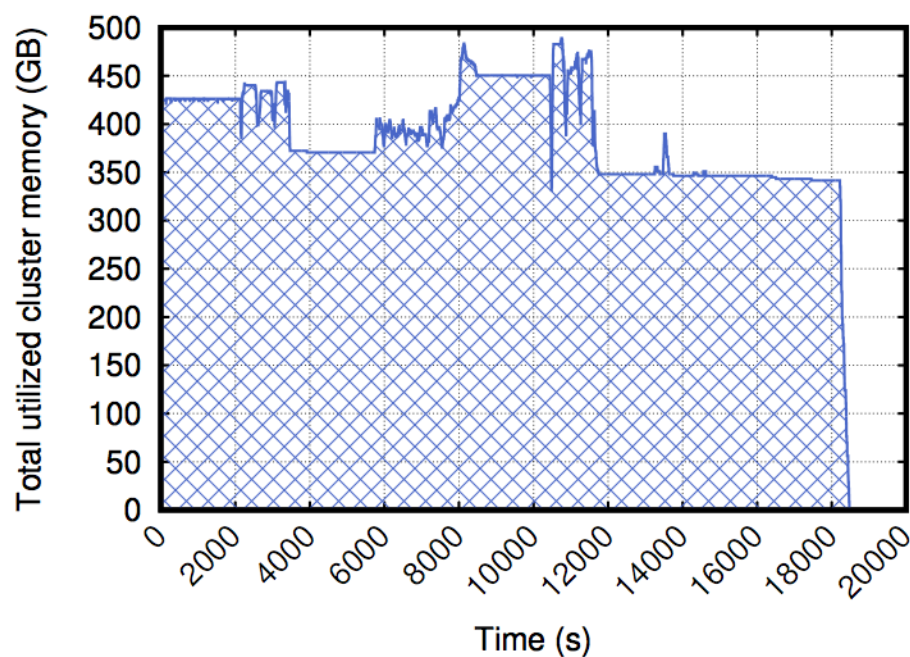
ÉCOLE POLYTECHNIQUE  
FÉDÉRALE DE LAUSANNE

# Cluster operators care about resource utilization

- ✓ Best bang for your buck!
- ✓ Maximize performance of data-parallel applications
- Idea: Efficient resource utilization through **under-provisioning**



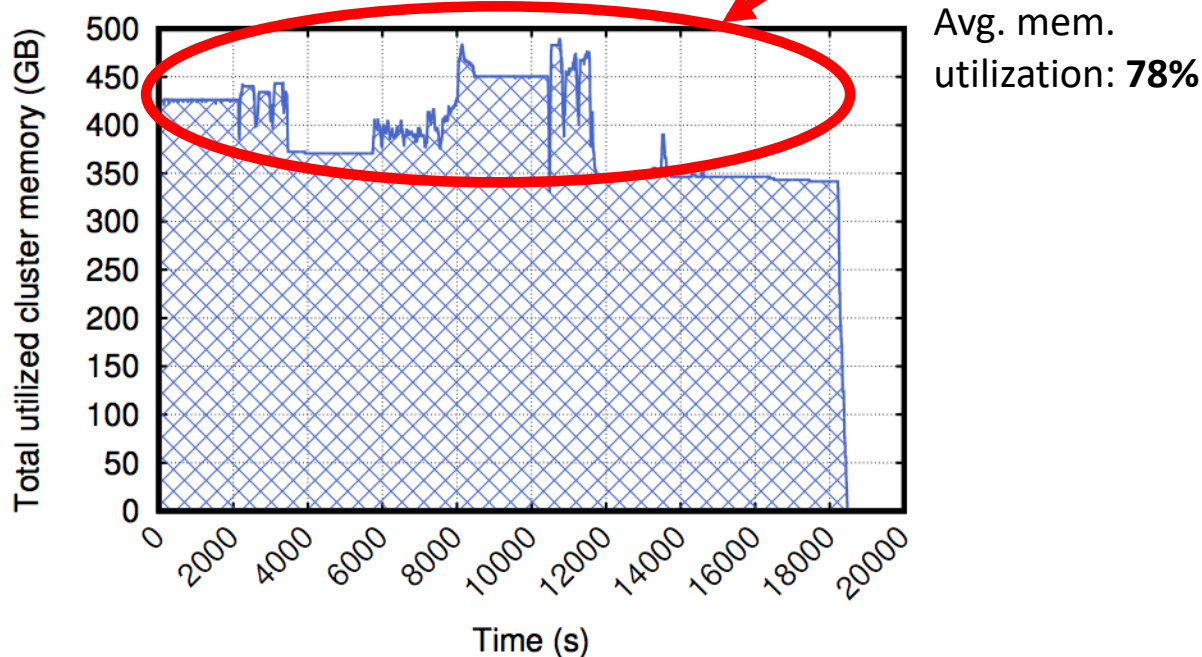
# Cluster memory is under-utilized!



Avg. mem.  
utilization: **78%**

# Cluster memory is under-utilized!

Leverage this idle memory!



# Impact of memory constraining applications

- Conventional wisdom: do not touch memory!
- Risks:
  - crashes
  - severe performance degradation (e.g., thrashing)



Can we safely, deterministically, and with modest impact constrain memory?

