Straggler Exploitation in Distributed Computing Systems with Task Grouping

Tharindu Adikari
University of Toronto

Joint work with Haider Al-Lawati,
Jason Lam, Zhenhua Hu, and Stark Draper

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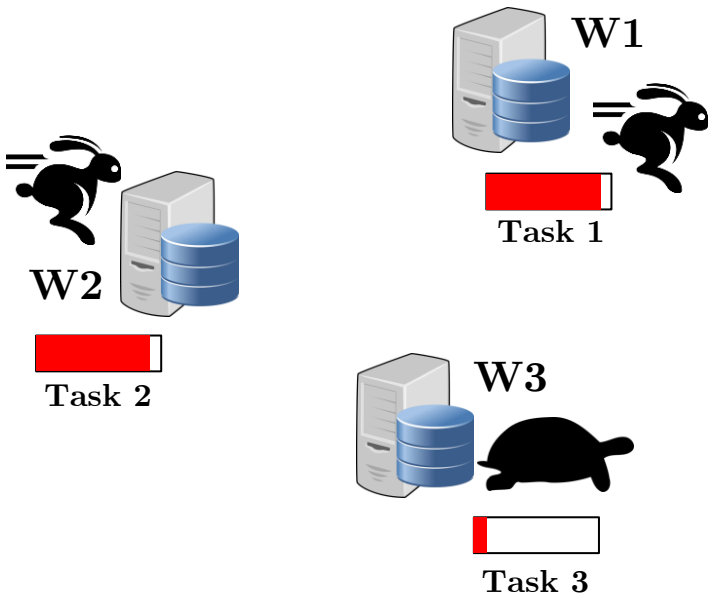
Stragglers **Lengthen** Running Time

Setup: 3 tasks, 3 workers



- Some nodes are **SLOW** (Stragglers).
- Have to wait for the **slowest node**!

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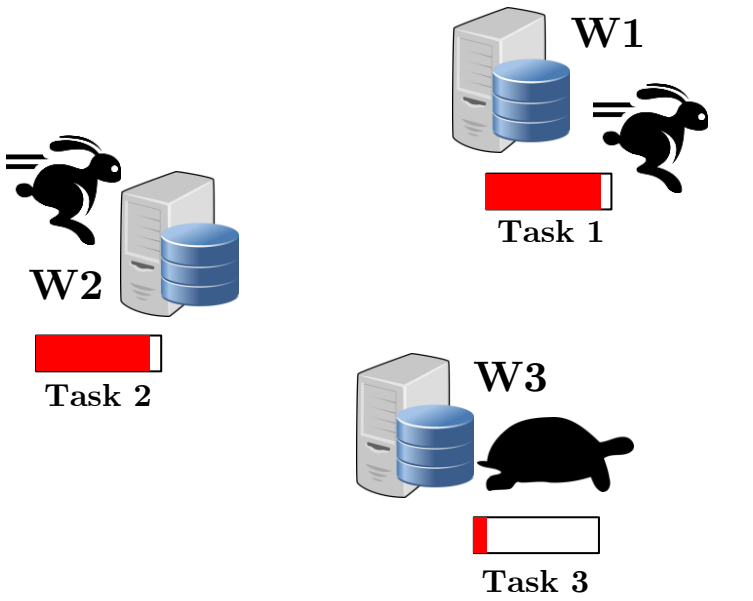

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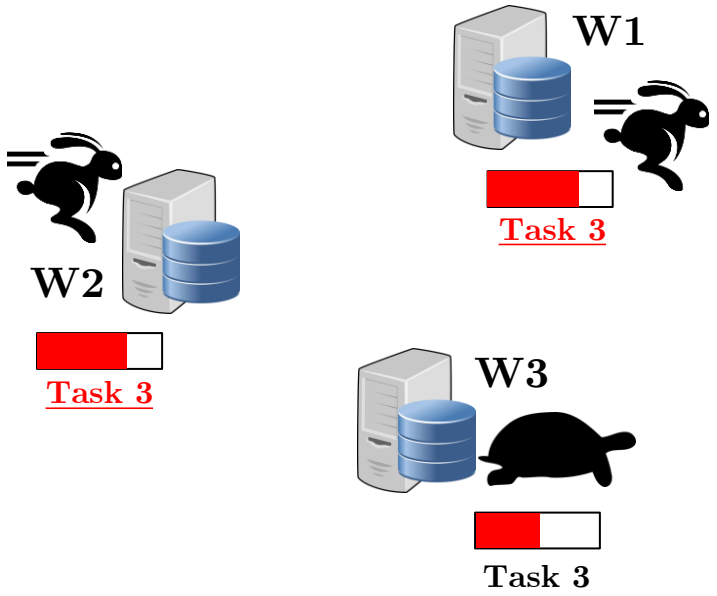
When tasks 1 & 2 finish

Standard replication



- **Replicate** Task 3 on W1 & W2.
- Store the result of the first to finish.

