



Riffle: Optimized Shuffle Service for Large-Scale Data Analytics



Haoyu Zhang

Brian Cho

Ergin Seyfe

Avery Ching

Michael J. Freedman

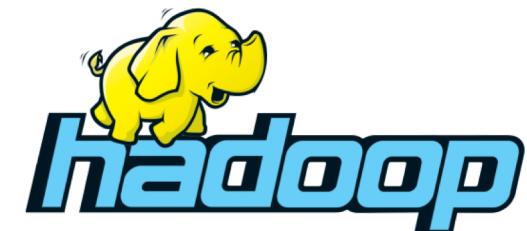
Batch analytics systems are widely used

- Large-scale SQL queries
- Custom batch jobs
- Pre-/Post-processing for ML

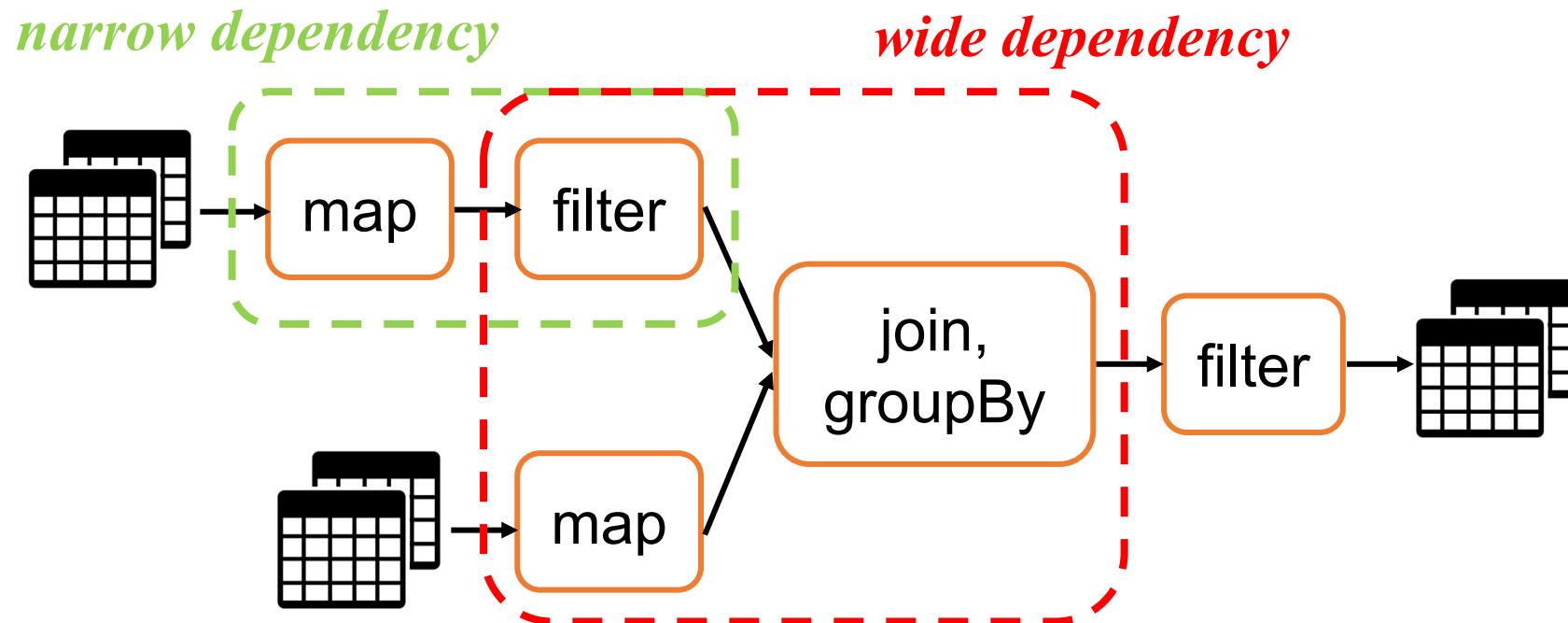
At **facebook**

10s of PB new data is generated