# Context: batch jobs and their memory usage

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Input

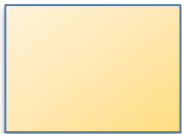


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**Input**



**Ideal**  
memory



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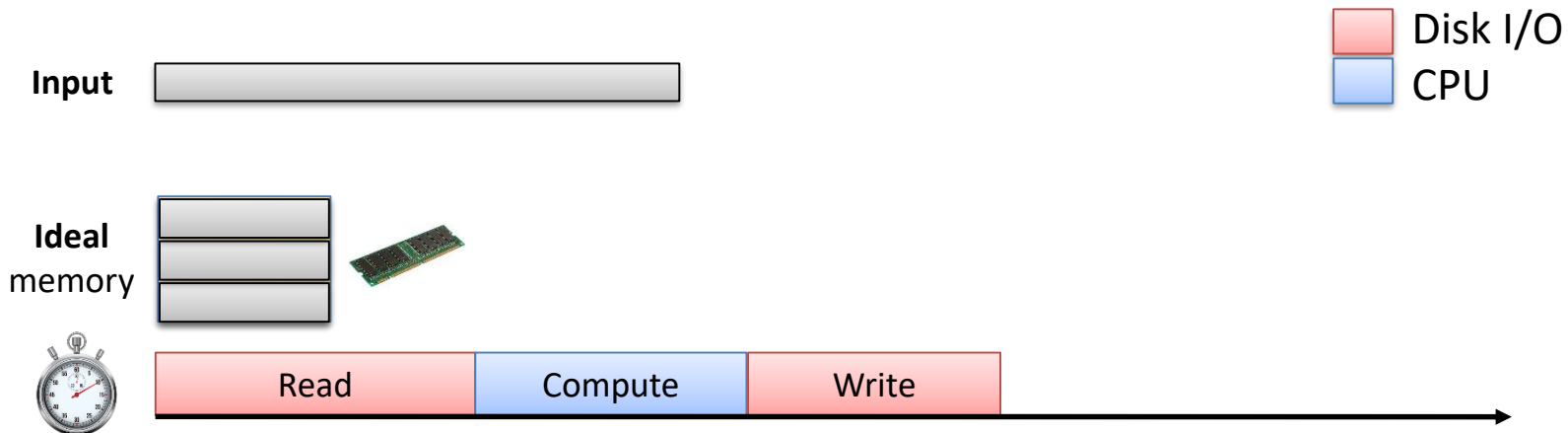
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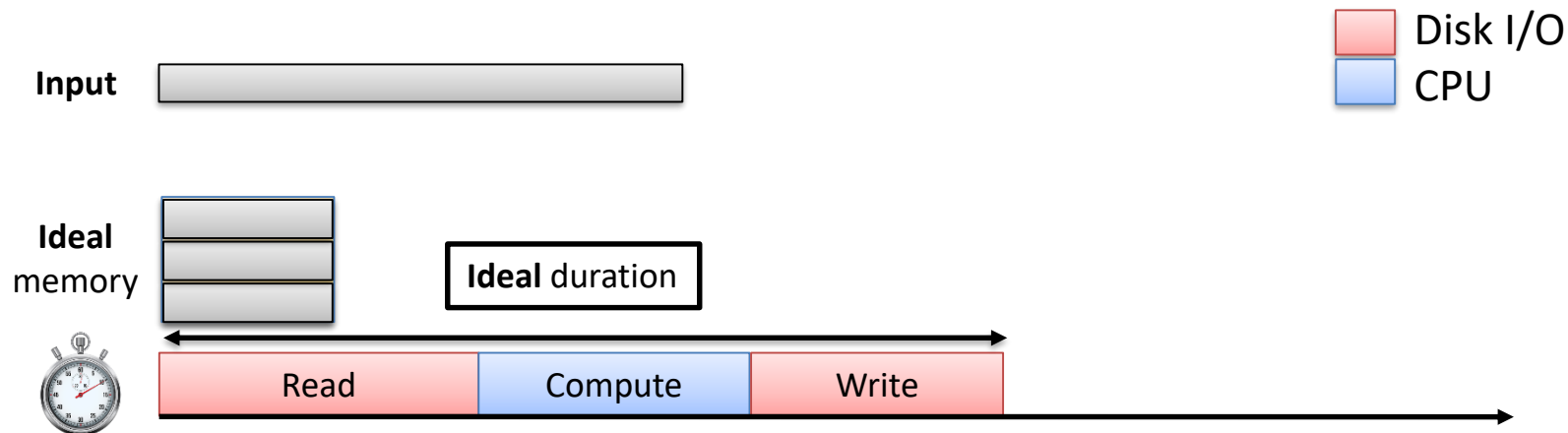
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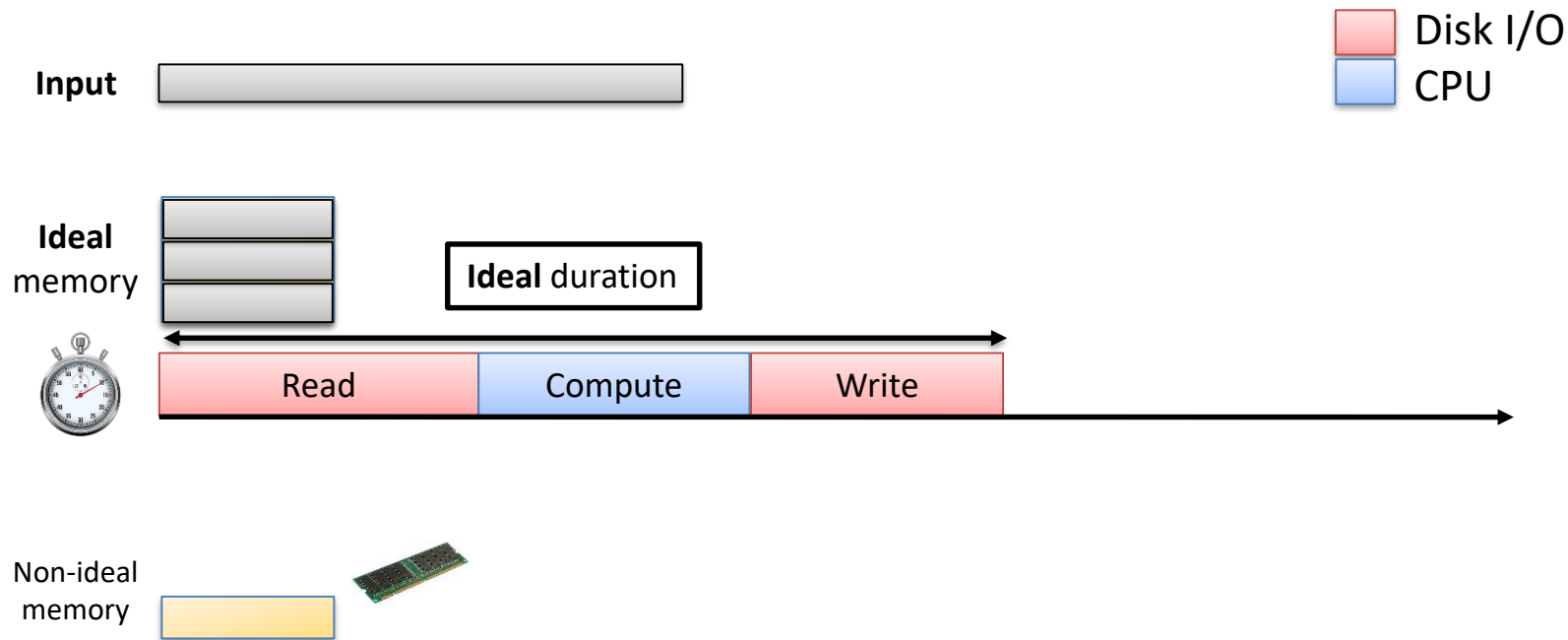
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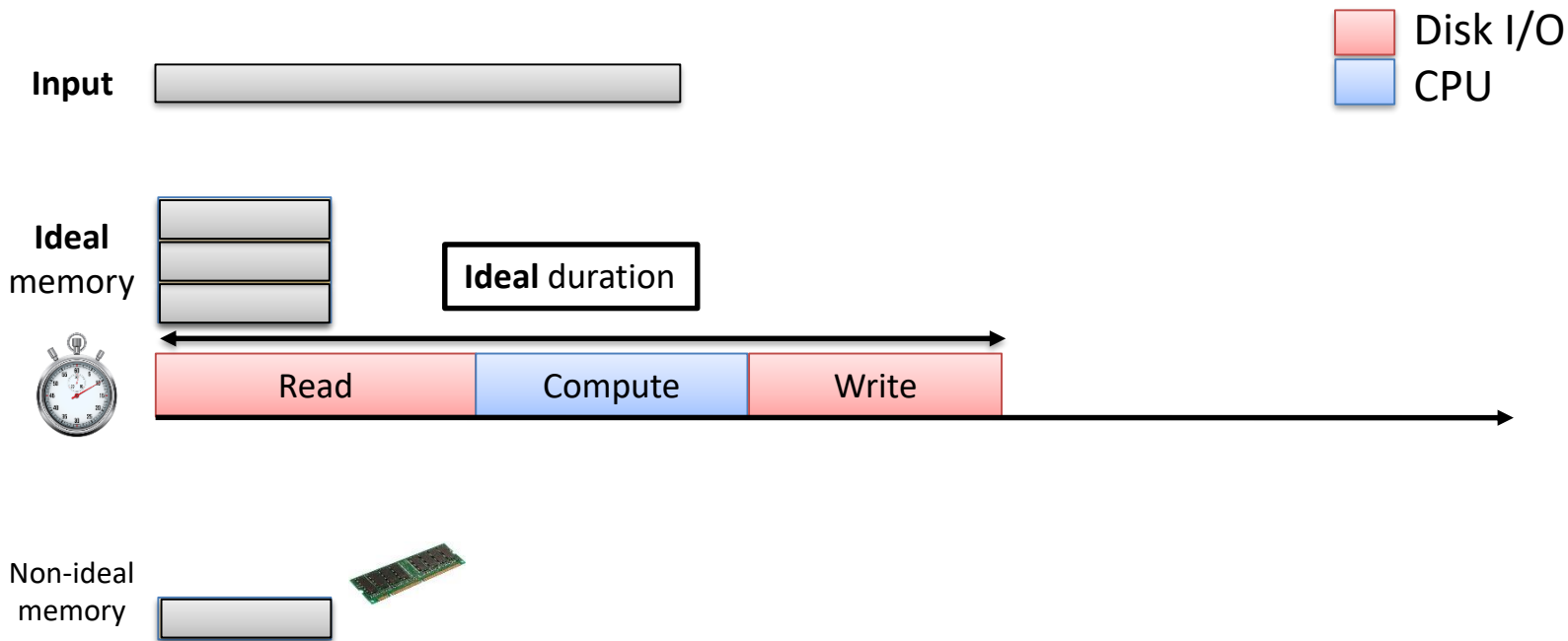
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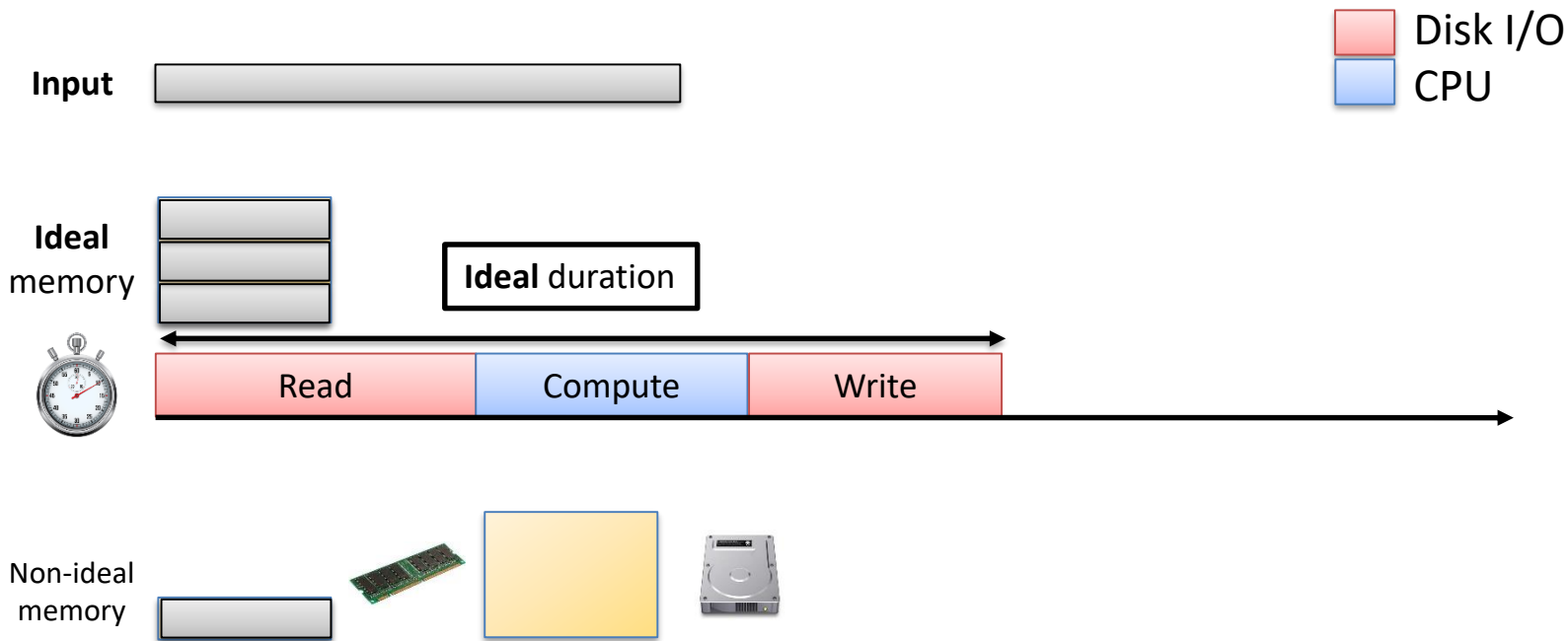
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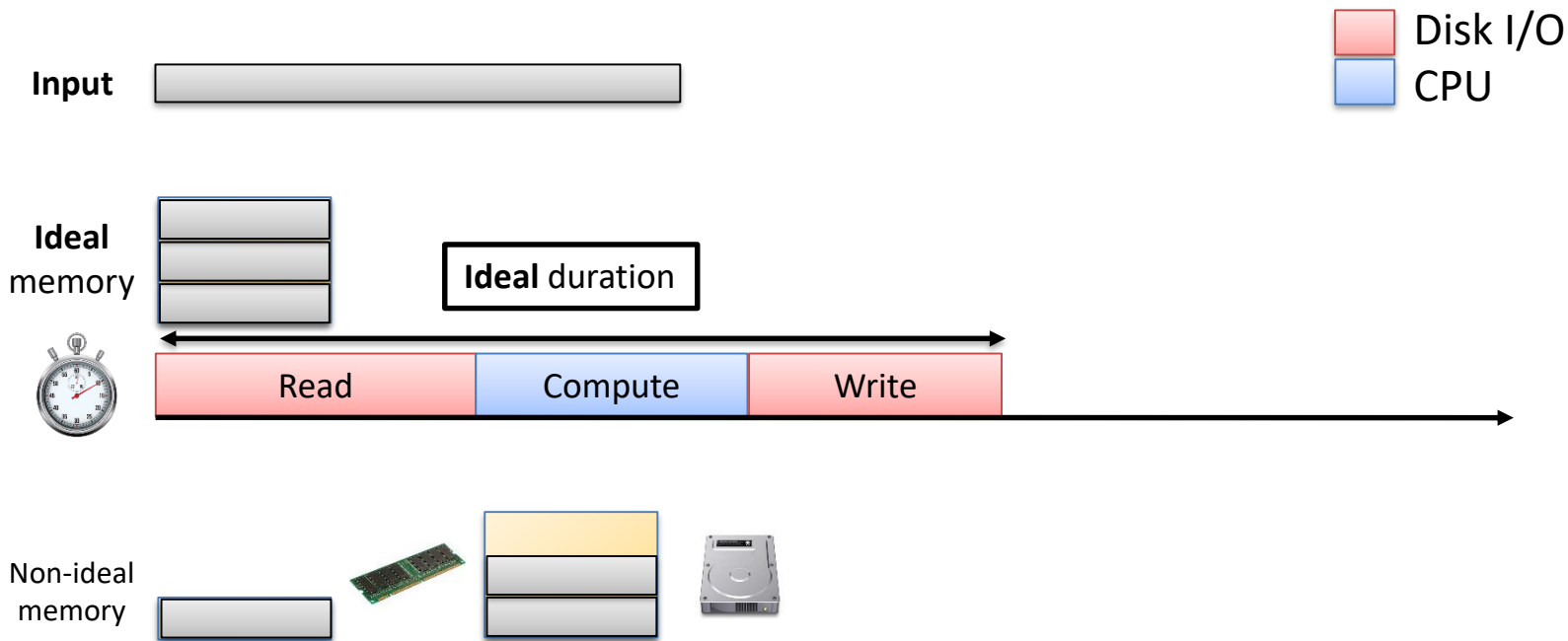
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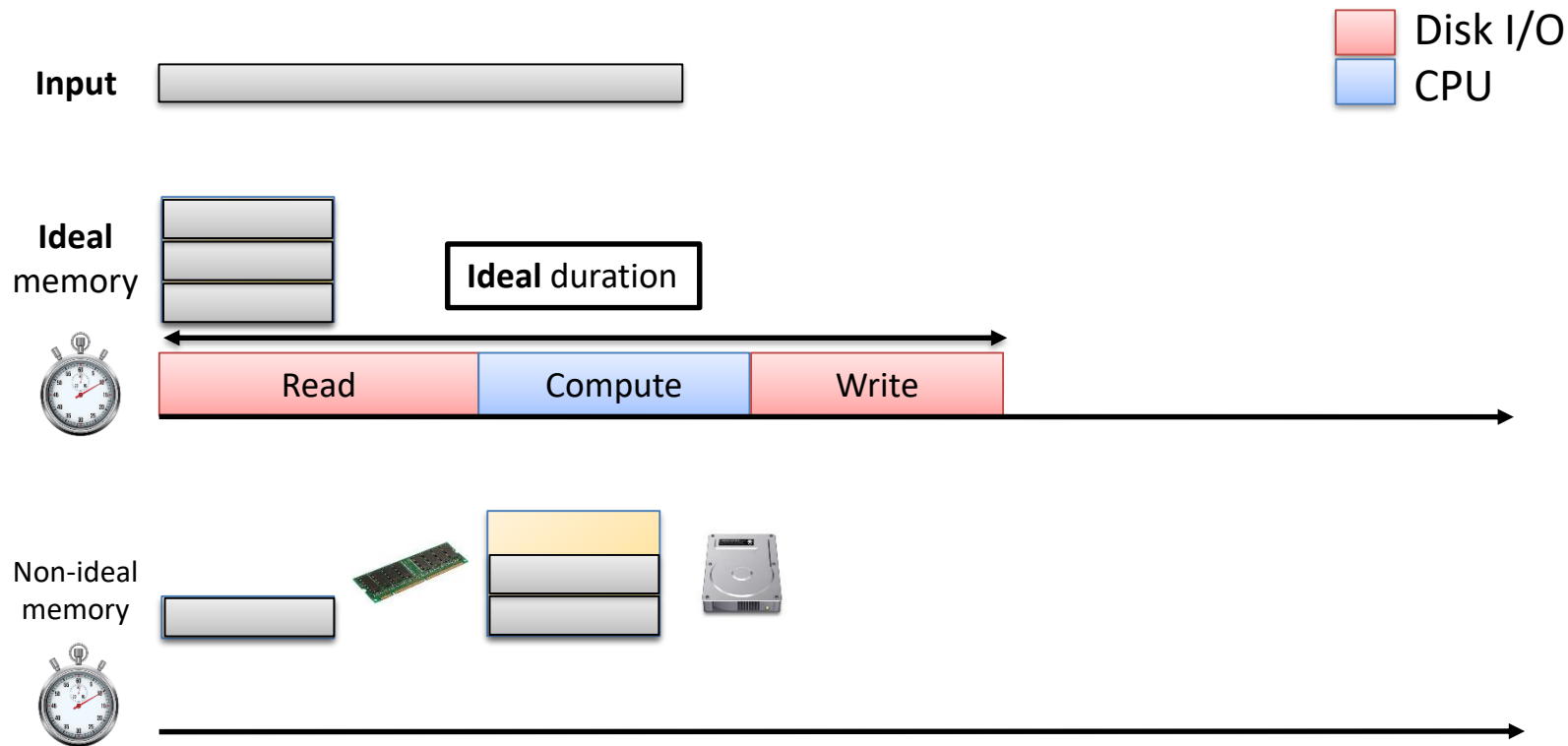
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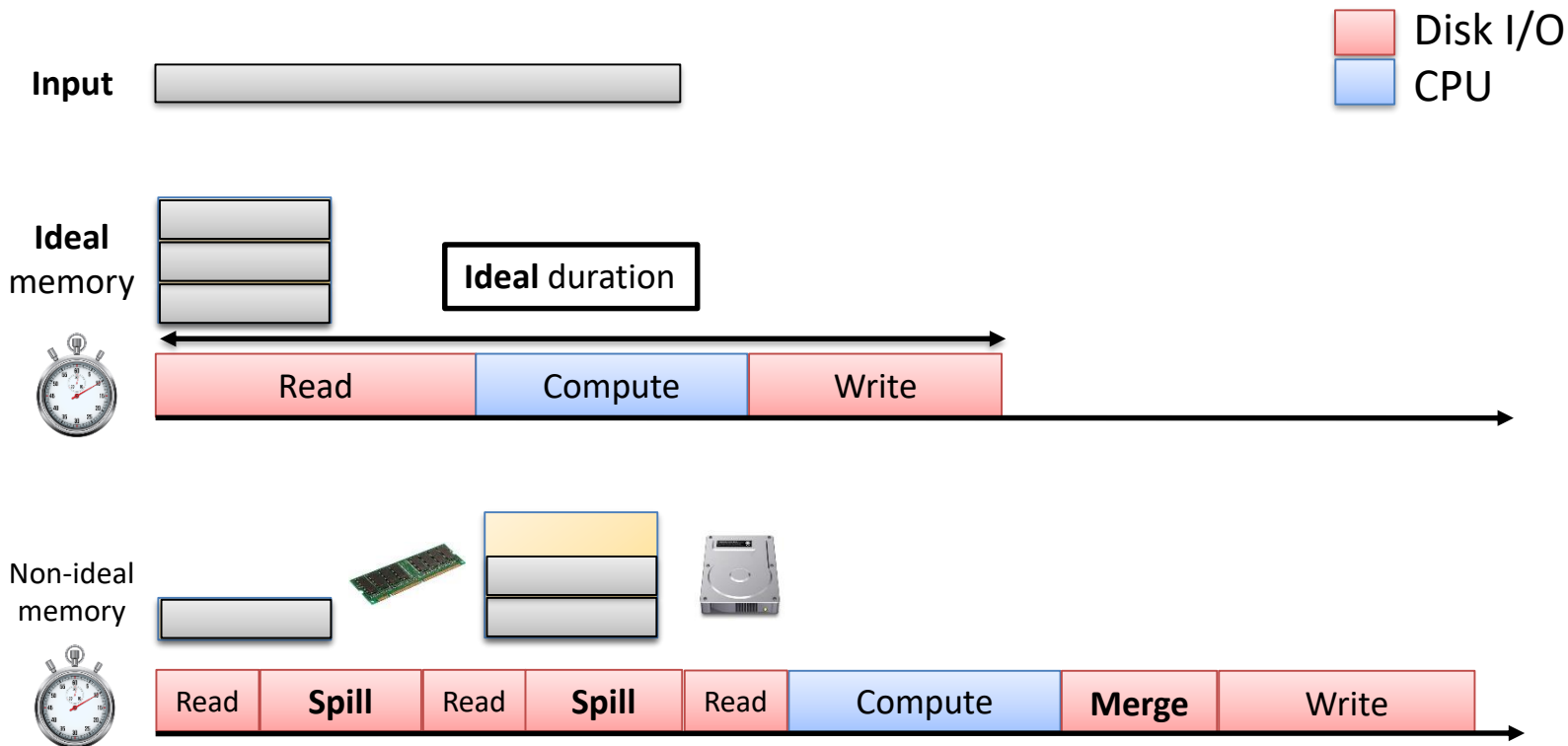
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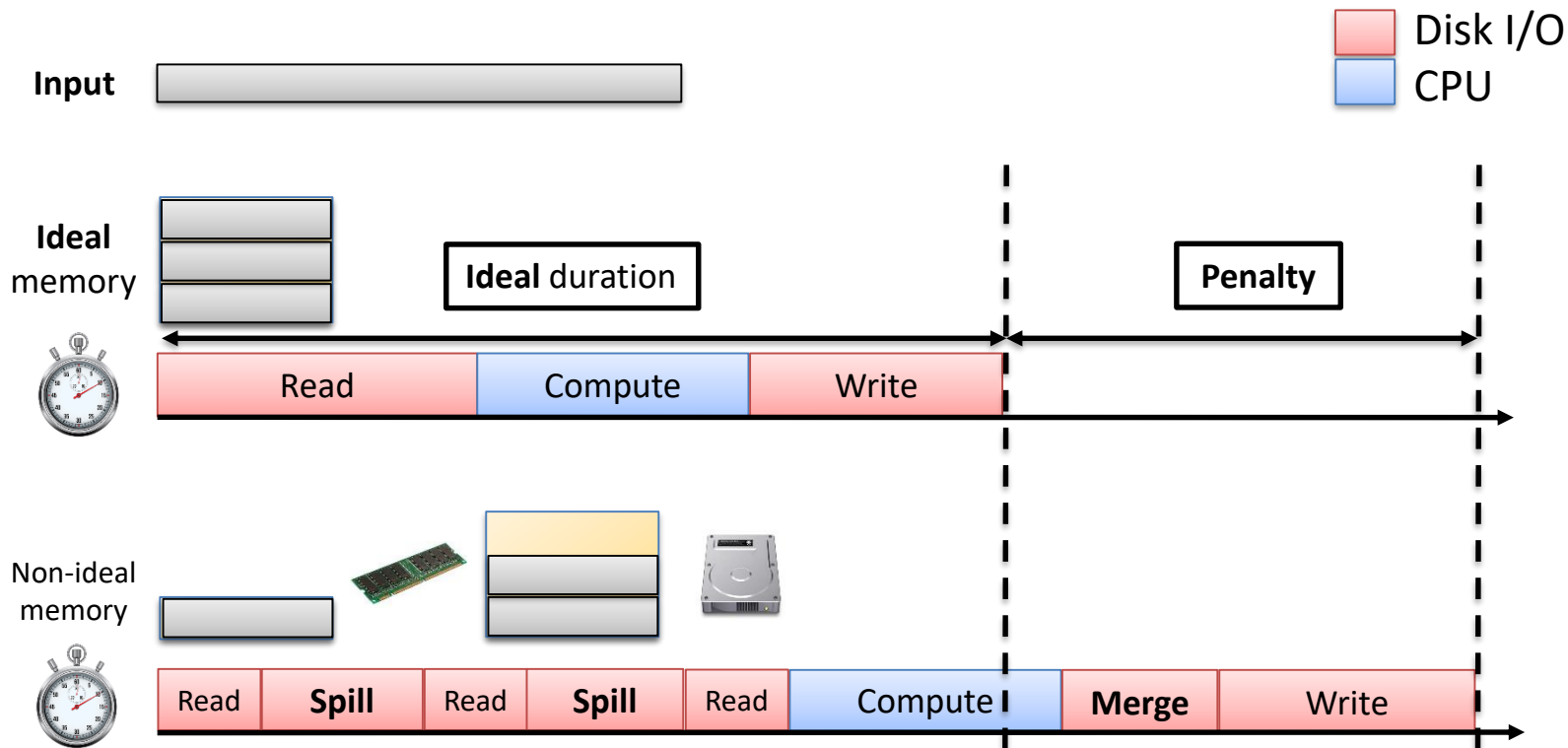
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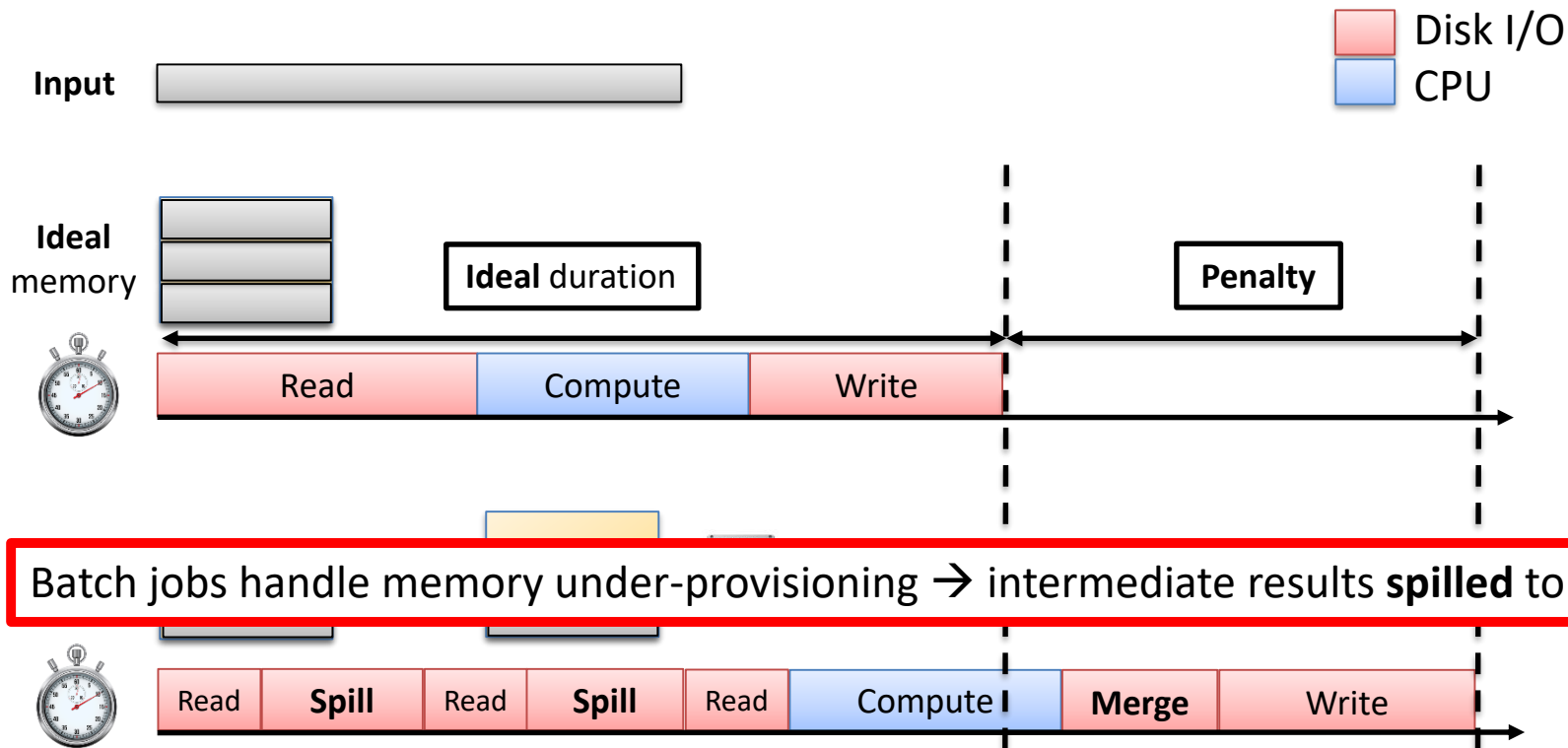
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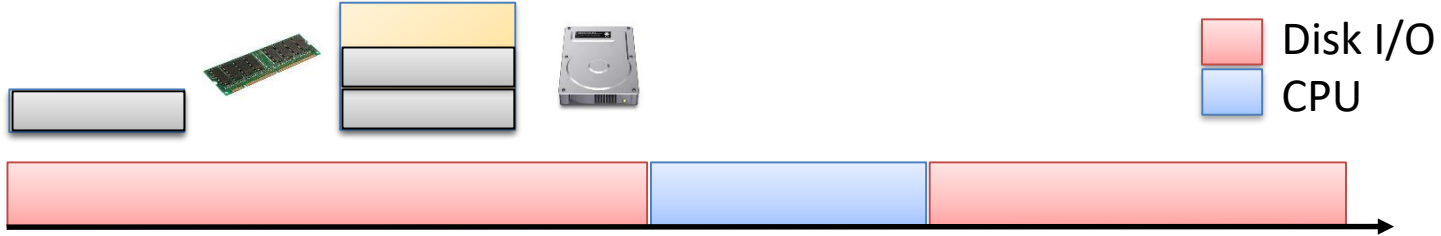
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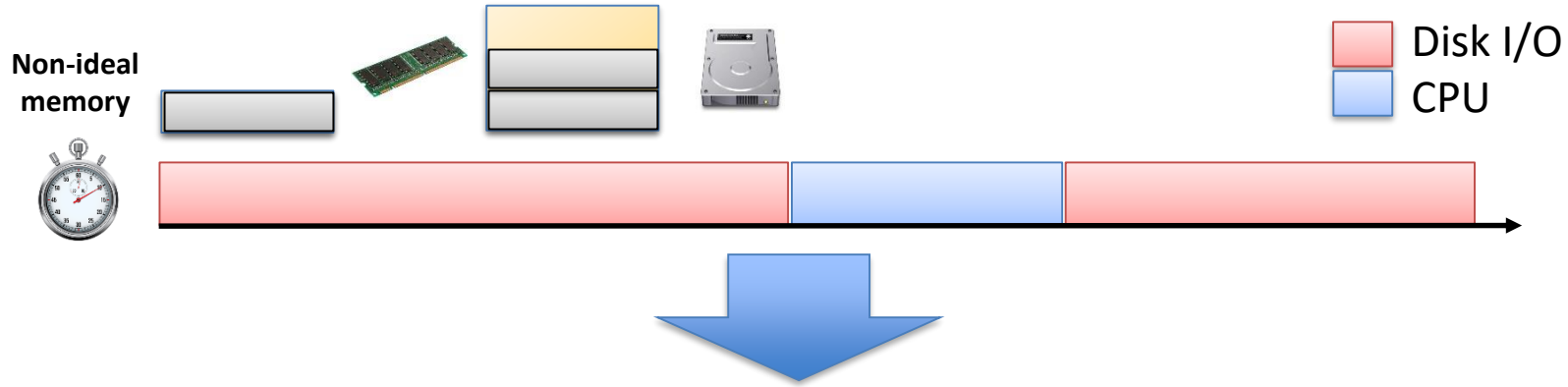
# MEMORY ELASTICITY