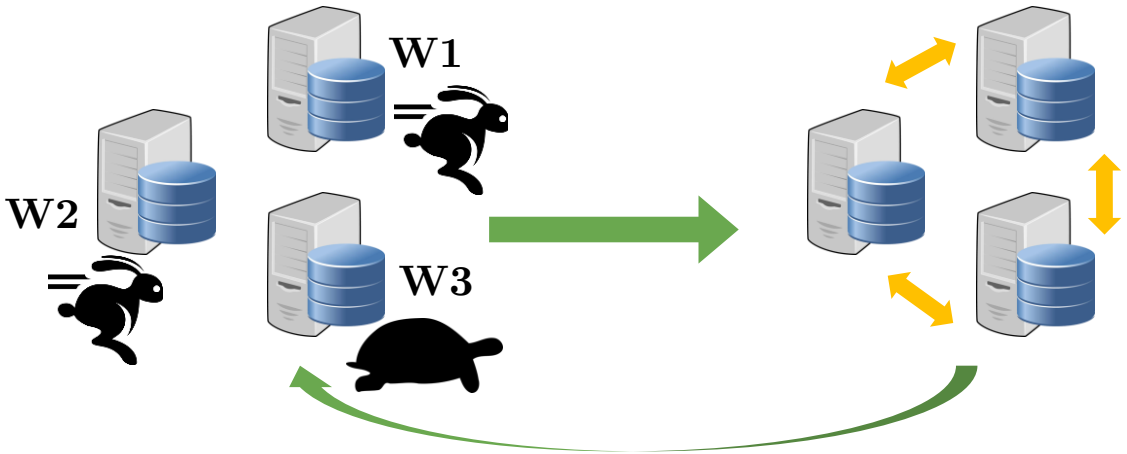
Algorithms exist for incorporating other information to prioritize replication: LATE, Mantri, MCP, Dolly

Zaharia (2008, 2013), Ananthanarayanan (2010), Chen (2013), Xu (2013, 2014, 2015)

Straggler **Exploitation** in SGD

Step 1: Compute
equal workloads

Step 2: Communicate
to synchronize



- Compute until a **time limit** in Step 1.
- Sync. with **partial results** in Step 2.

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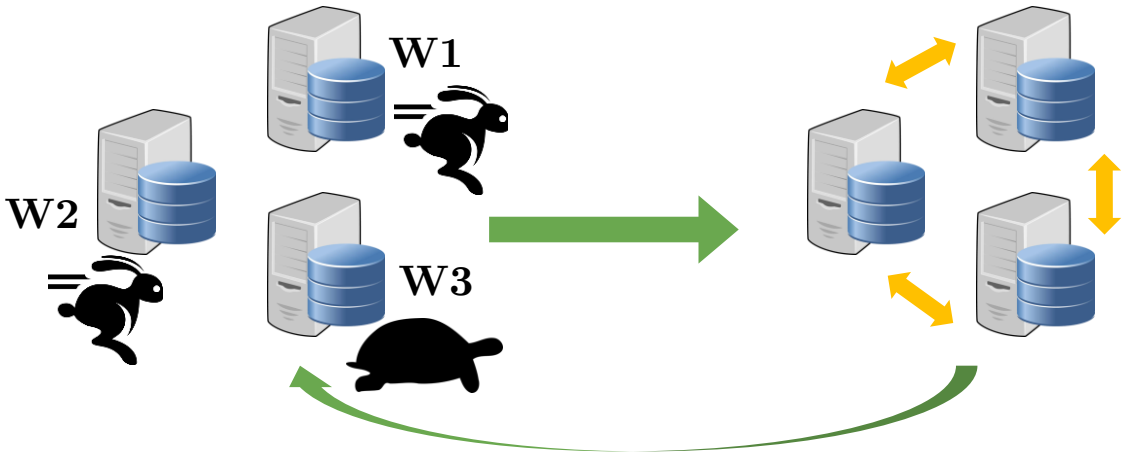
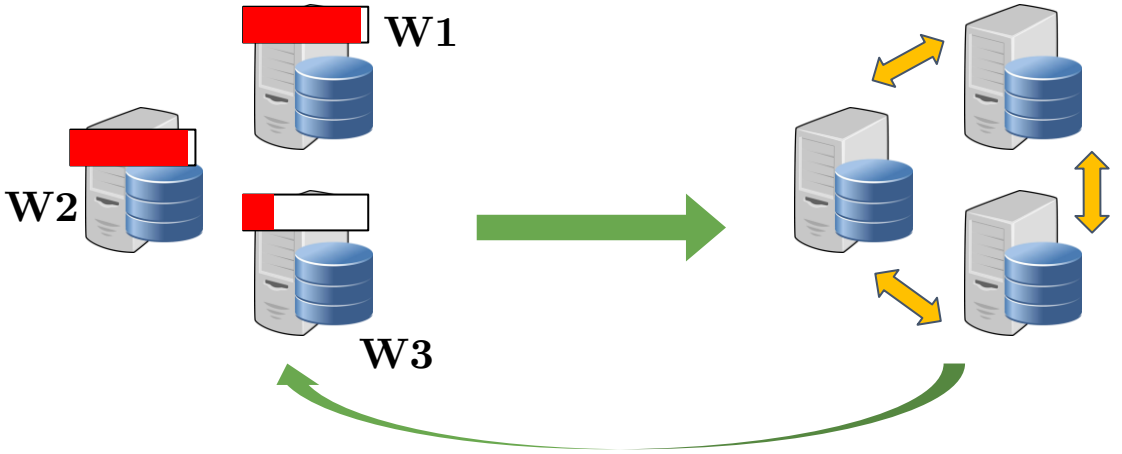


- Compute until a **time limit** in Step 1.
- Sync. with **partial results** in Step 2.