every day for batch processing

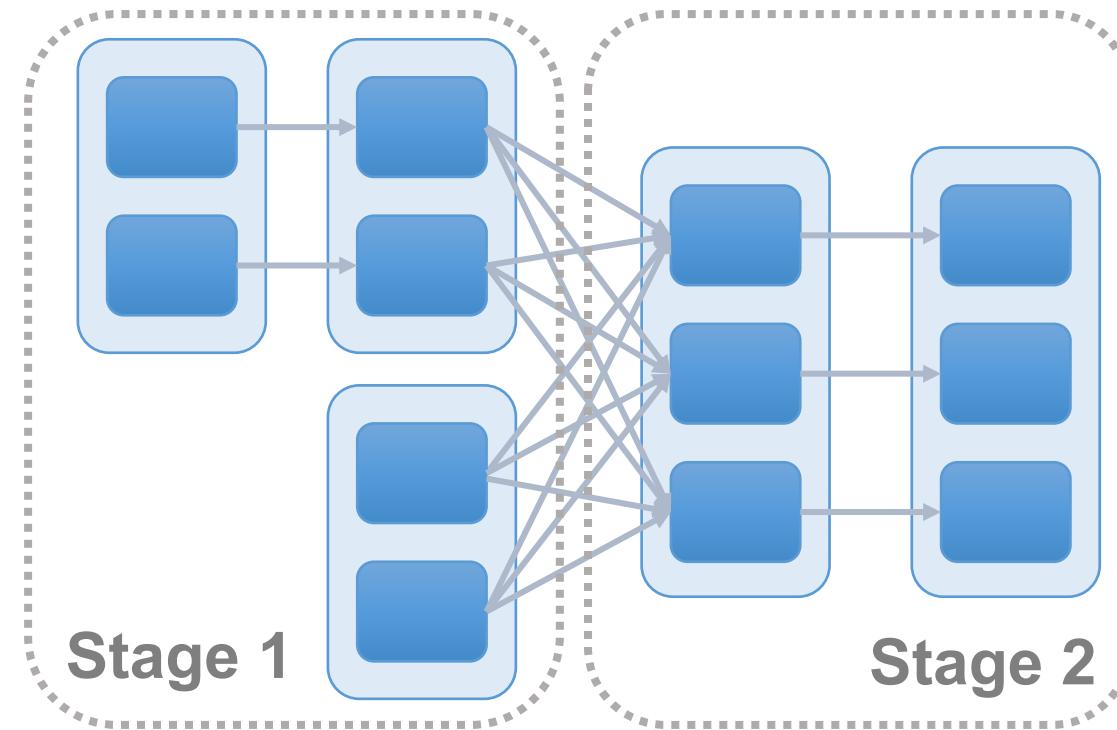
100s of TB data is added to be
processed by a single job



Batch analytics jobs: logical graph

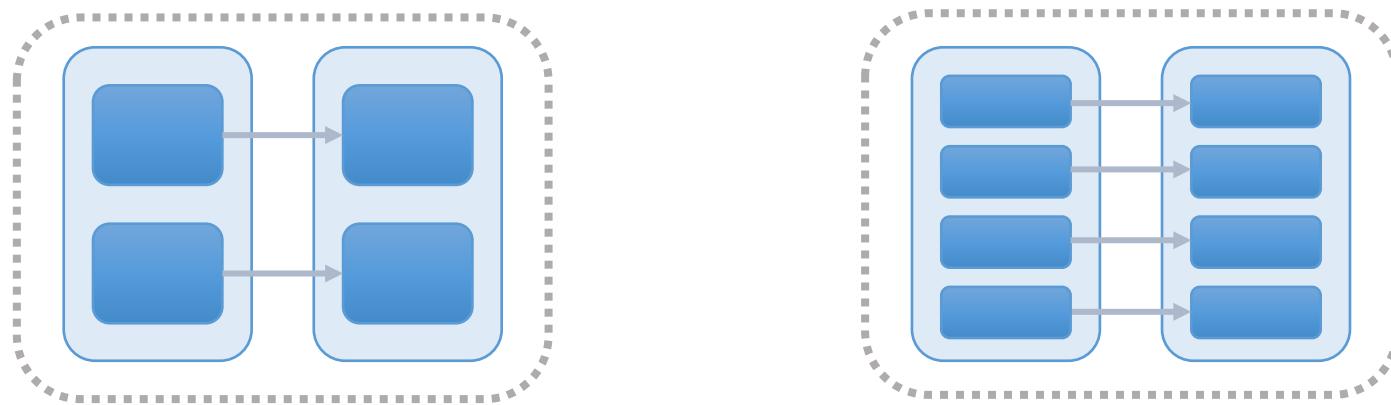


Batch analytics jobs: DAG execution plan



- Shuffle: all-to-all communication between stages
- >10x larger than available memory, strong fault tolerance requirements
→ on-disk shuffle files