# What is Memory Elasticity?

Non-ideal  
memory

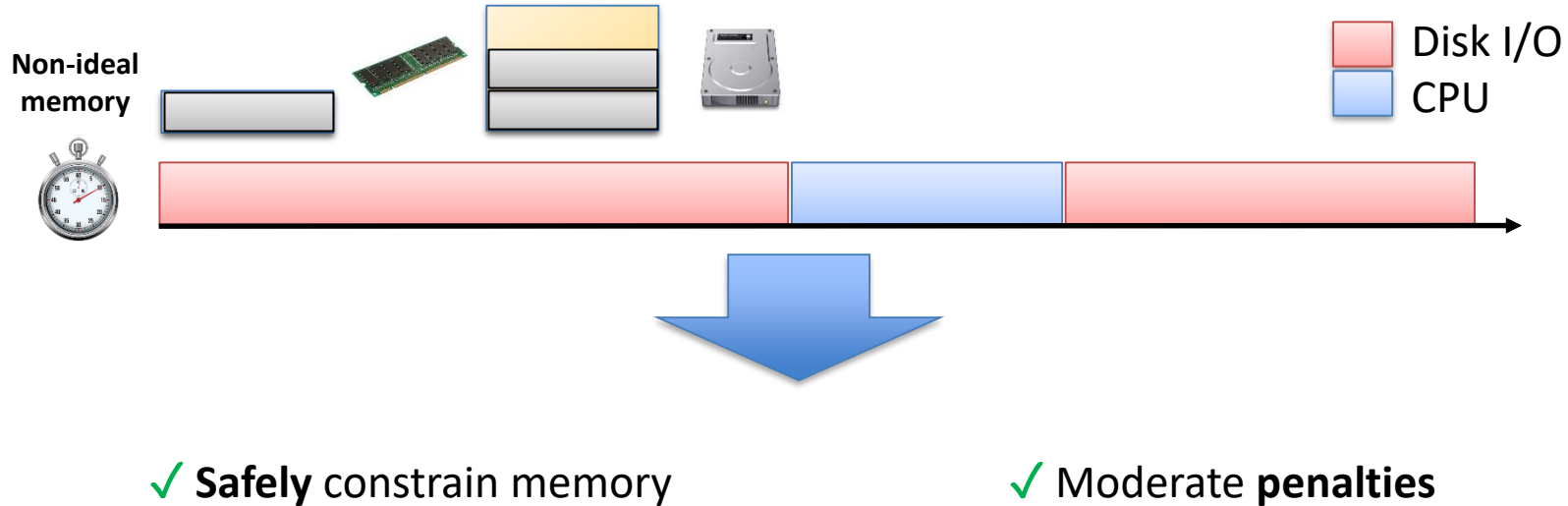


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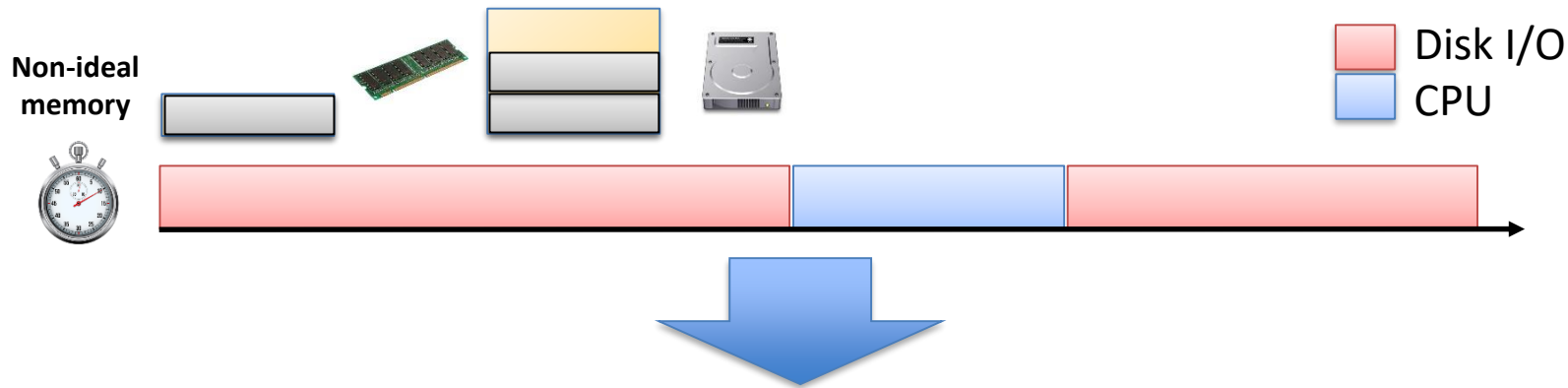


✓ **Safely** constrain memory

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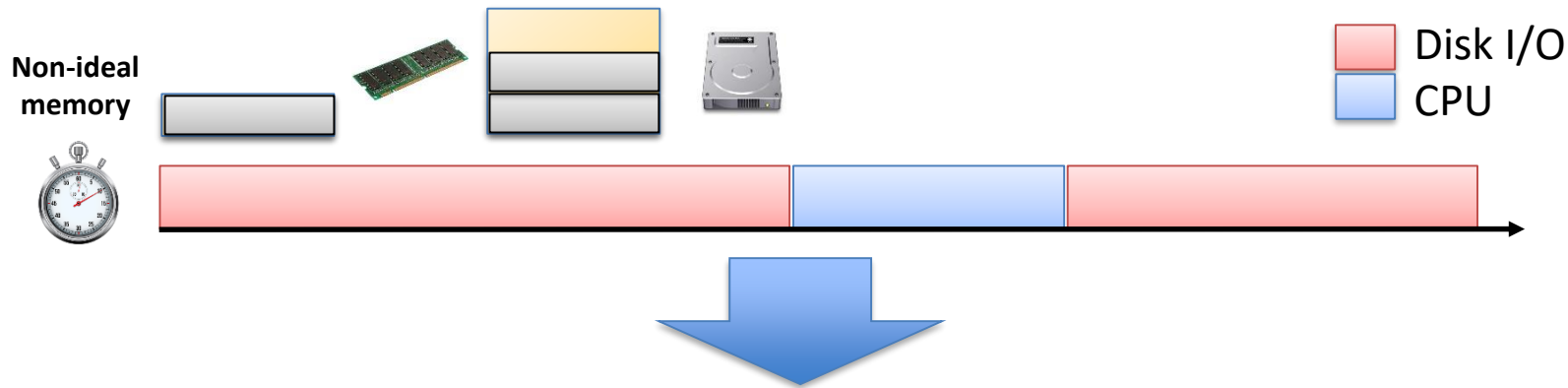


✓ **Safely** constrain memory

✓ Moderate **penalties**

✓ Highly **predictable**

# What is Memory Elasticity?



✓ **Safely** constrain memory

✓ Moderate **penalties**

✓ Highly **predictable**

✓ **Ubiquitous** for most data-parallel apps

# An empirical study of Memory Elasticity

- Analysis of 18 jobs across 8 different applications
- Constrain tasks' memory → measure **penalty**
- Bypass disk buffer cache (to not mask impact of spilling to disk)

# Questions about Memory Elasticity

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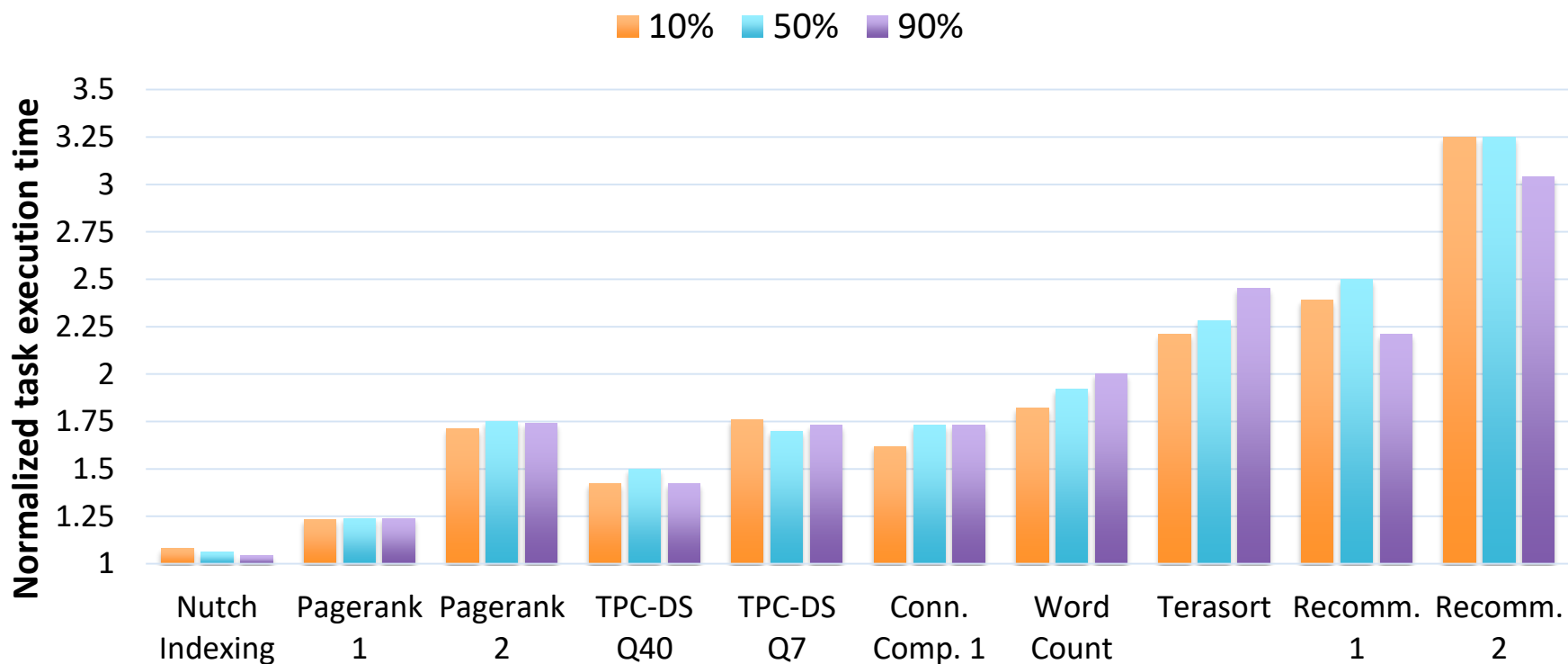
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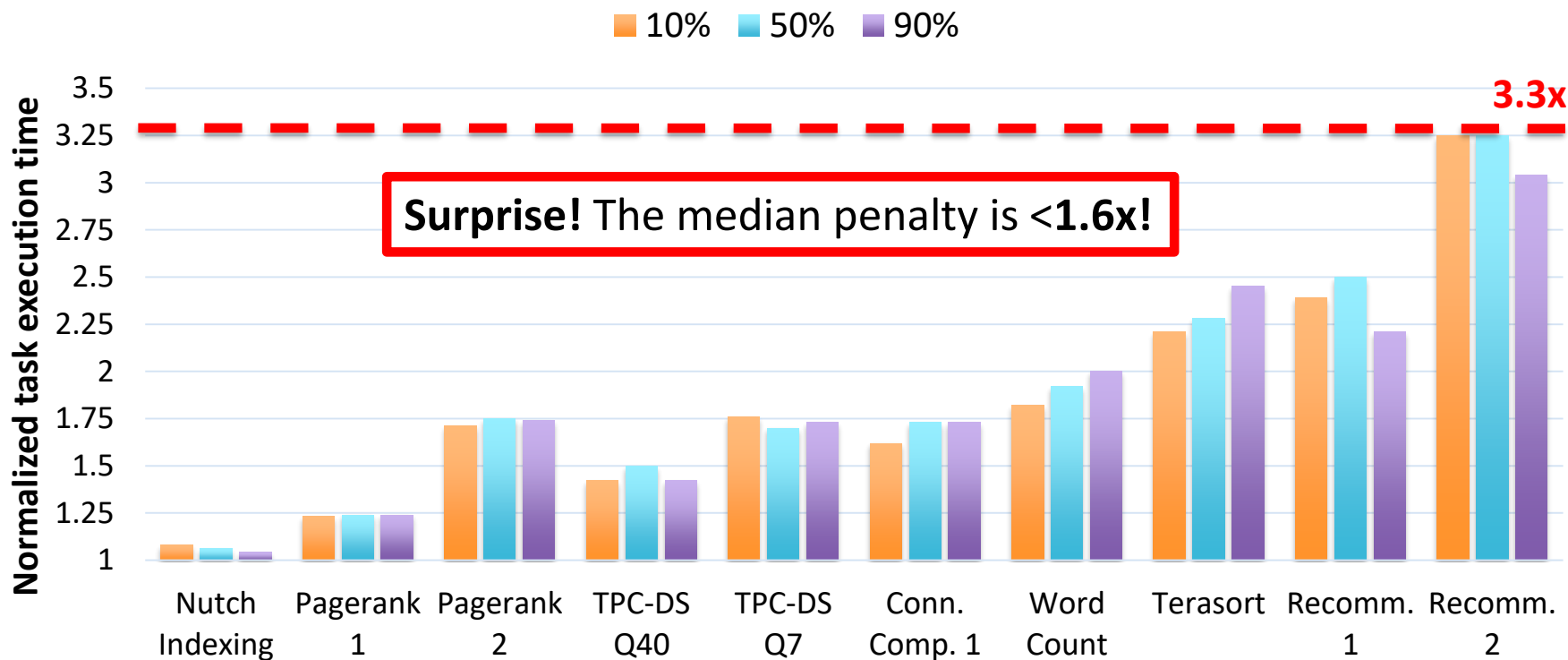
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**NOT  
SO  
MUCH!**