Step 1: Compute
For only 10 seconds

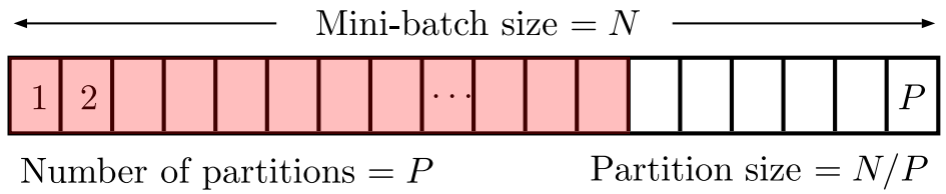
Step 2: Communicate
Partial computations



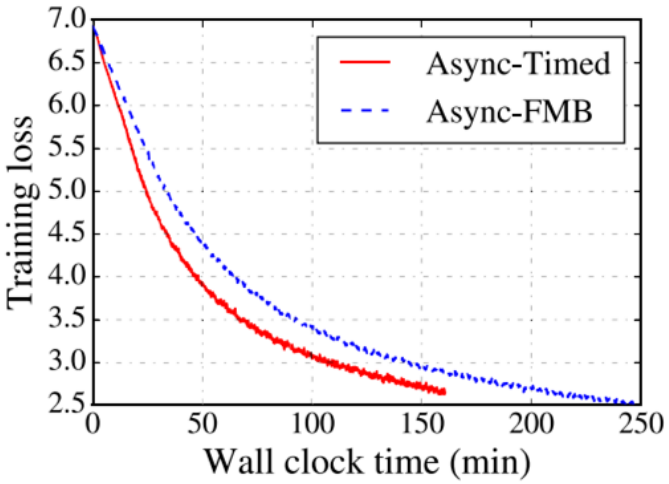
- Everybody's work is taken into account!
- Time for an iteration is LOWER!

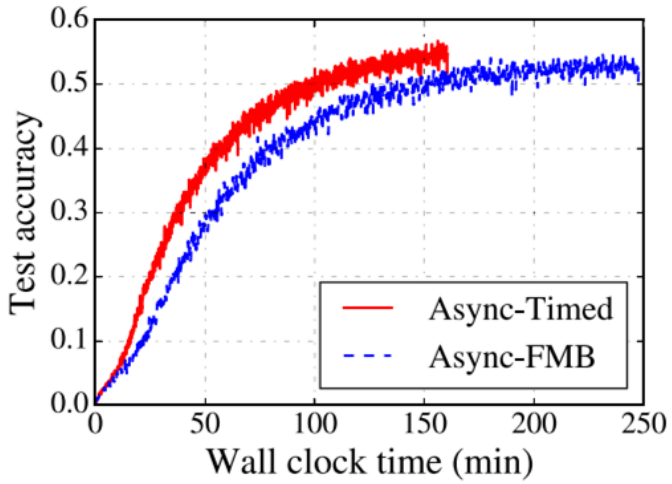
Ferdinand et al. (2017), Reisizadeh et al. (2019), Al-Lawati et al. (2021)

Straggler **Exploitation** in SGD: Results



The higher the granularity of splitting,
the higher the chance of stopping at the time limit.





AlexNet training on ImageNet dataset,
3 workers, natural stragglers.

Async-FMB : Equal workload approach
50% accuracy by **150 mins**

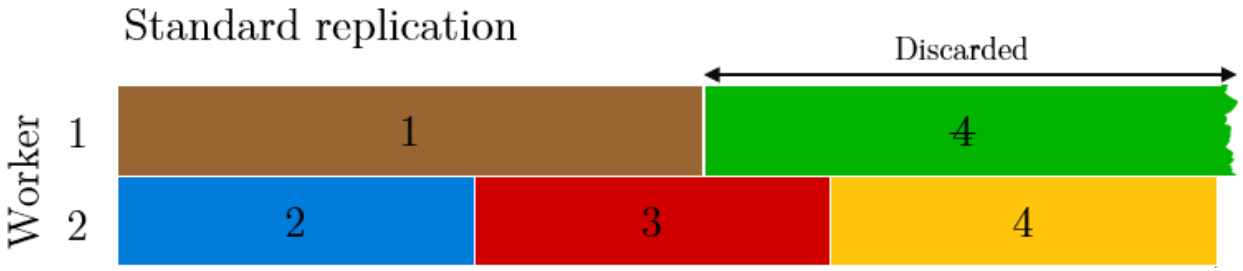
Async-Timed: Time-limited approach
50% accuracy by **100 mins**

Time limited approach is around **33% faster!**

Al-Lawati et al. (2021)

Straggler **Exploitation** with **General Computations**

- Computations must be exact (unlike 'stochastic' gradient descent).
- Hard to implement a time limit. >> Key Idea: **Increase task granularity**.