The case for tiny tasks



- Benefits of slicing jobs into small tasks
 - Improve parallelism [Tinytasks HotOS 13] [Subsampling IC2E 14] [Monotask SOSP 17]
 - Improve load balancing [Sparrow SOSP 13]
 - Reduce straggler effect [Dolly NSDI 13] [SparkPerf NSDI 15]

The case against tiny tasks



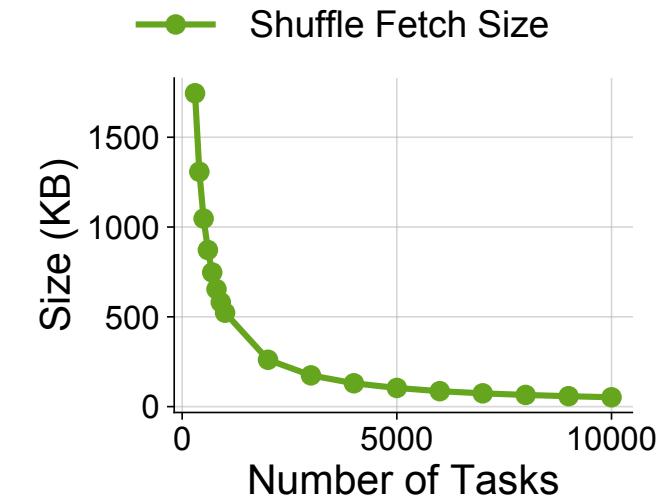
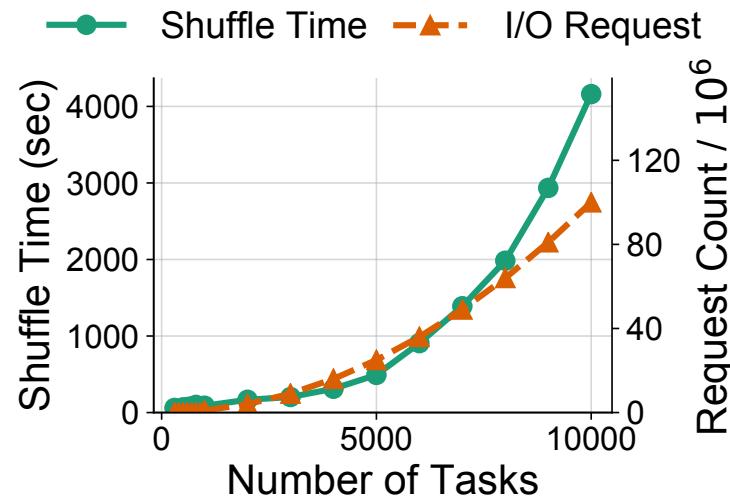
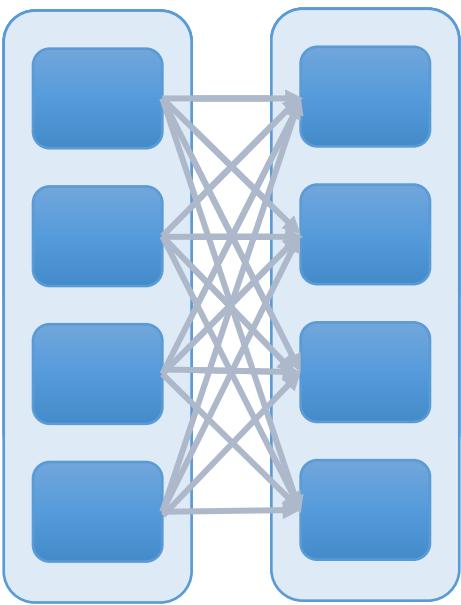
Although we were able to run the Spark job with such a high number of tasks, we found that there is significant performance degradation when the number of tasks is too high.