# Elasticity of Hadoop workloads: **Reducers**



# Elasticity of Hadoop workloads: Reducers



# Why are the penalties so modest?

Data buffer – most of app. memory

- Memory pressure absorbed by data buffer

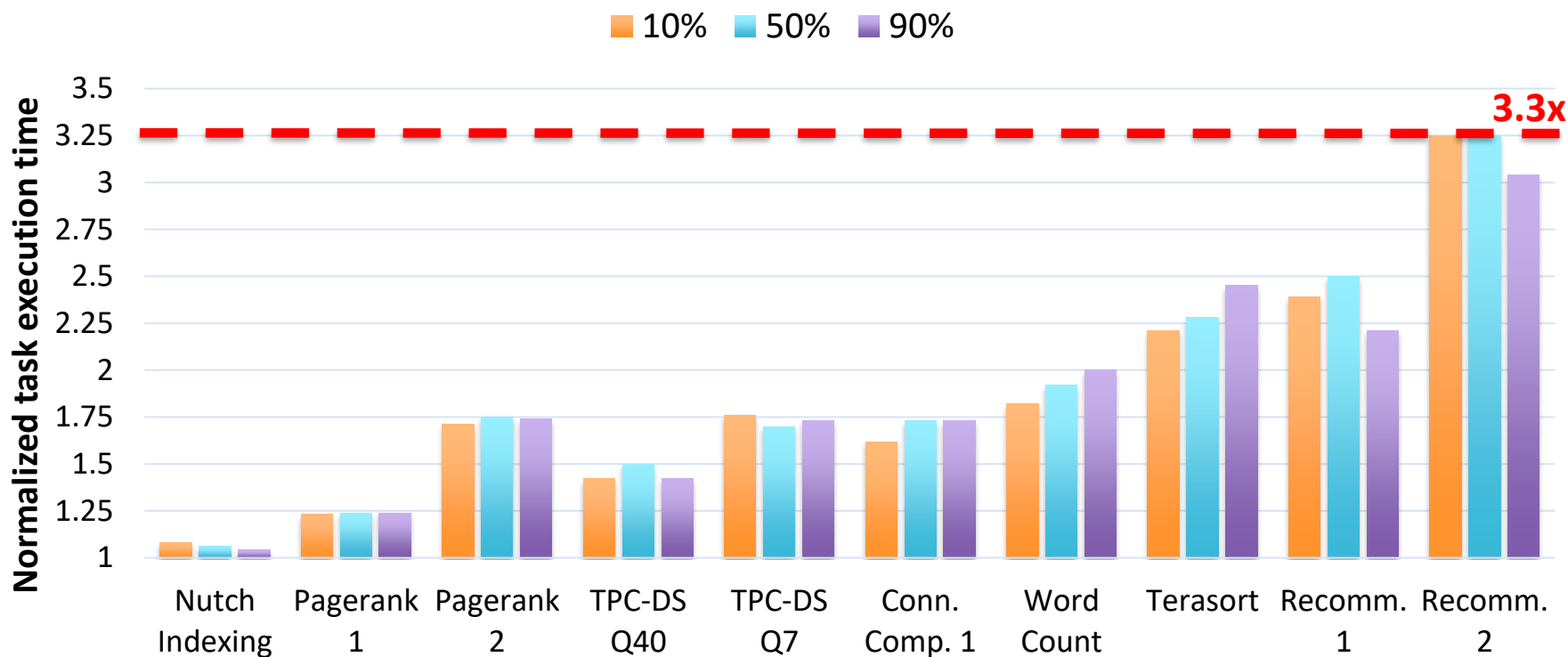
Sequential disk access

- Spilling records to disk is faster than OS paging

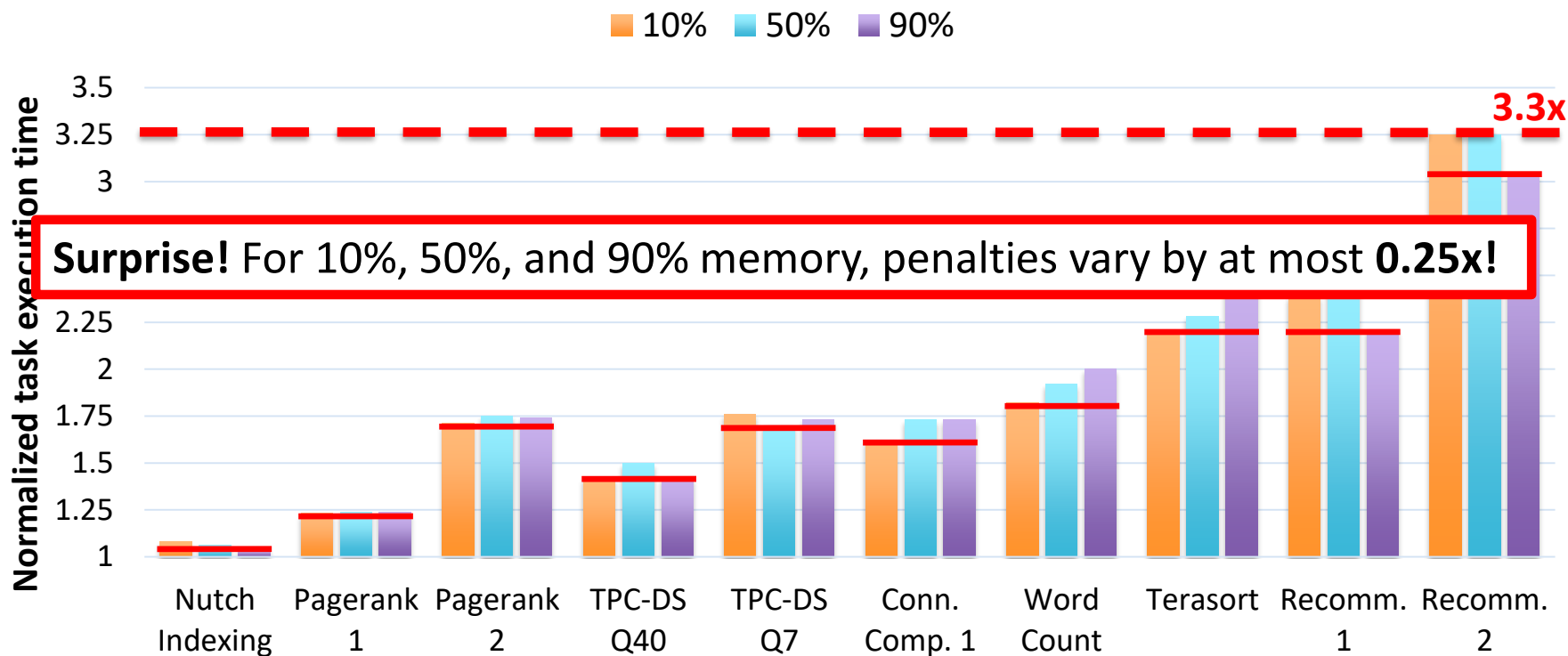
Logarithmic external merge algorithms

- Merge steps required  $\ll$  disk spills

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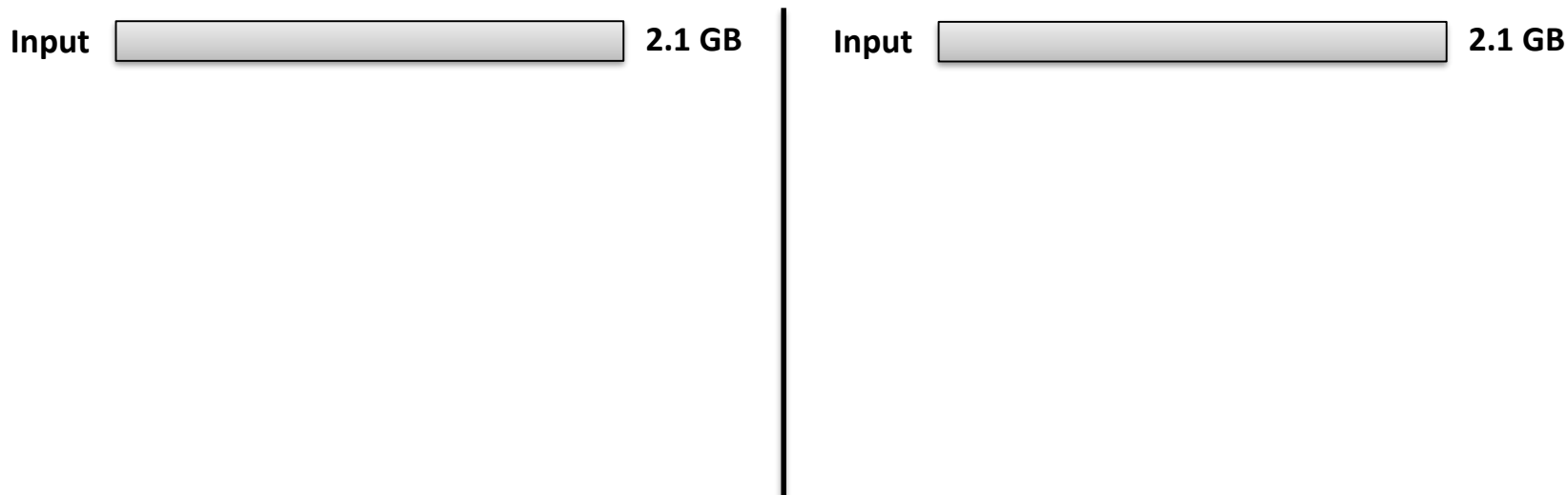


# Why do penalties vary so little w/ memory?

- Static spilling threshold → comparable data spilling for 90% and 10% of memory

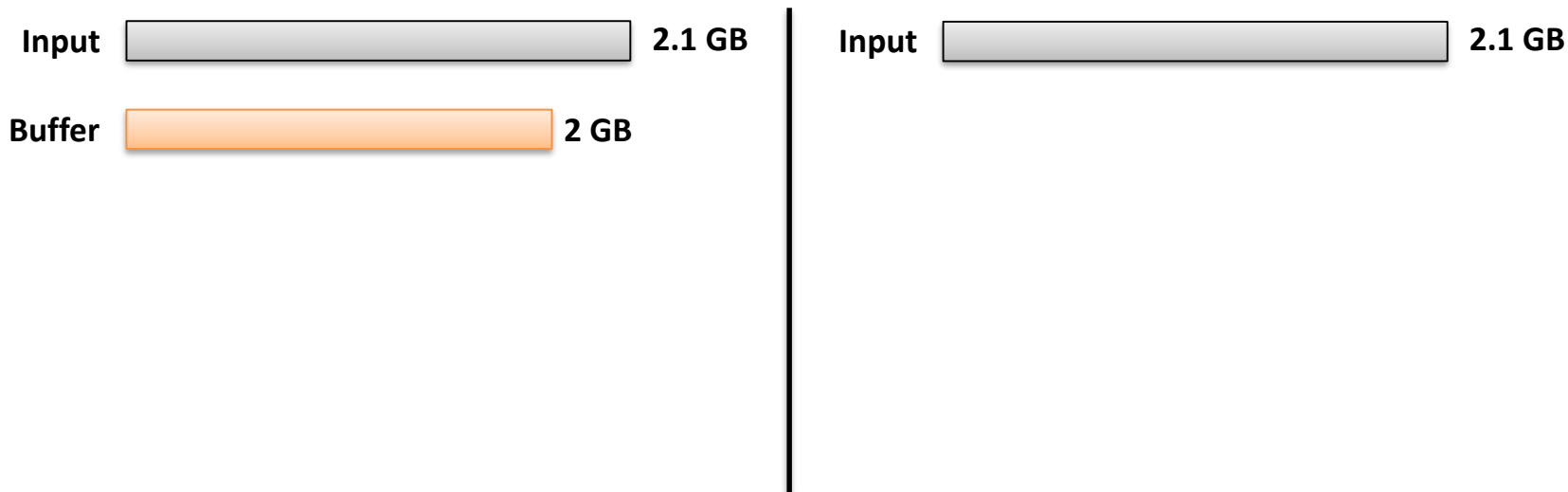
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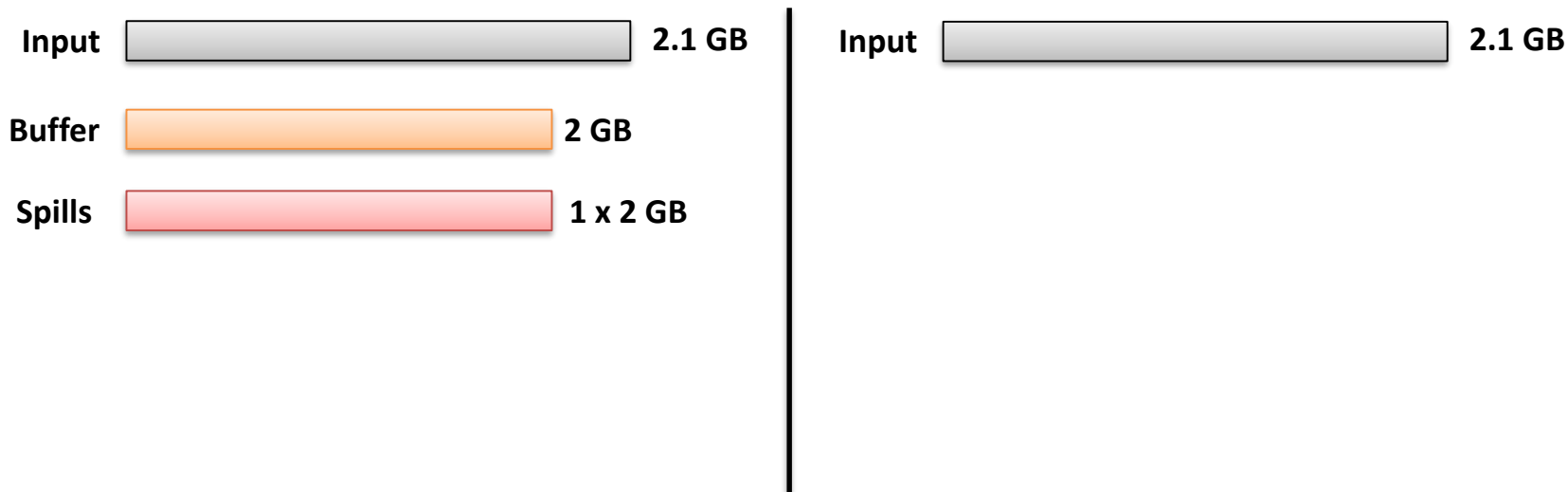
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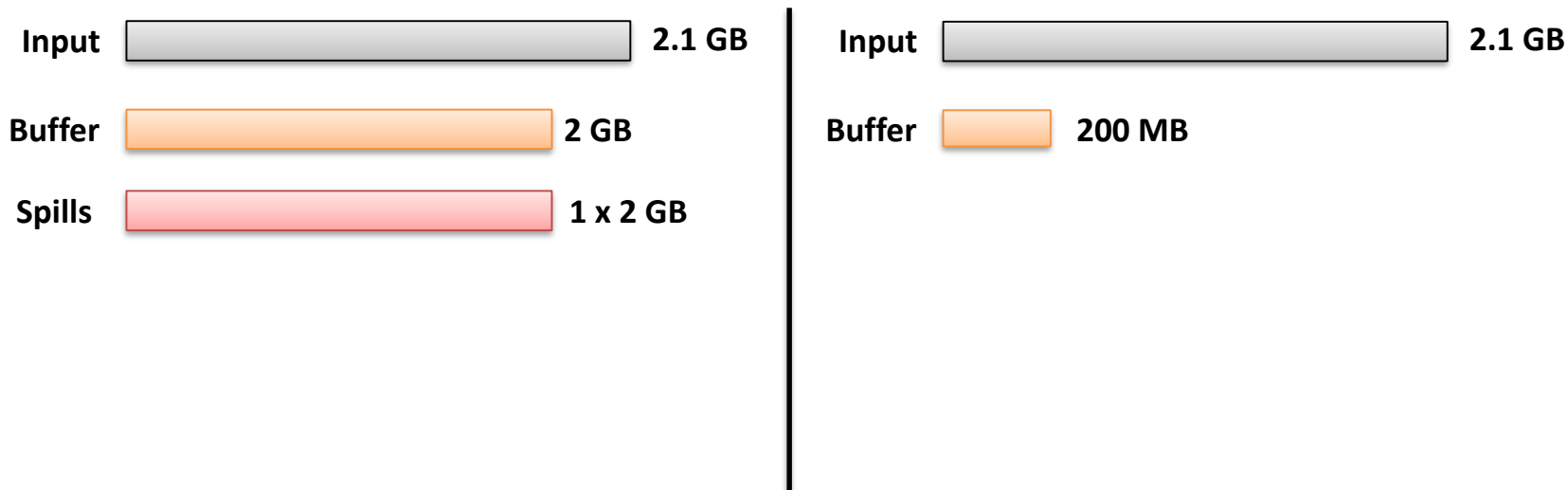
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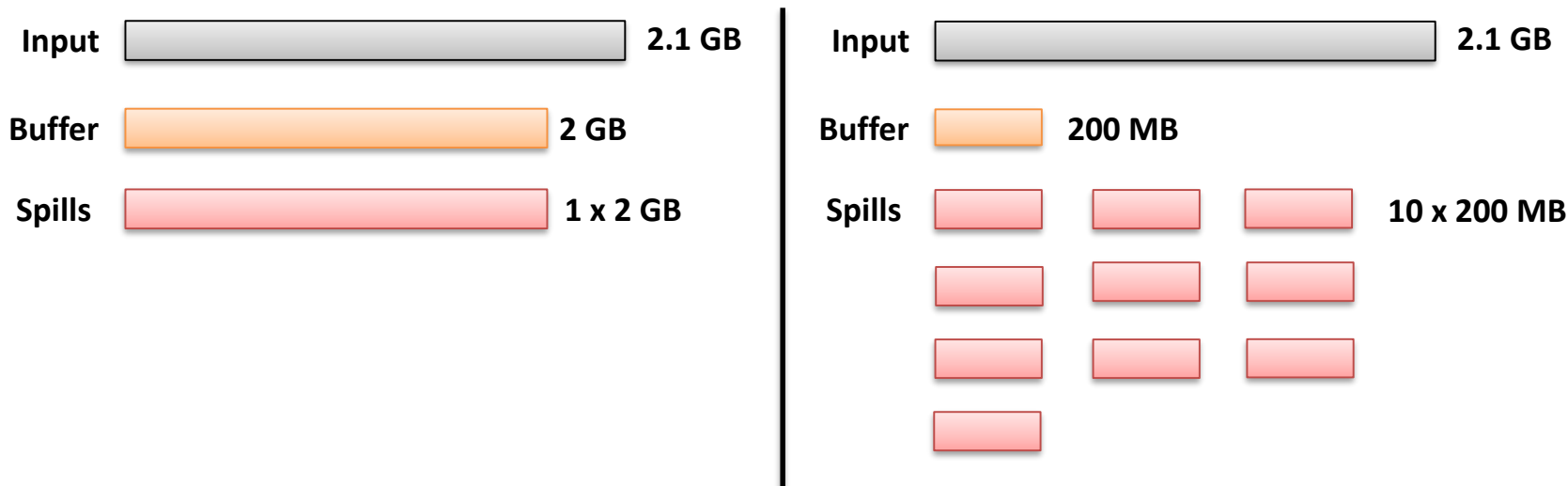
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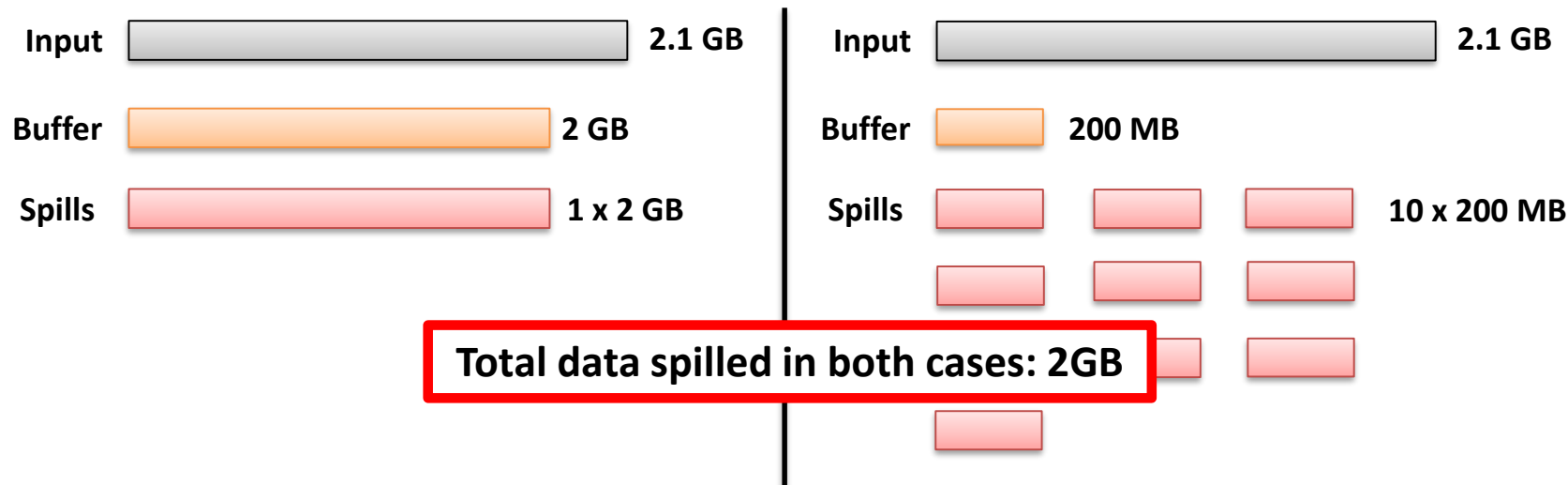
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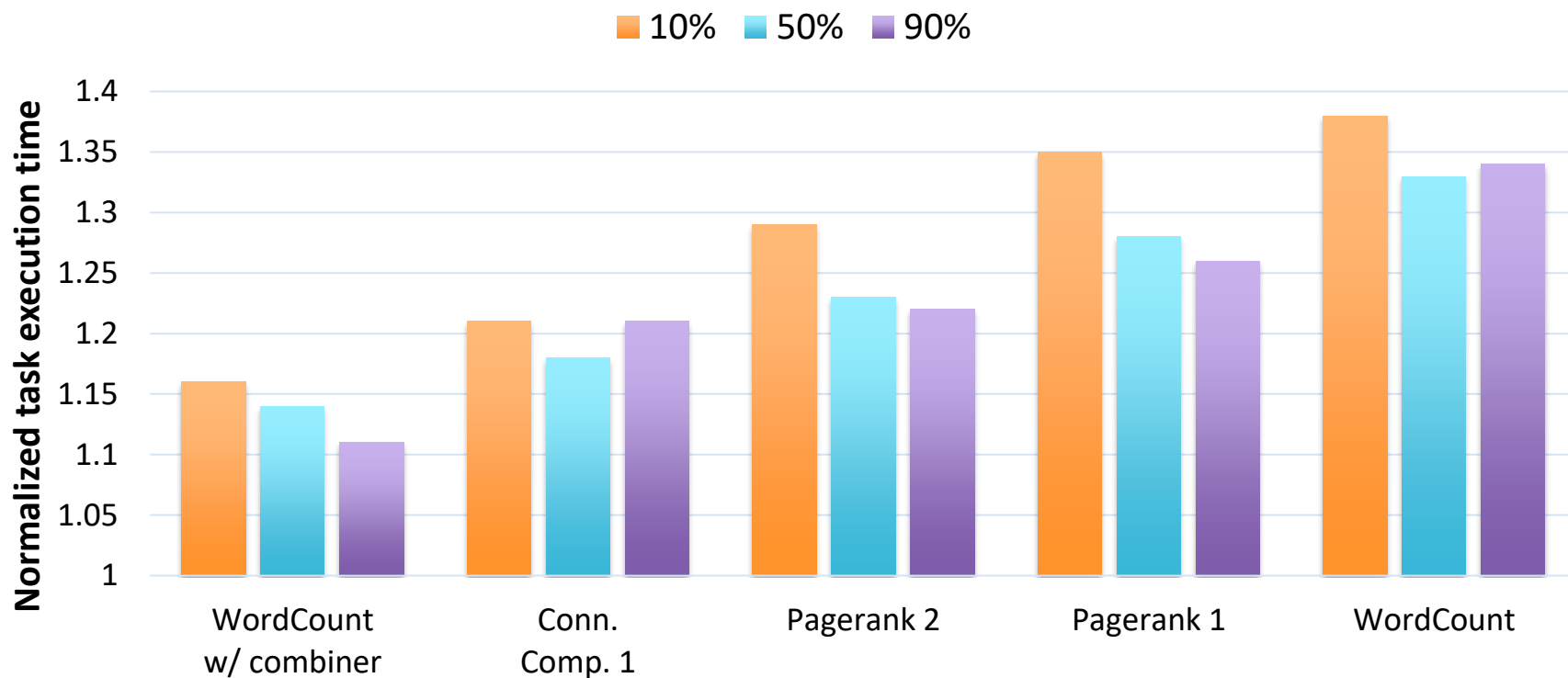