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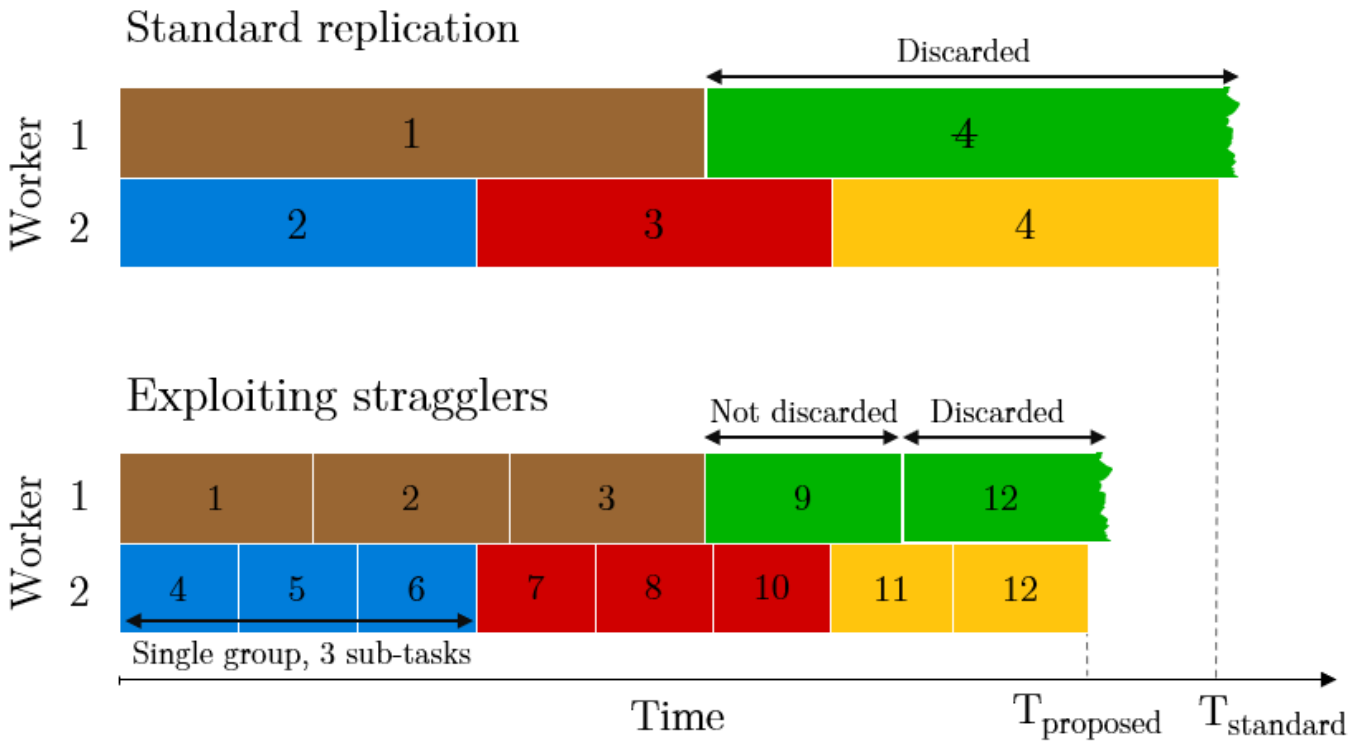

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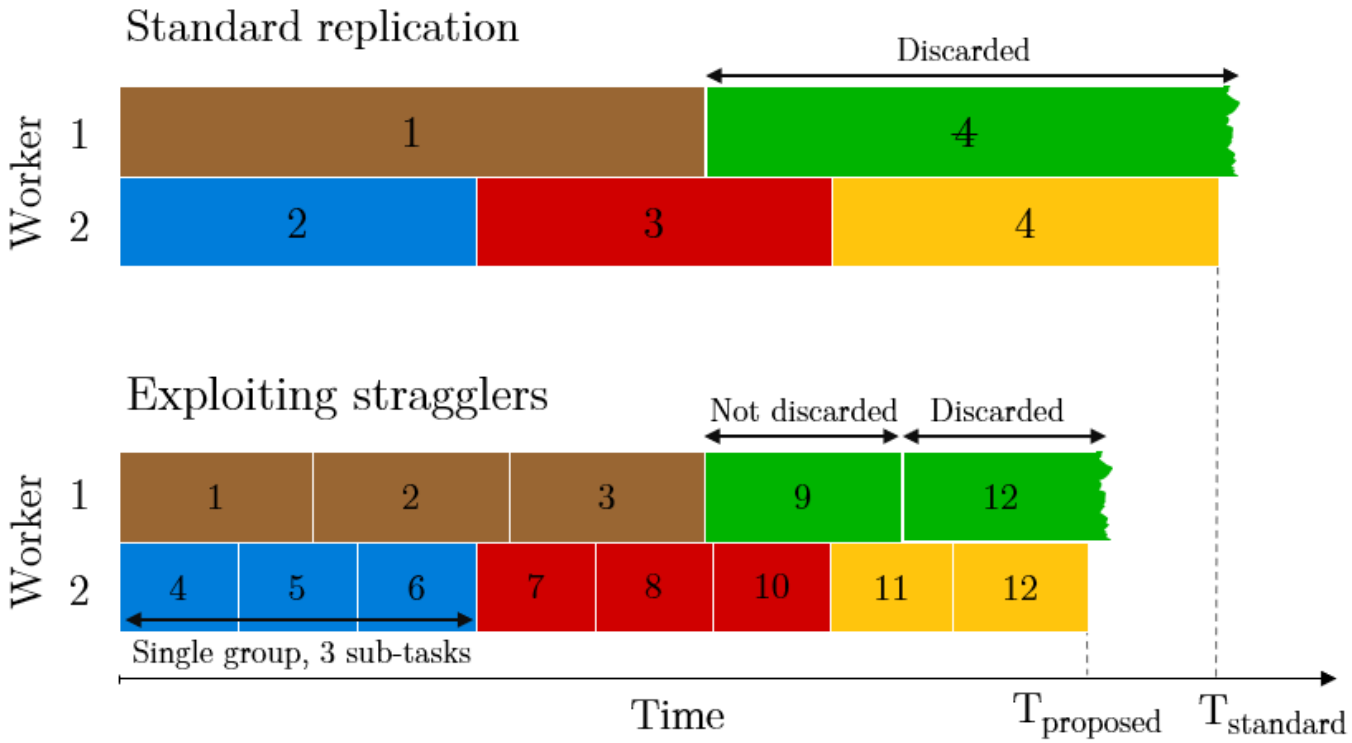