- Engineering experience often argues against running too many tasks
 - Medium scale → very large scale (10x larger than memory space)
 - Single-stage jobs → multi-stage jobs (> 50%)

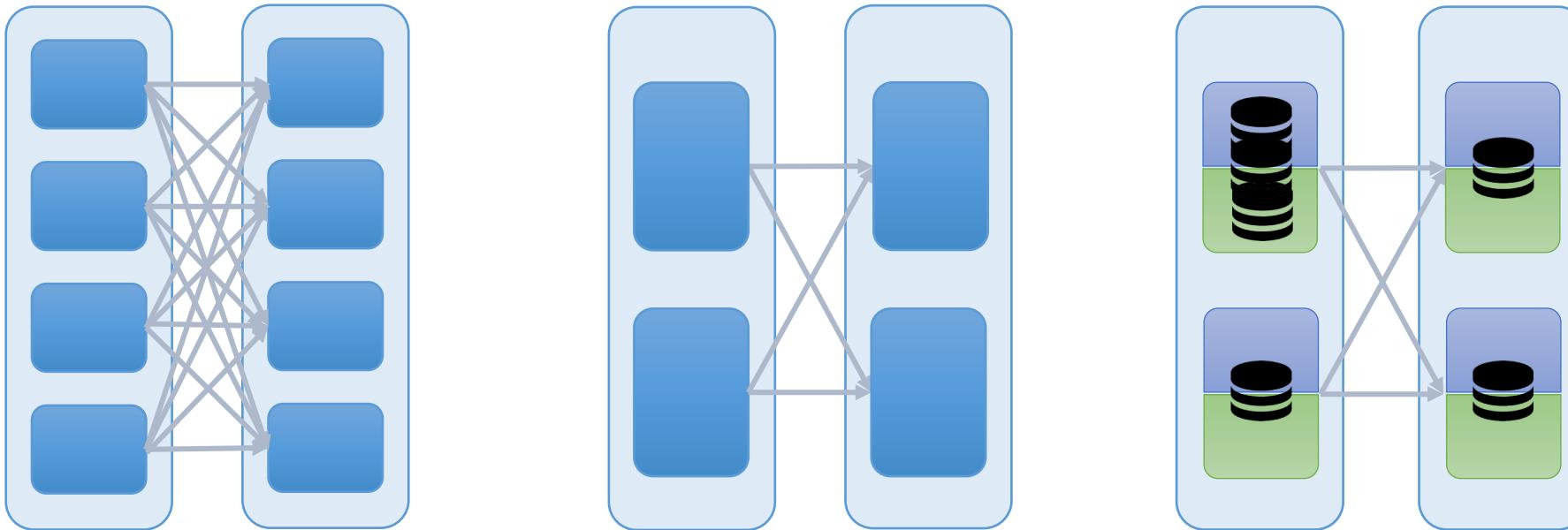
[*] Apache Spark @Scale: A 60 TB+ Production Use Case. <https://tinyurl.com/yadx29gl>

Shuffle I/O grows quadratically with data



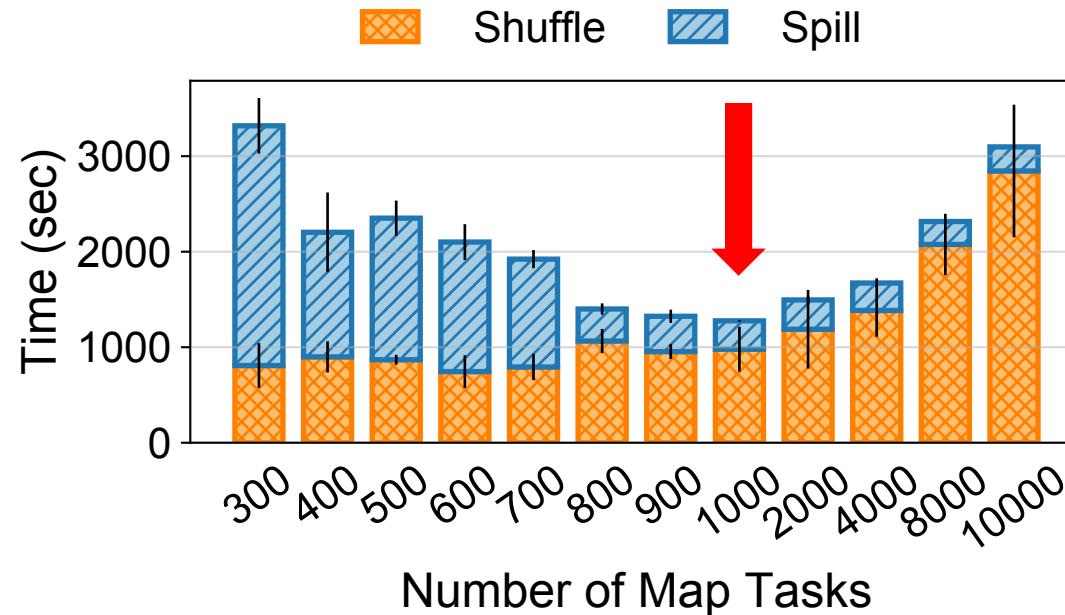
- Large amount of fragmented I/O requests
 - Adversarial workload for hard drives!