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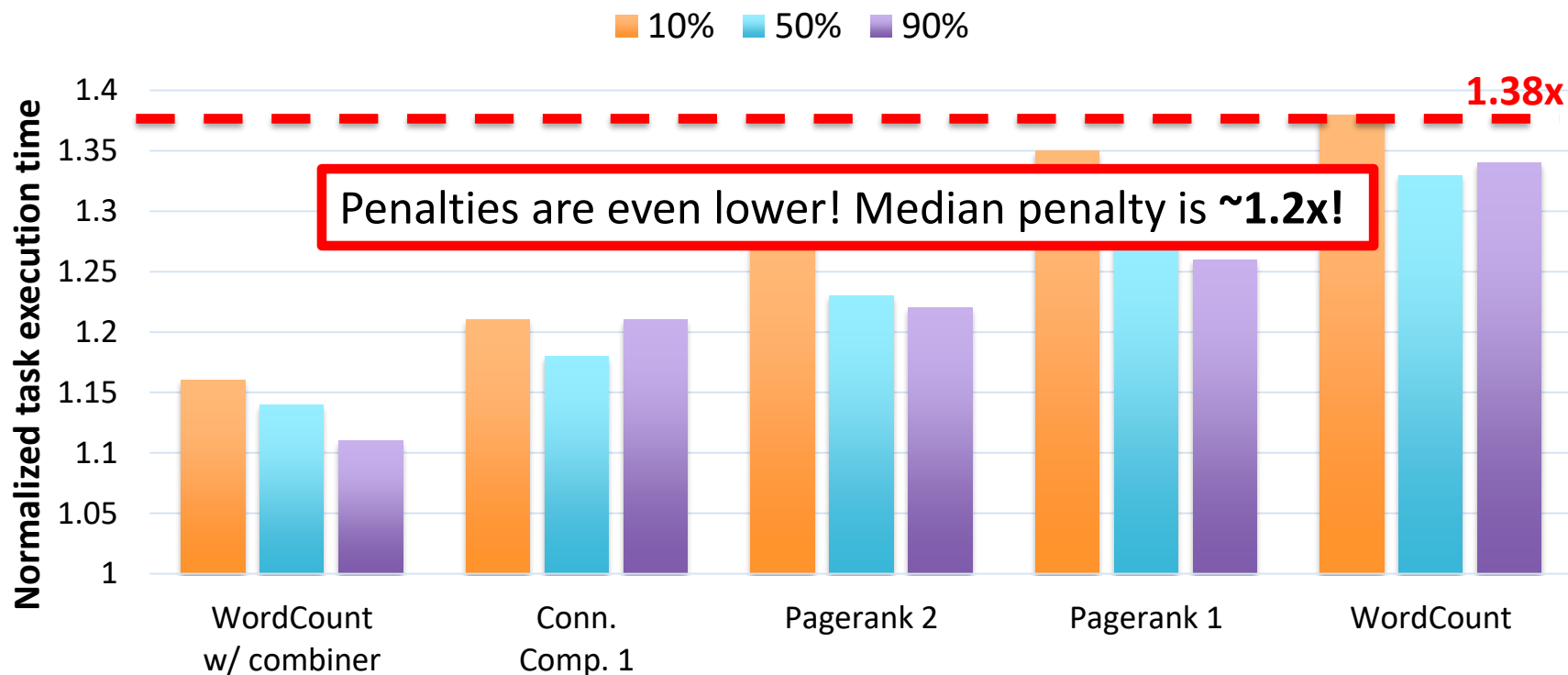
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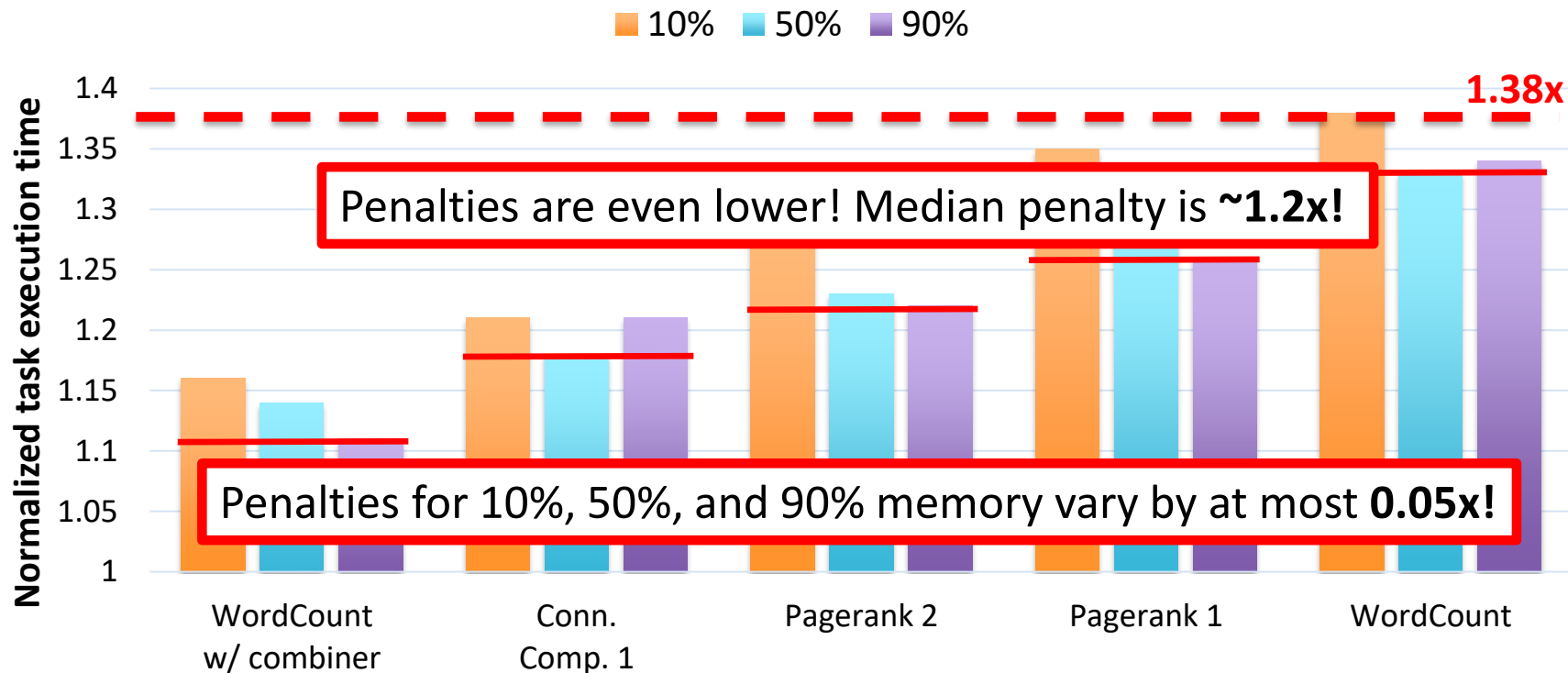
# Elasticity of Hadoop workloads: **Mappers**



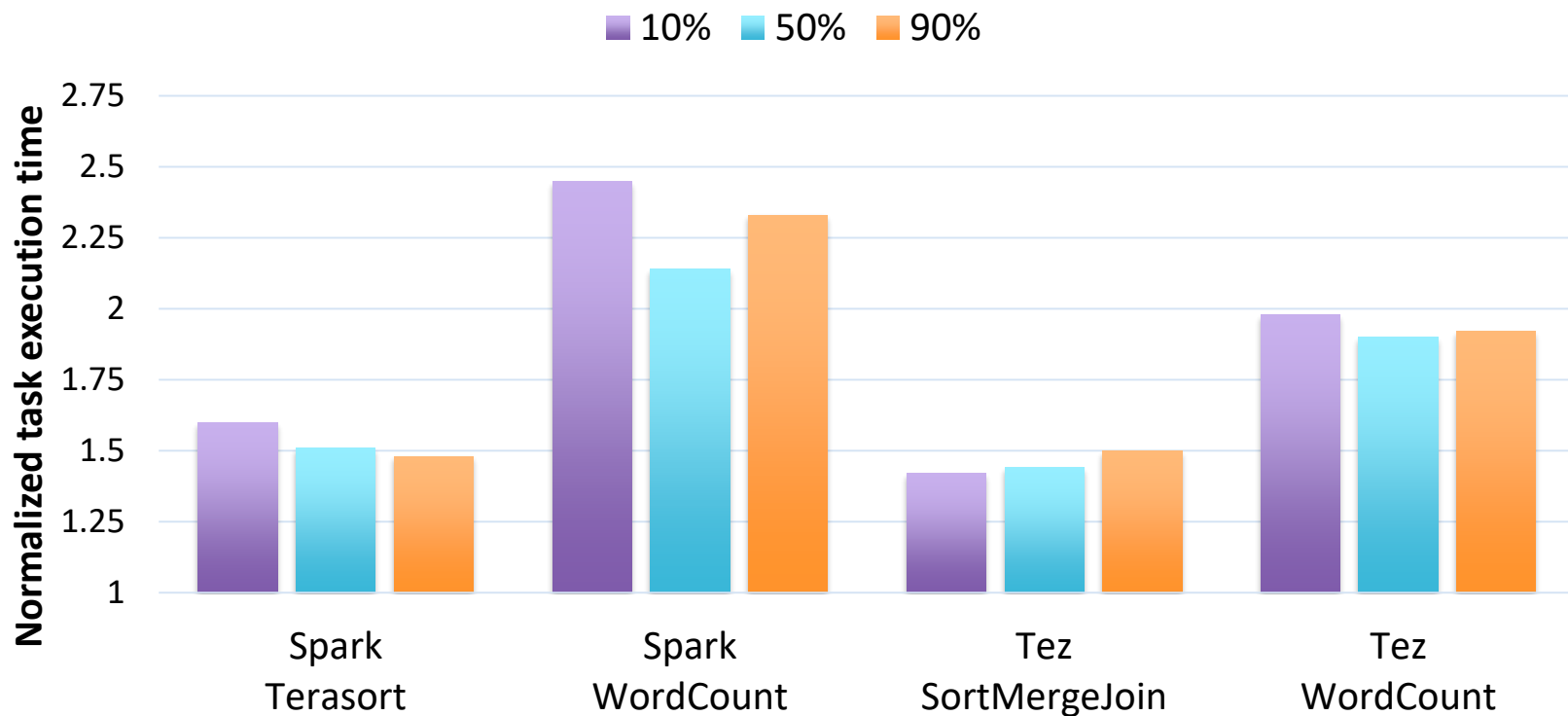
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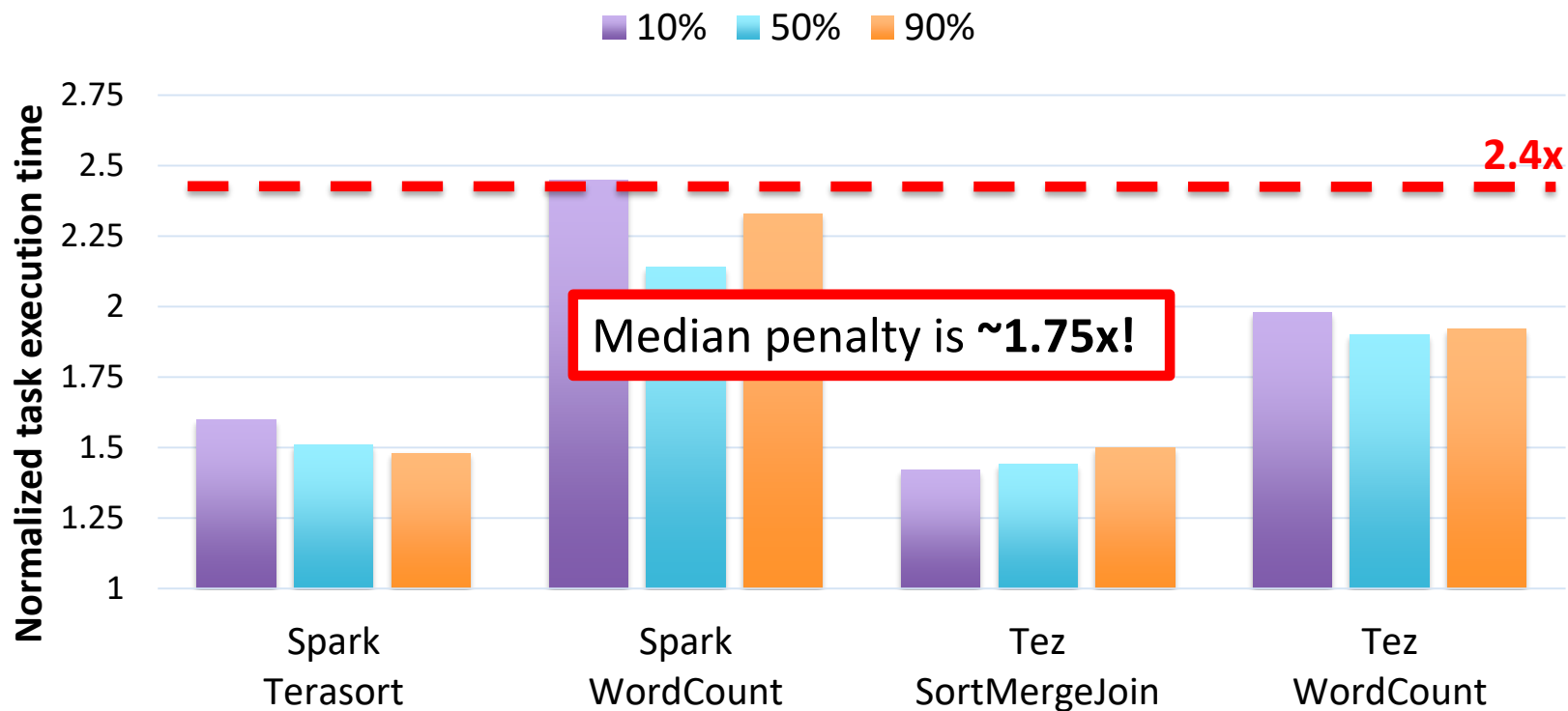
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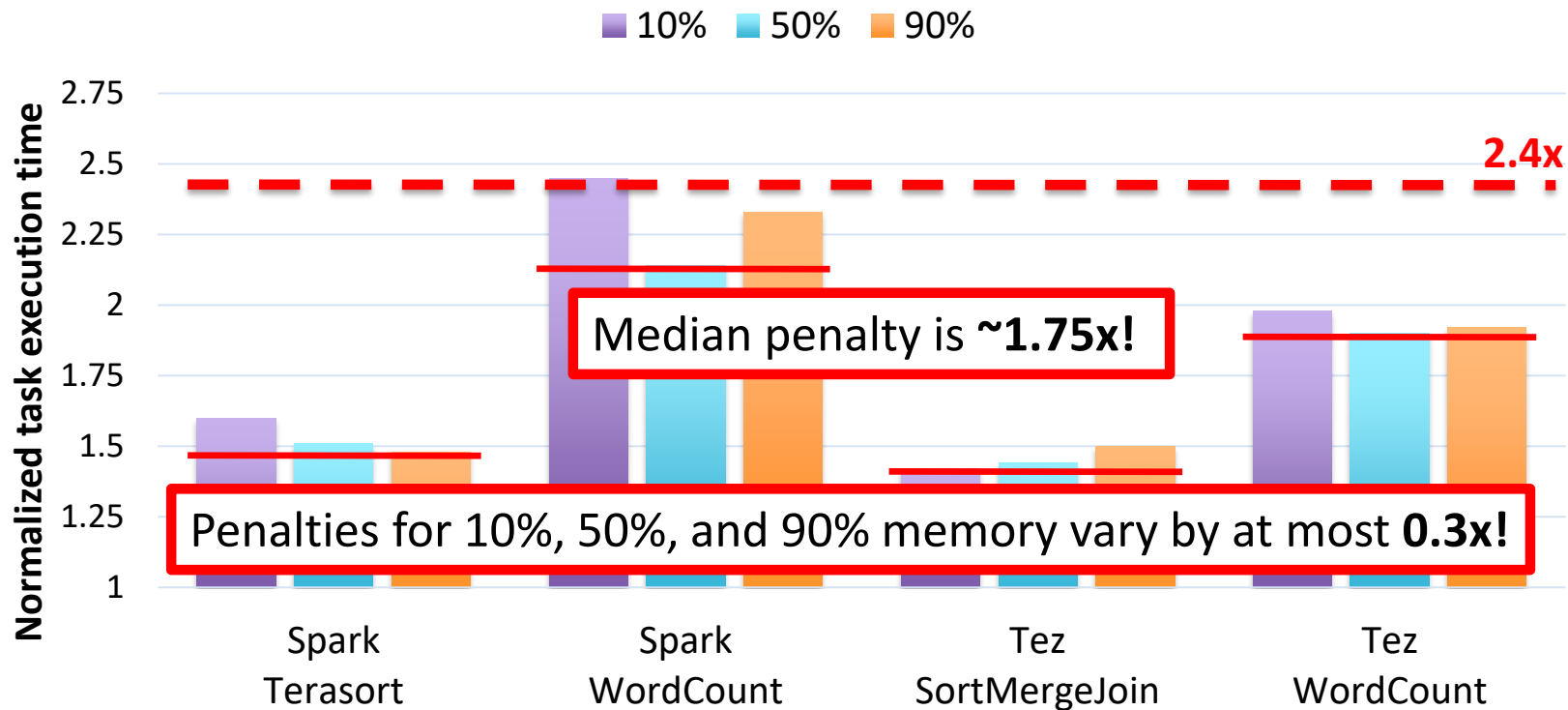
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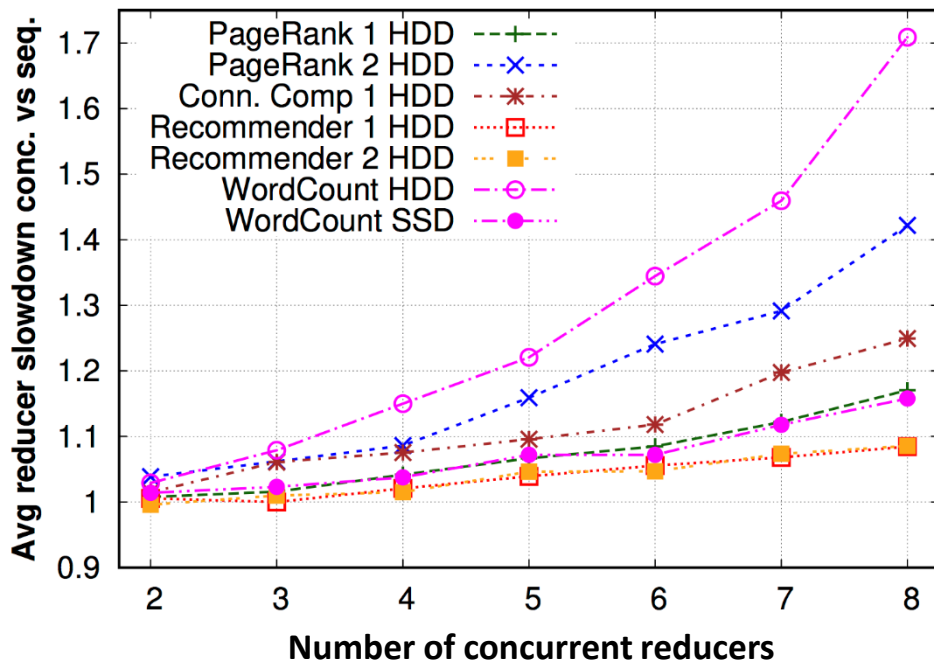