- Hard to split some tasks into **sub tasks**.
- Second method resembles **grouping** of tasks.

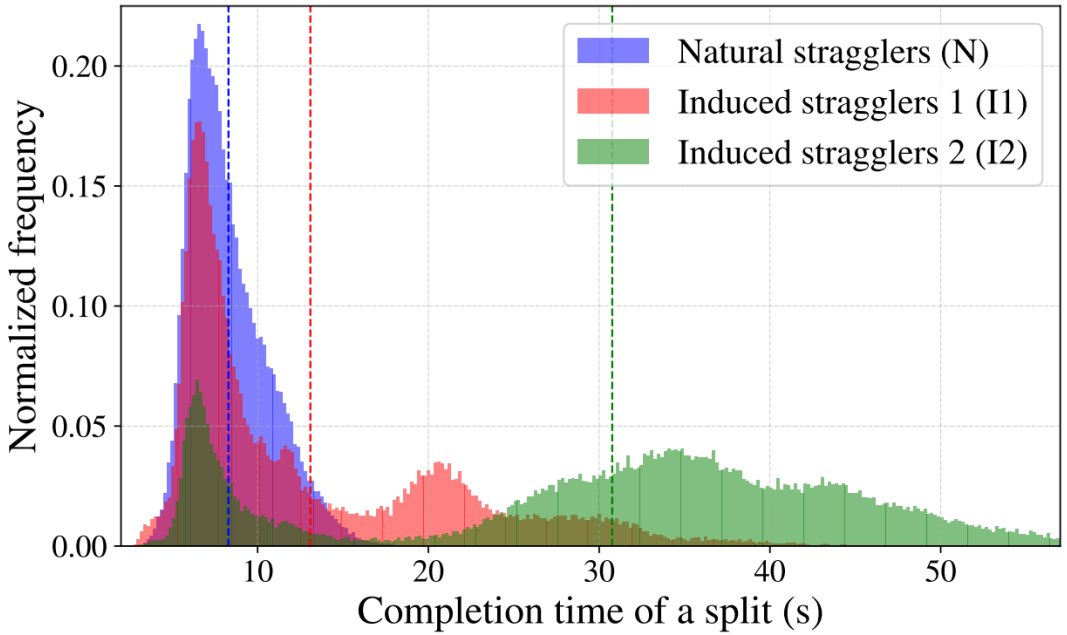
- Methodology summary:

1. **Assign groups of tasks to workers.**
2. **Increase worker updates.**
3. **Skip completed tasks.**

Amazon EC2 Tests

32 workers, 50 GB word count workload.
392 files (tasks) of 128 MB each.

Implementation with YARN and HDFS.