# Elasticity of Spark and Tez workloads



# Does the additional I/O cause disk contention?

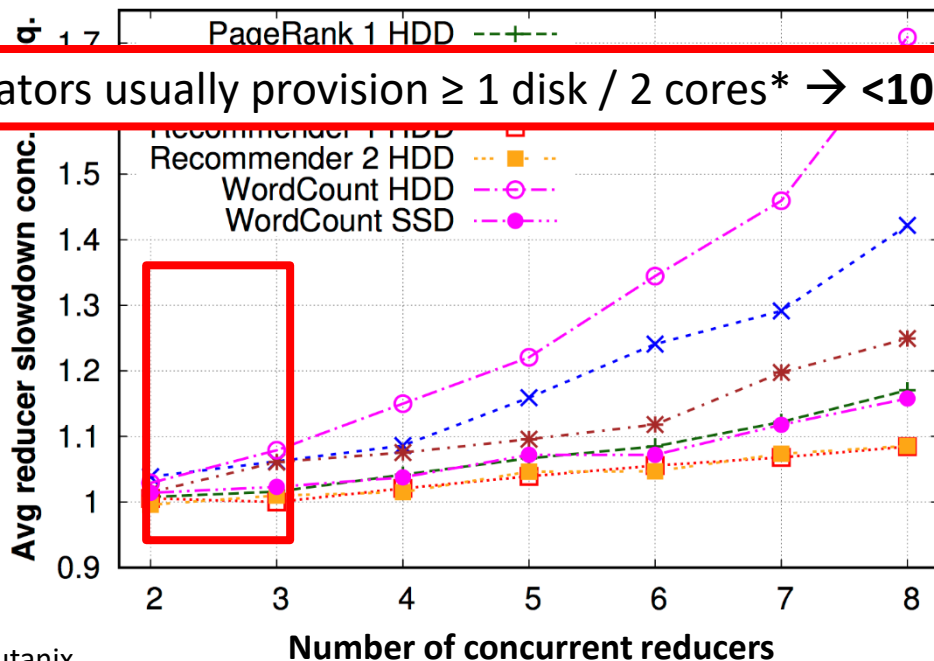
- Measure slowdown of elastic tasks on same machine spilling to the same disk



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Cluster operators usually provision  $\geq 1$  disk / 2 cores\*  $\rightarrow$  **<10% slowdown!**



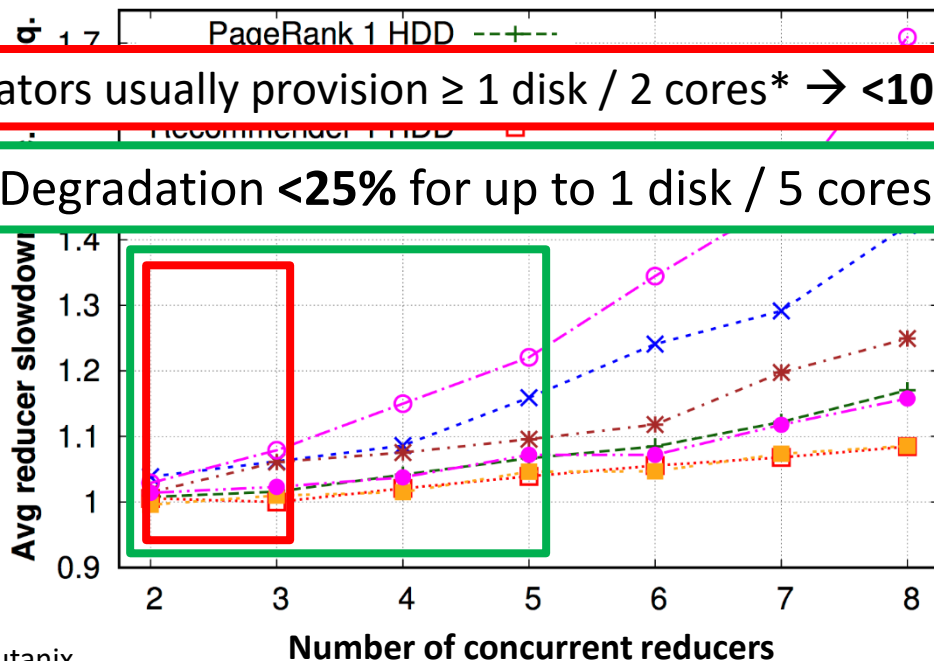
\* Facebook (2010) and Nutanix

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Degradation **<25%** for up to 1 disk / 5 cores!



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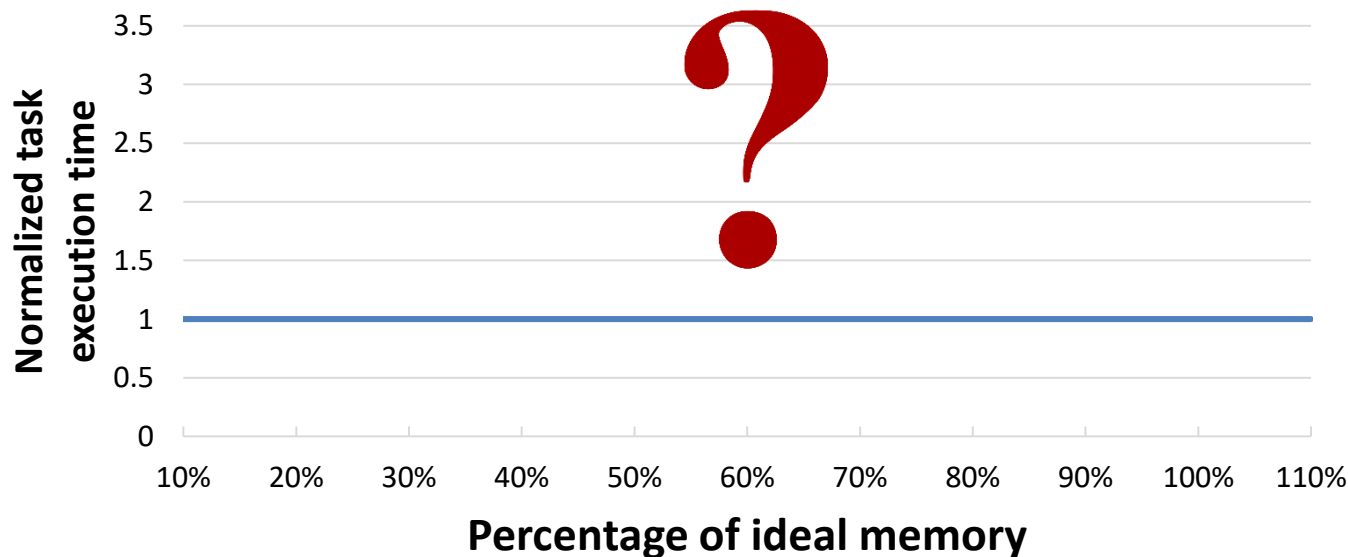
# Summary: Memory Elasticity of real workloads

- ✓ **Modest performance penalties (<1.6x median)**
- ✓ **Similar penalties for 10% and 90% of ideal memory**
- ✓ **Disk contention negligible for existing clusters' setup (<10%)**

# MODELING MEMORY ELASTICITY

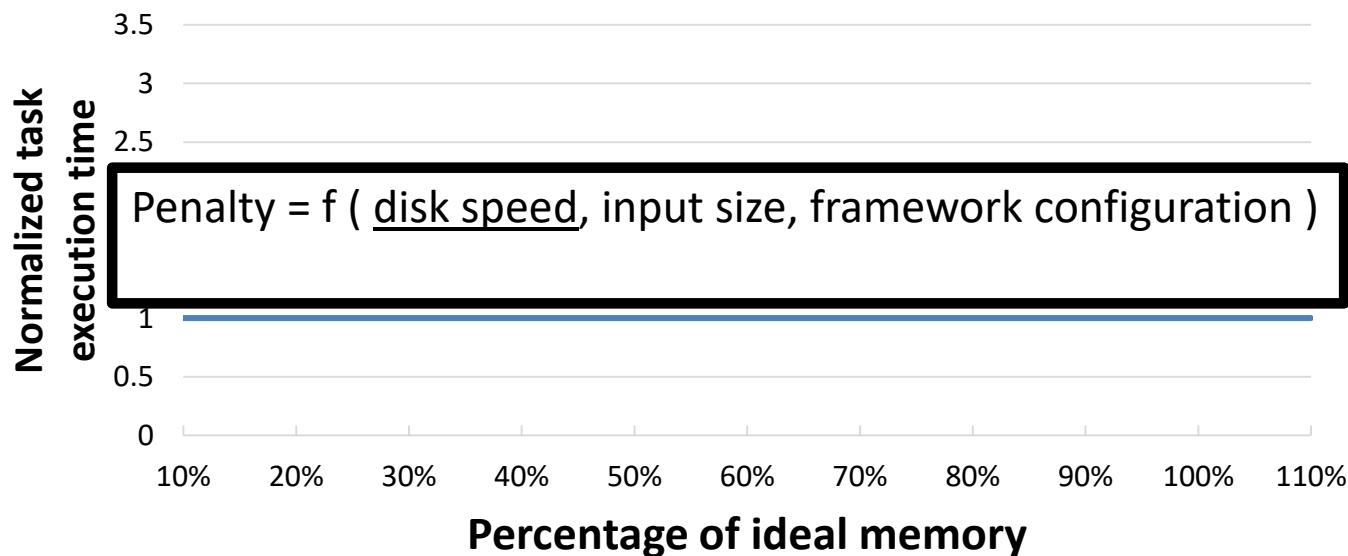
# Modeling Memory Elasticity

- How does penalty vary for a task?



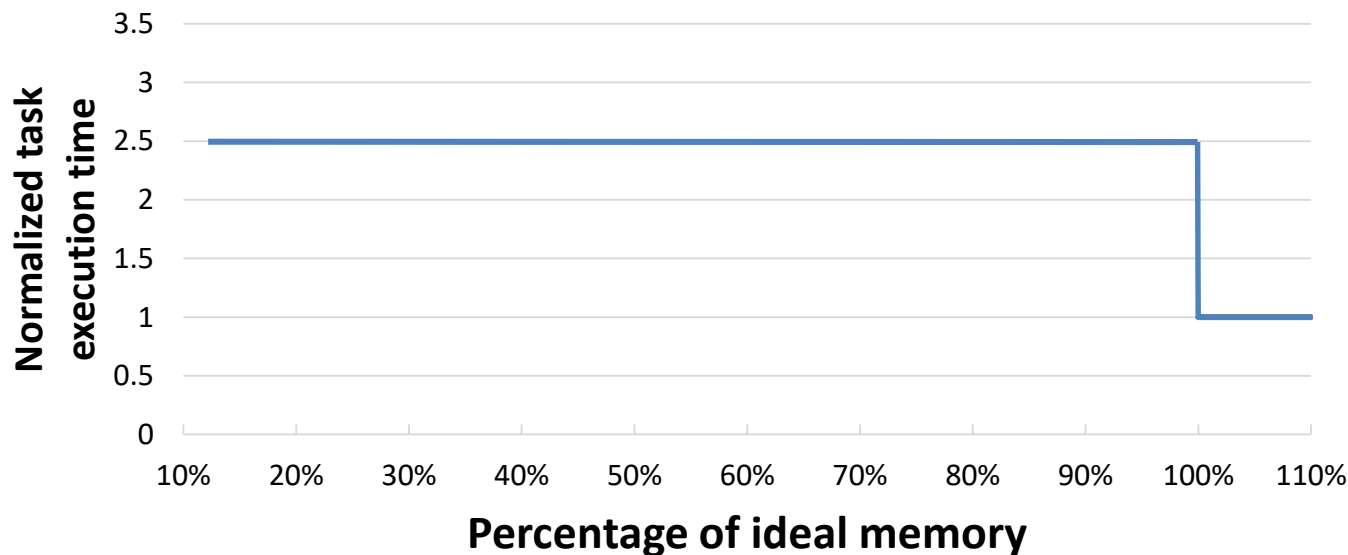
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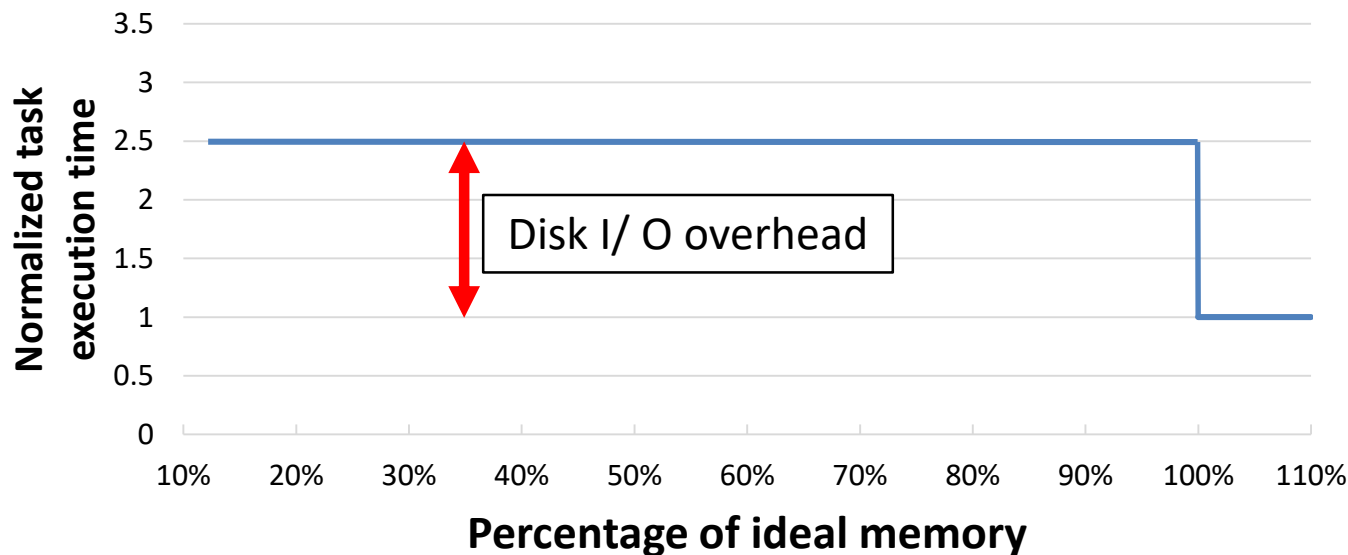
# Modeling Memory Elasticity

- Penalties vary little between percentages → step model



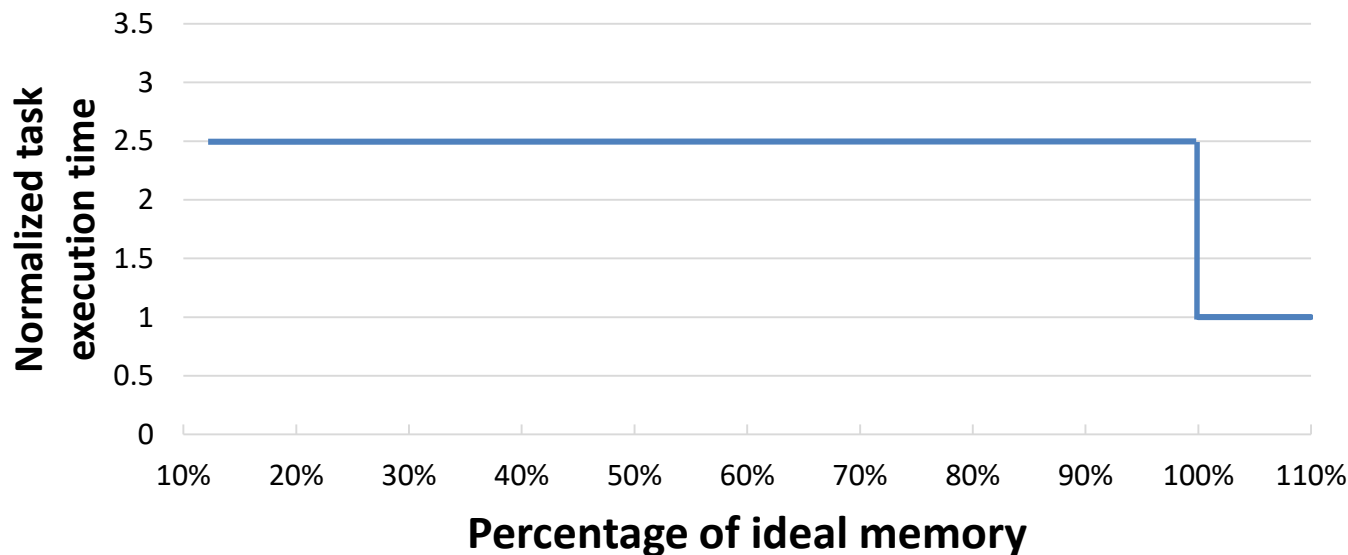
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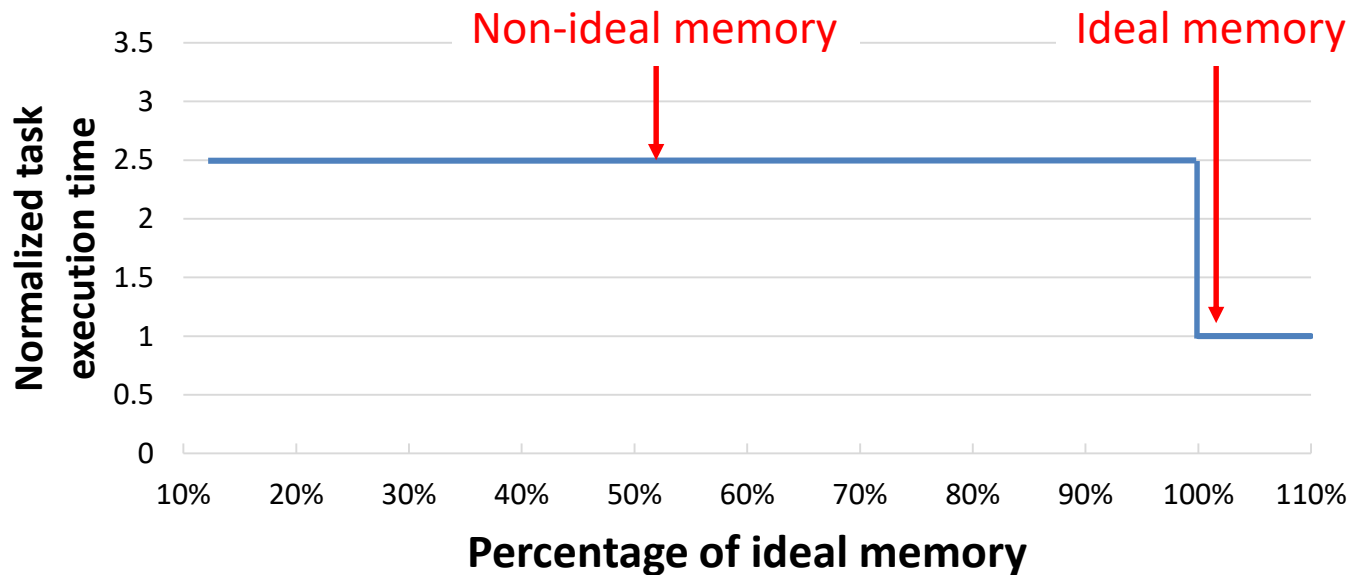
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- Requires 2 profiling runs → infers all other points



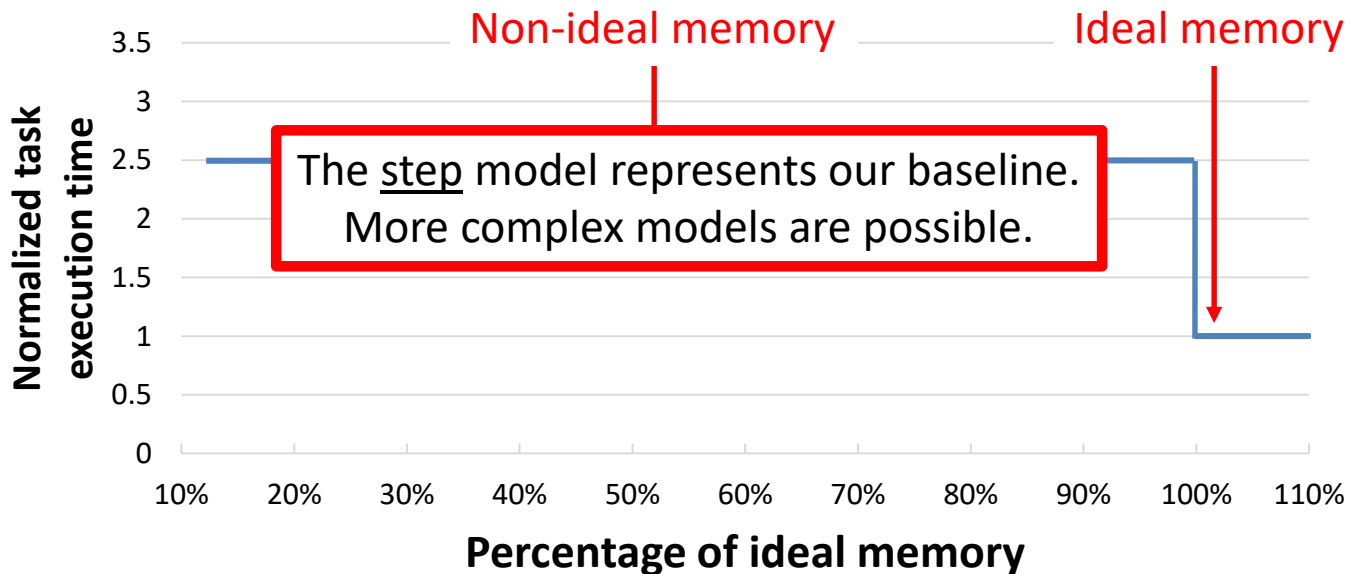
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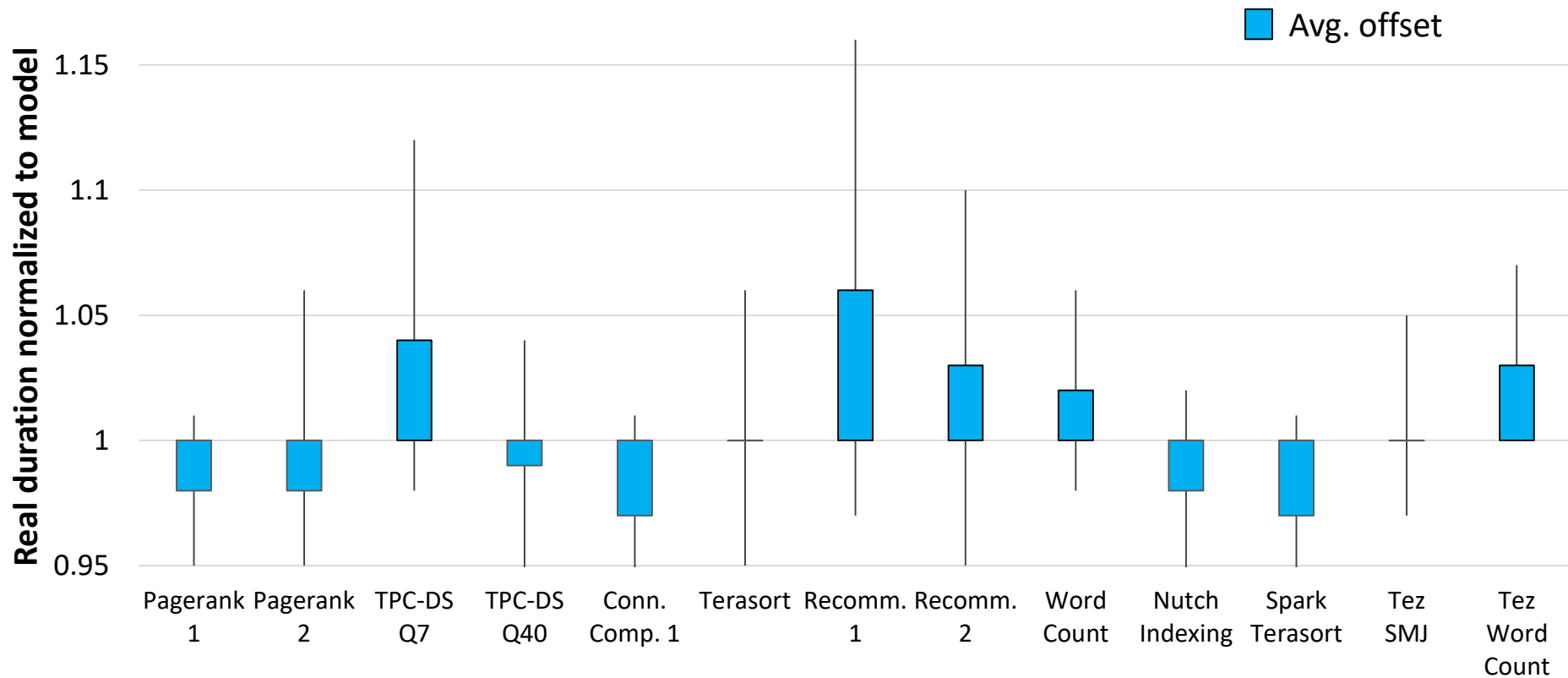


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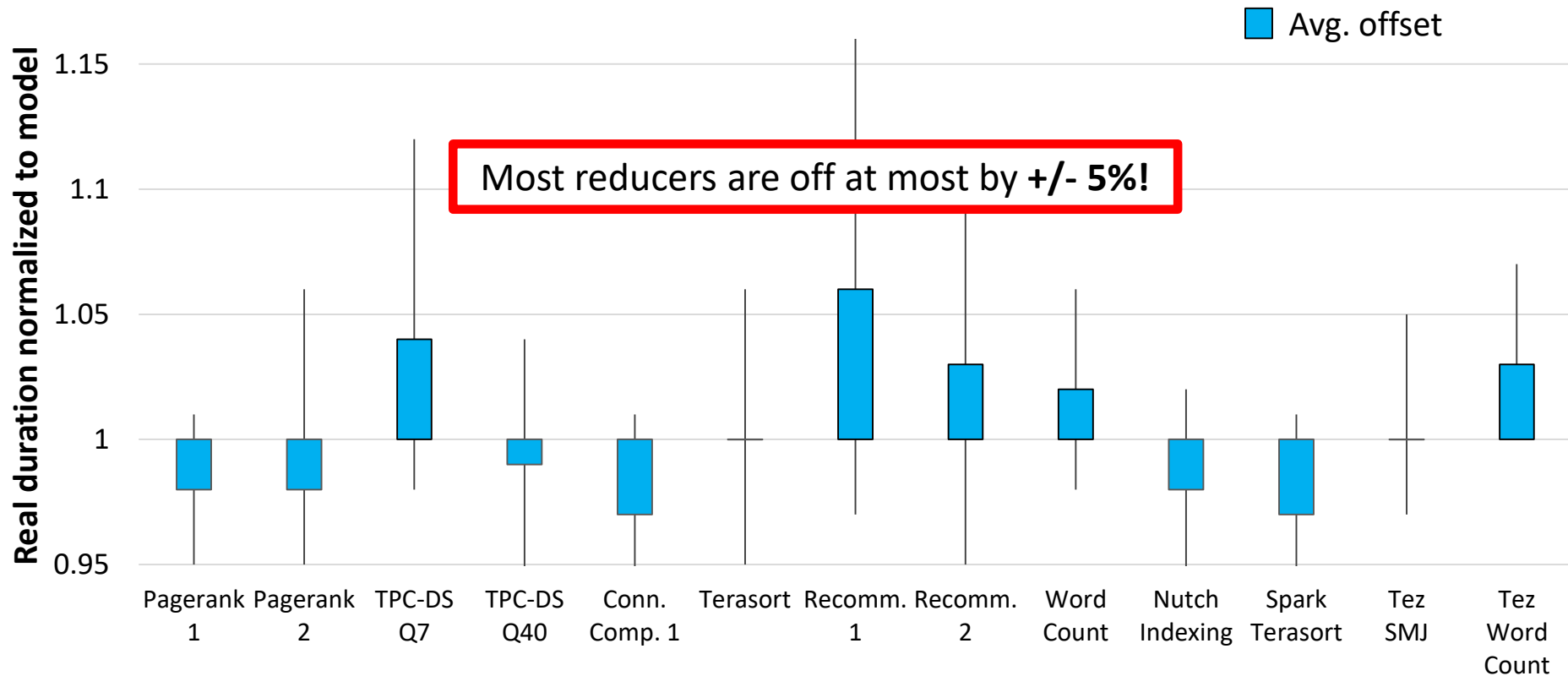
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# Accuracy of our reducer model



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## Summary: Modeling memory elasticity

- ✓ **Step model is adequate (more complex models available)**
- ✓ **Only 2 profiling points → full model**
- ✓ **Models are very robust (+/- 5% error for most reducers)**

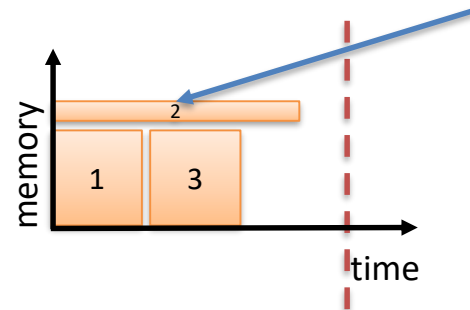
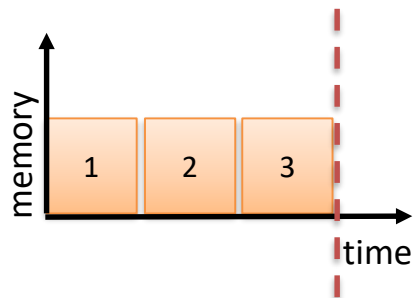
# **LEVERAGING MEMORY ELASTICITY IN CLUSTER SCHEDULING**

# How can a scheduler reason about Memory Elasticity?

Trade-off between

↓ task **queueing** time

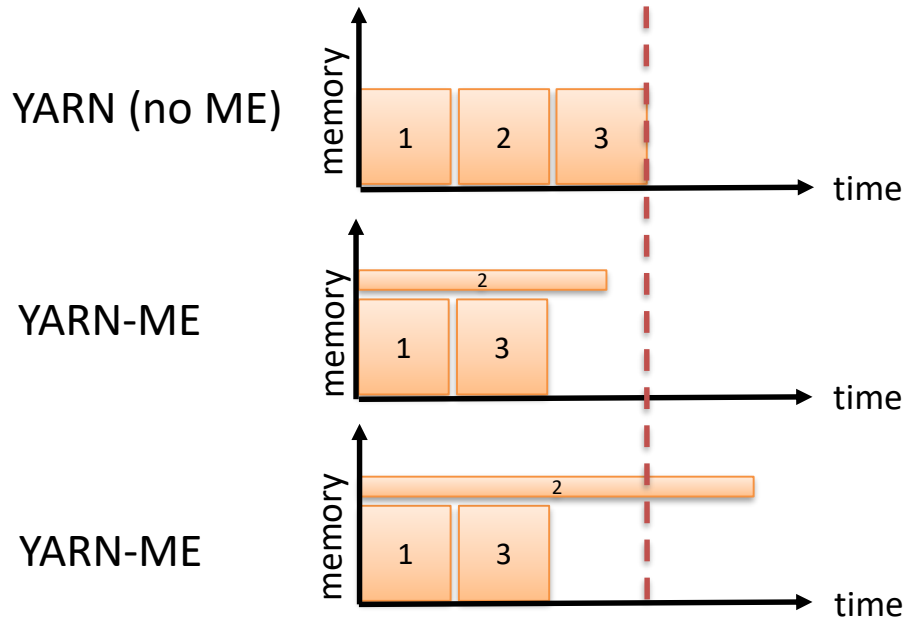
↑ task **execution** time



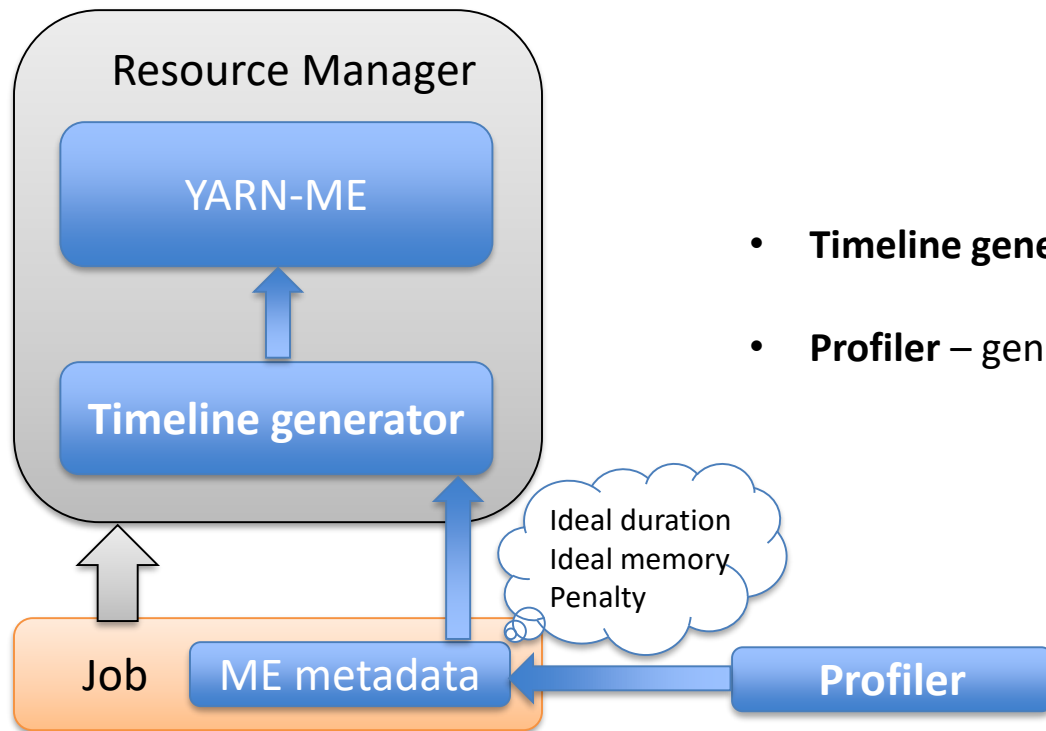
**Elastic allocation**

# YARN-ME: Decision process

- Make an elastic allocation iff it does not exceed the expected job completion time