Amazon EC2 Tests

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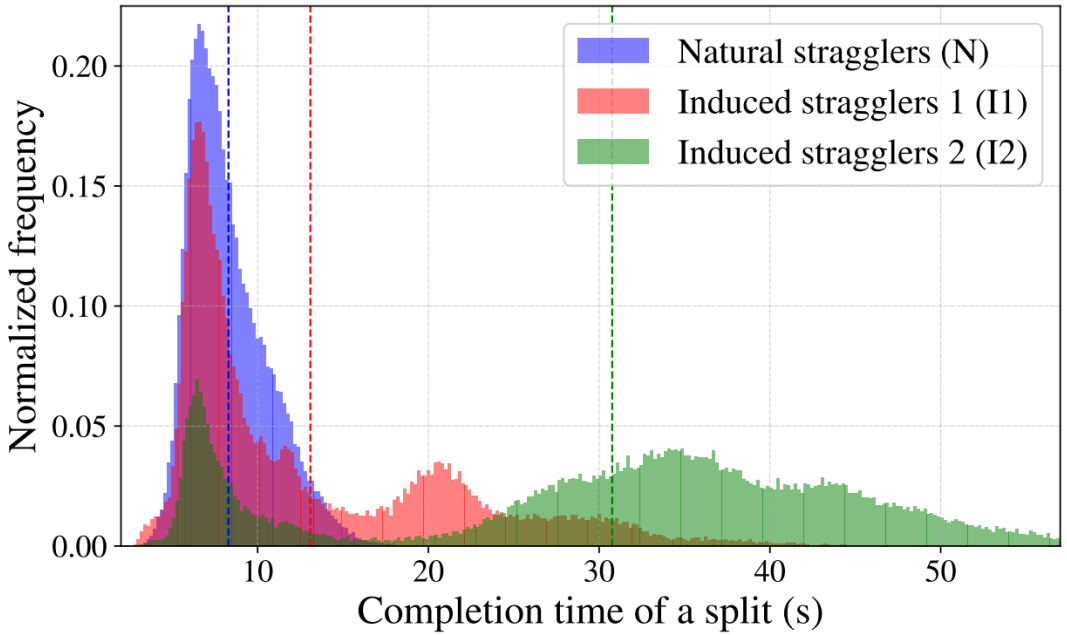
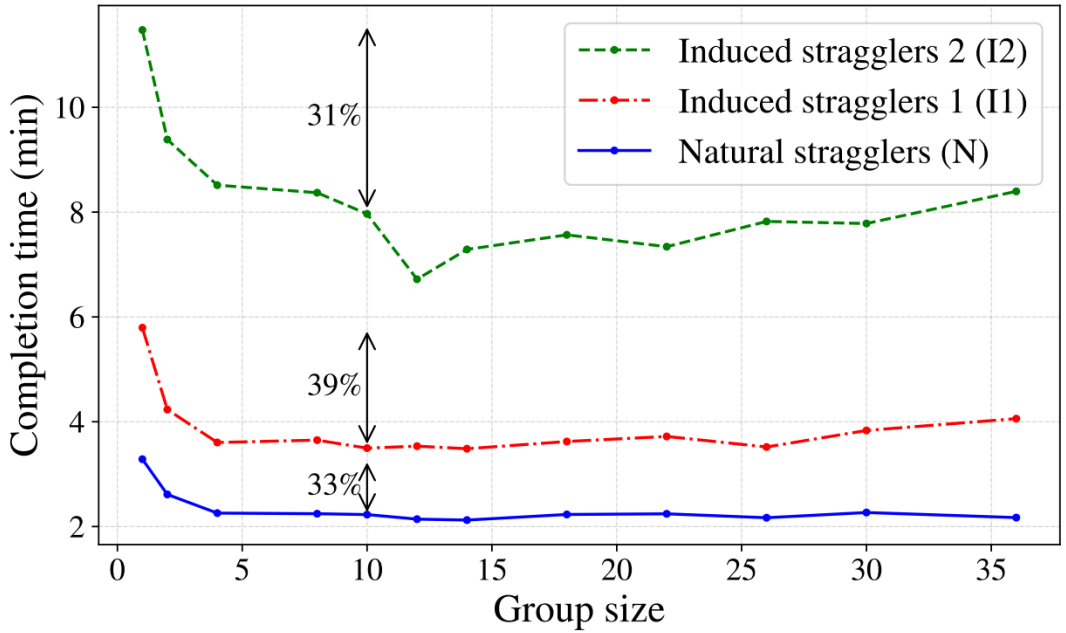
Implementation with YARN and HDFS.

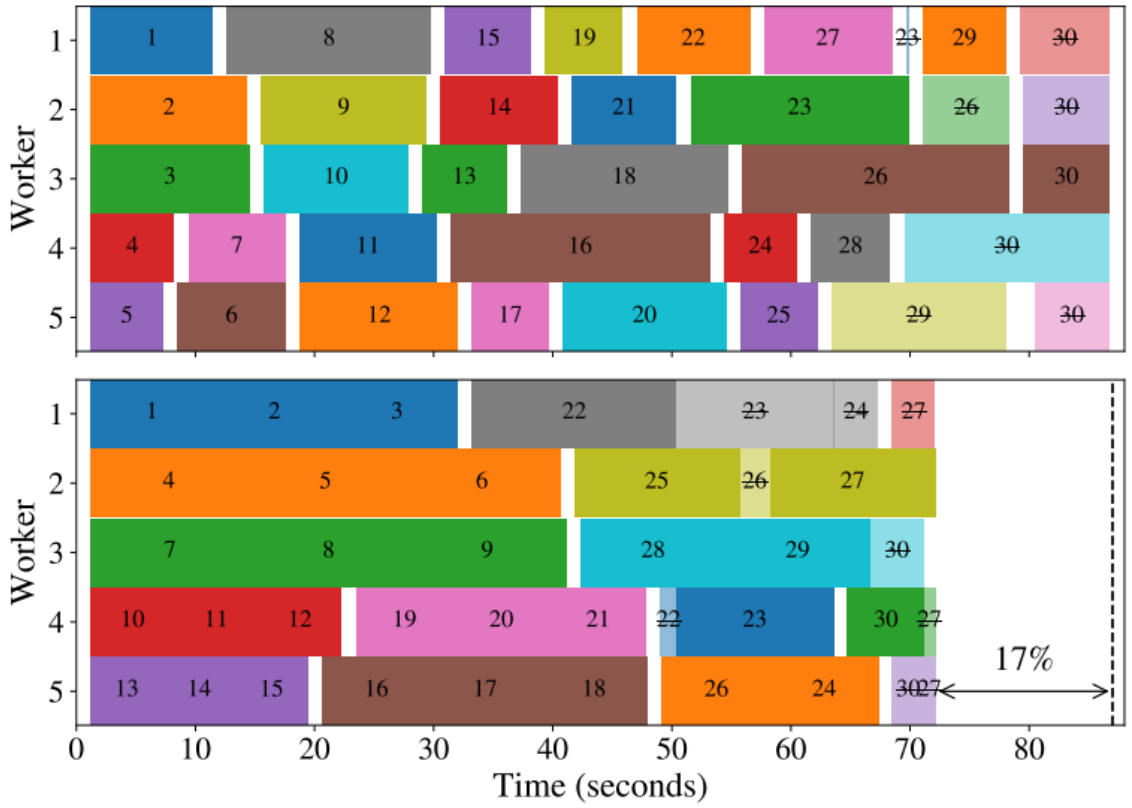
Baseline: Group size = 1 (standard replication).

Key observation: Time savings increase with the straggler severity.





Source of Time Savings



- Grouping reduces overhead (whitespace between tasks).
- How much savings is due to the reduction of overhead?
- Conduct simulation-based experiments.

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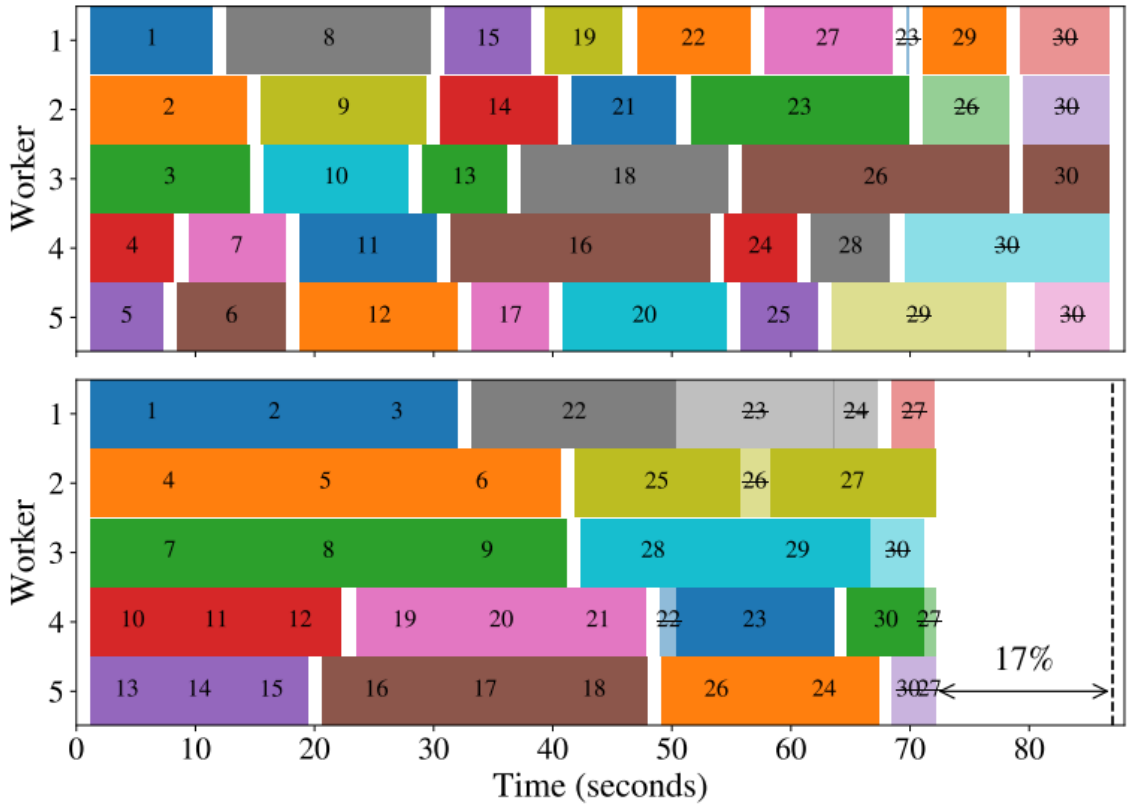