# YARN-ME: Design and components

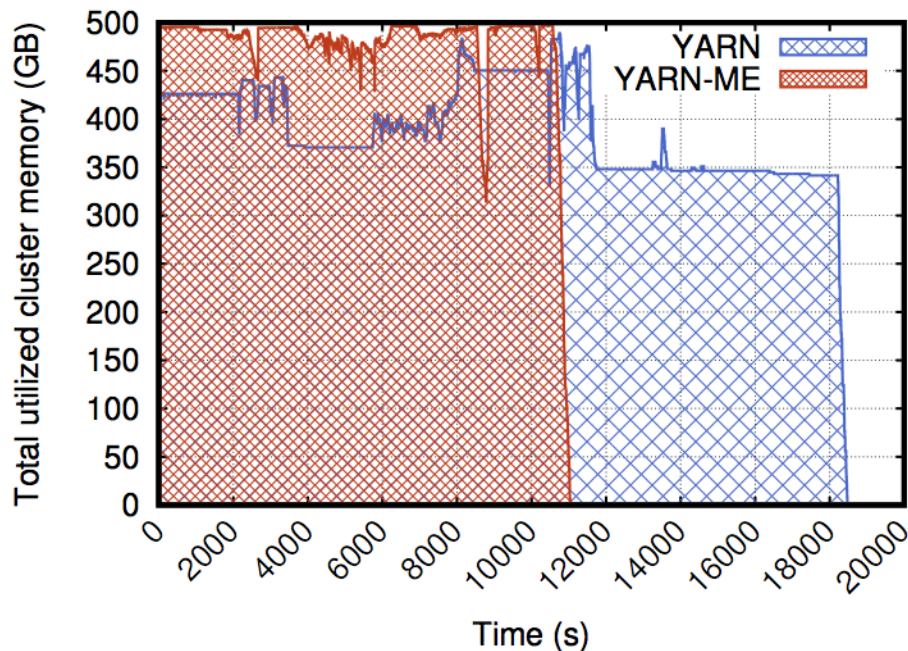


## Components

- **Timeline generator** – computes expected JCTs
- **Profiler** – generates the model metadata

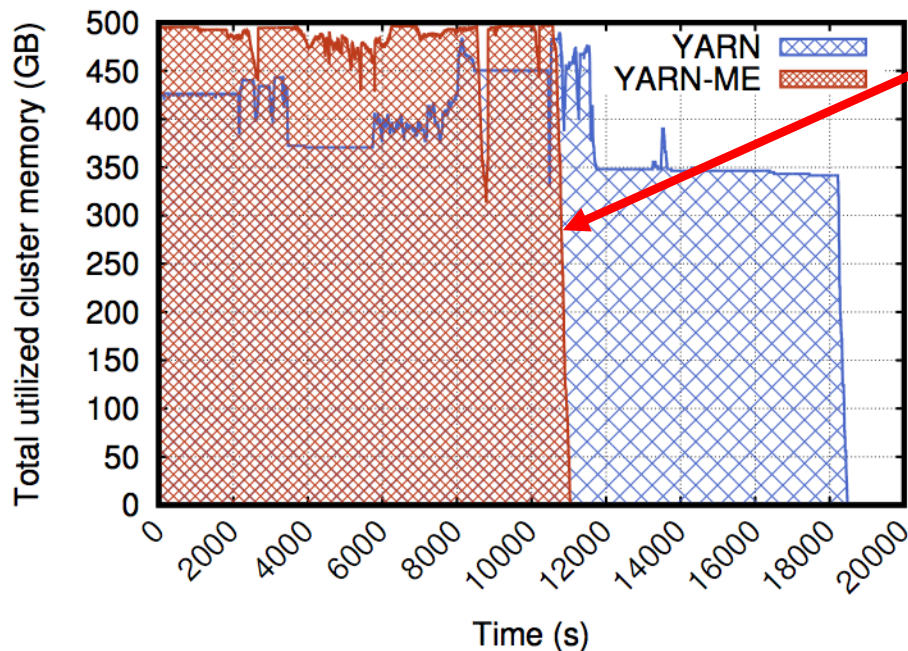
# Memory utilization analysis for YARN-ME

- 50 node cluster
- Homogeneous trace: 5x Pagerank jobs



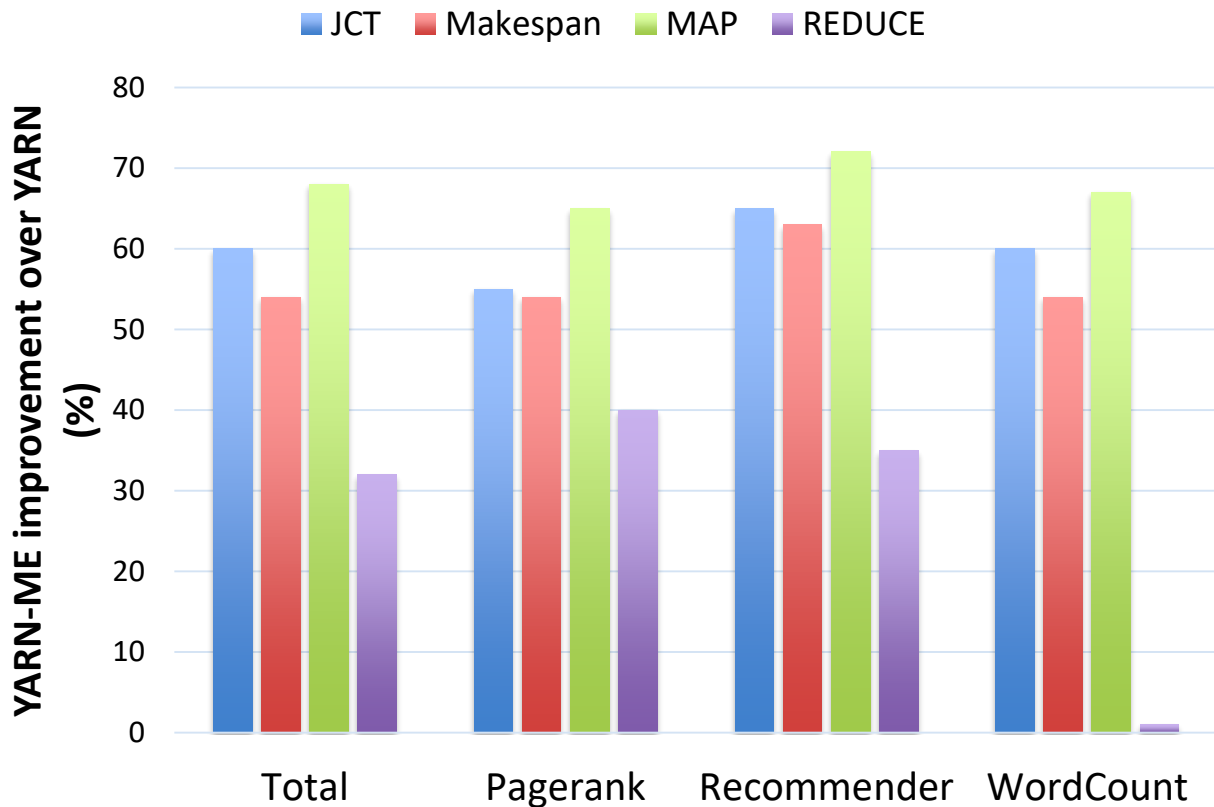
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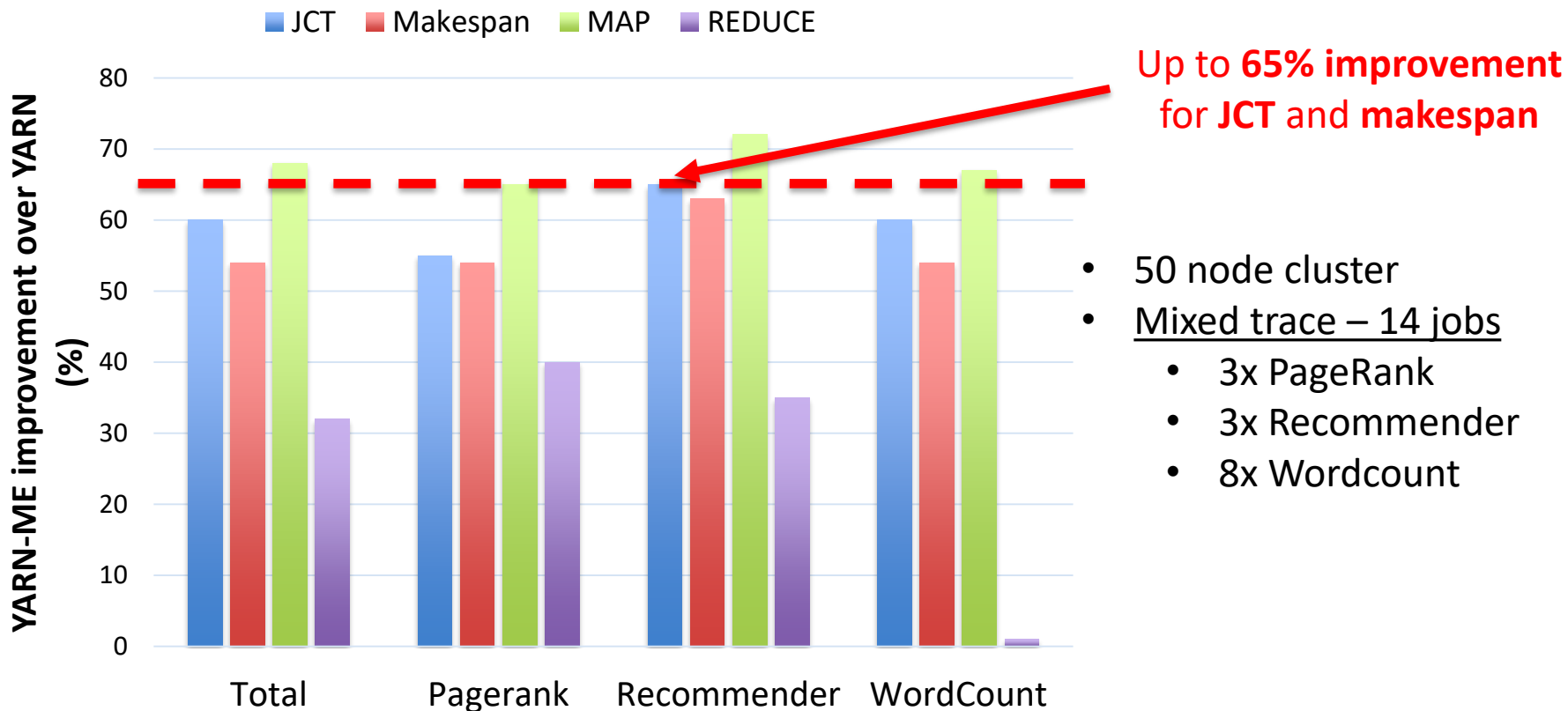
Memory utilization  
increased to **95%**

# What gains can YARN-ME achieve for heterogeneous workloads?

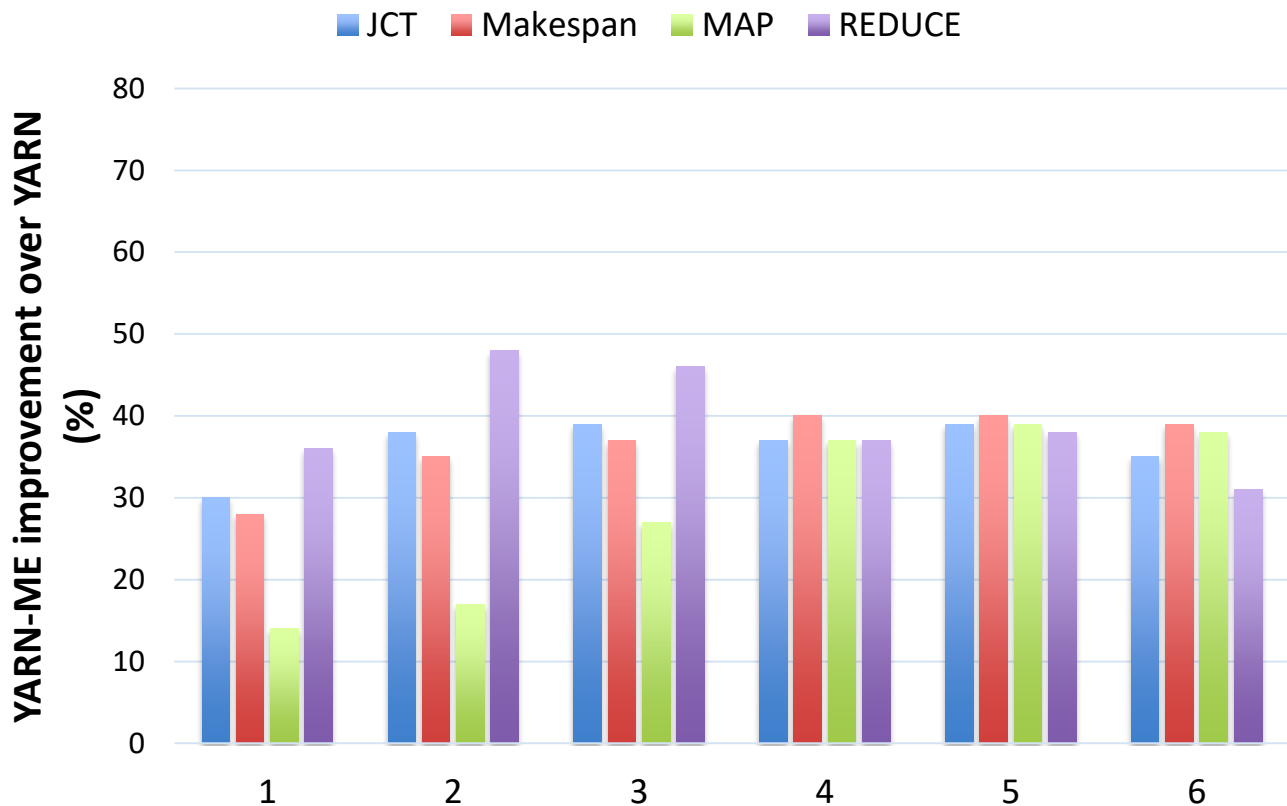


- 50 node cluster
- Mixed trace – 14 jobs
  - 3x PageRank
  - 3x Recommender
  - 8x Wordcount

# What gains can YARN-ME achieve for heterogeneous workloads?

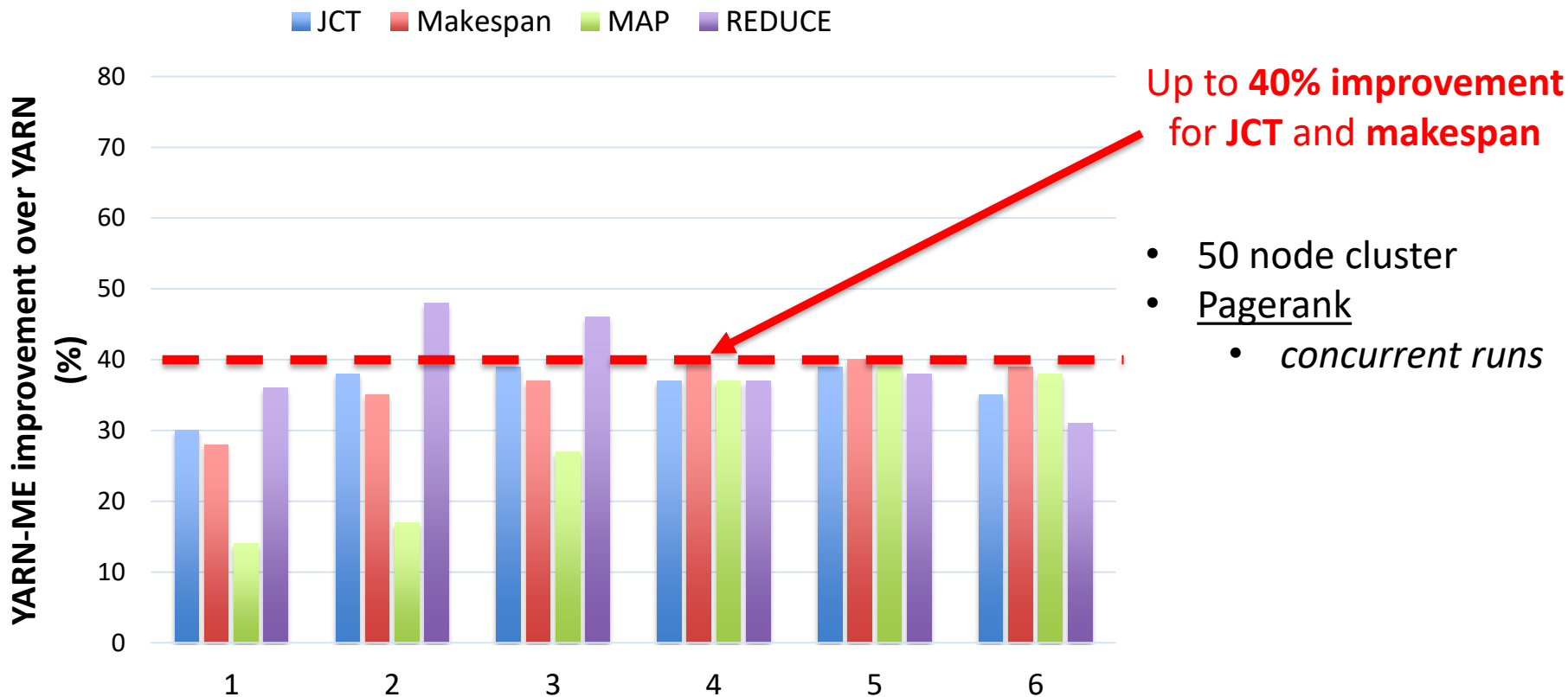


# What gains can YARN-ME achieve for homogeneous workloads?



- 50 node cluster
- Pagerank
  - *concurrent runs*

# What gains can YARN-ME achieve for homogeneous workloads?



# Trace-driven simulation of YARN-ME

- We built DSS (the Discrete Scheduler Simulator)
  - and it is open-source!

## Trace parameter sweep

- > 8,000 traces
- up to 3,000 nodes
- results comparable to real workloads

## Robustness analysis

- > 20,000 traces
- YARN-ME is robust to model mis-estimations

# Related work

- Efficient packing → better resource utilization
  - Tetris [**SIGCOMM '14**], GRAPHENE [**OSDI '16**]
- Collocate batch-jobs with latency-critical services
  - Heracles [**ISCA '15**]
- Resource over-committing
  - Apollo [**OSDI '14**], Borg [**EuroSys '15**]
- Suspend tasks under memory pressure
  - ITask [**SOSP '15**]

# Conclusion: Don't cry over spilled records!

- ✓ Memory Elasticity → highly **predictable**, low penalty
- ✓ Memory Elasticity in scheduling → trade task **queueing-time** for **running-time**
- ✓ YARN-ME → up to 60% improvement in average JCT
- ✓ DSS code available: <https://github.com/epfl-labos/dss>