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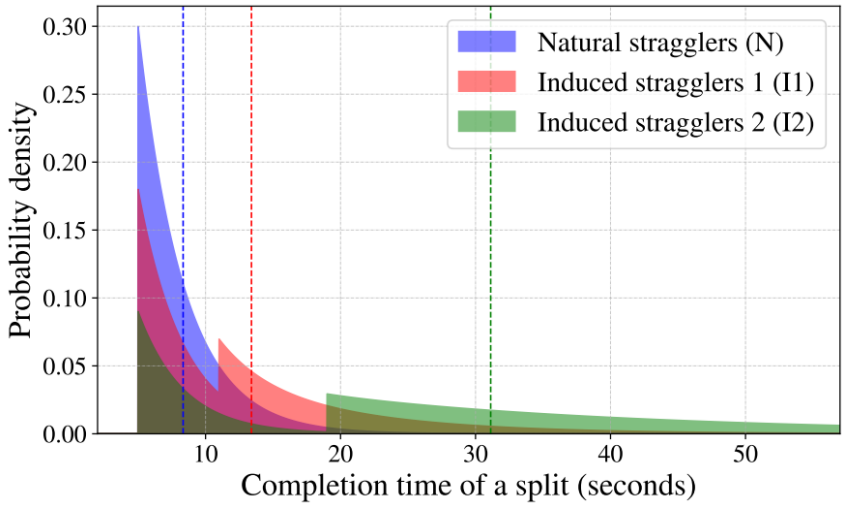
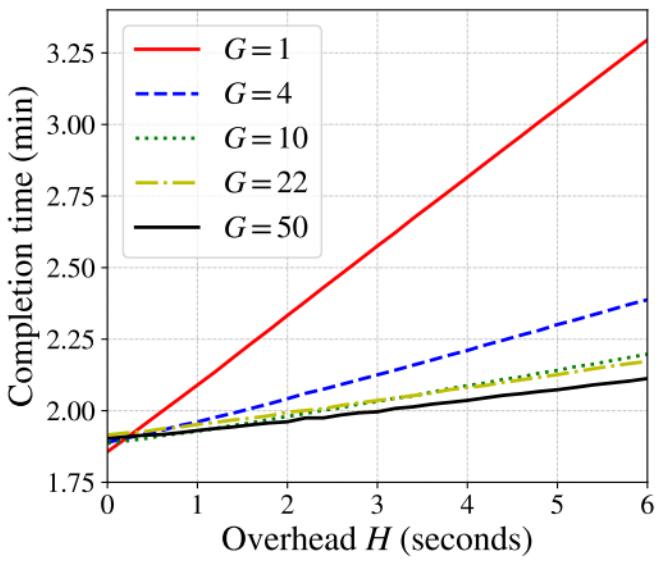
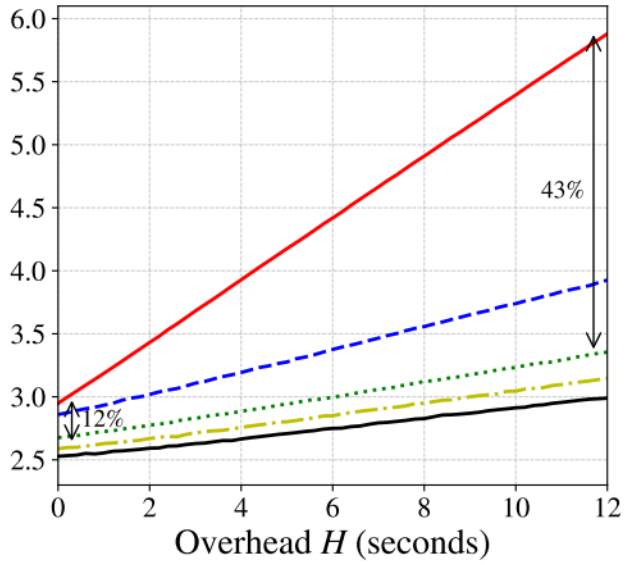


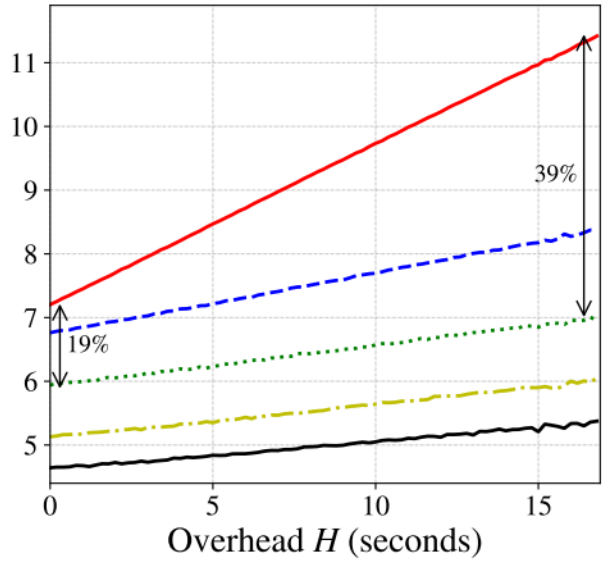
Overhead Reduction **vs.** Straggler **Exploitation**



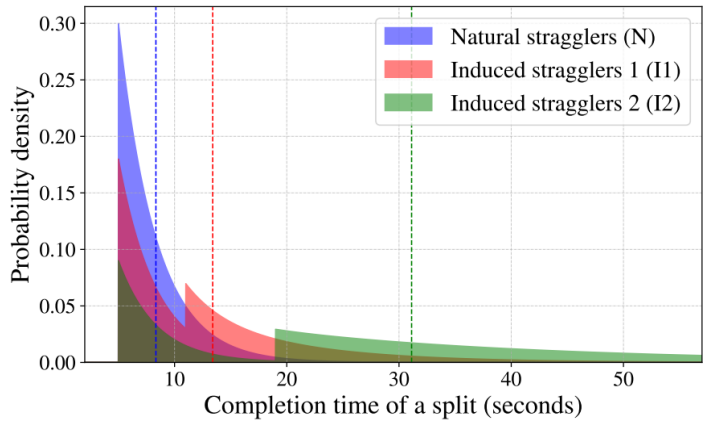
(a) With PDF (N).



(b) With PDF (I1).



(c) With PDF (I2).



Key observation: Time savings even if overhead=0, if stragglers are severe enough.

Conclusions and **Next Steps**

Talk summary:

- Proposed an algorithm for exploiting work performed by straggling workers.
- The key idea is to increase granularity of work assigned to workers.

Possible future work:

- An analysis that characterizes the performance improvement using of the group size parameter.
- A method for predicting the optimal group size for a given straggler profile/set of tasks.

Thank you! Questions?

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