Strawman: tune number of tasks in a job

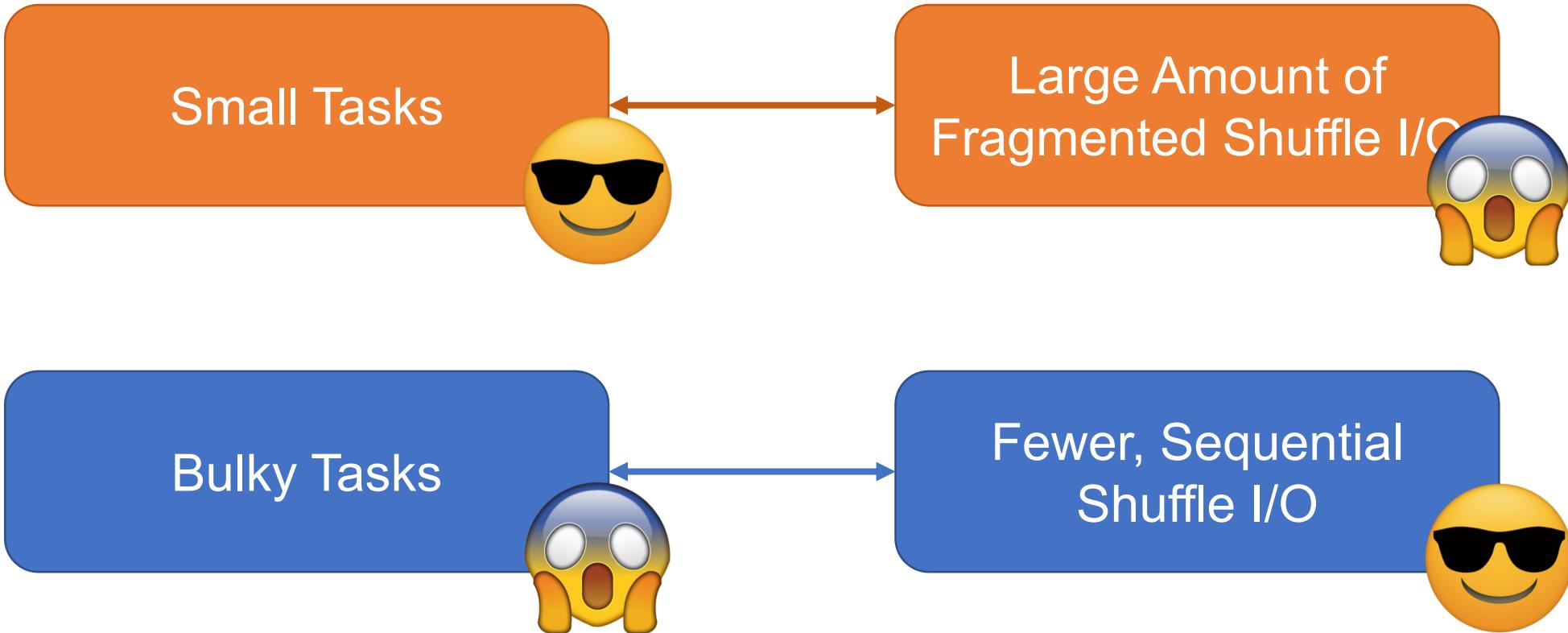


- Tasks spill intermediate data to disk if data splits exceed memory capacity
- Larger task execution reduces shuffle I/O, but increases spill I/O

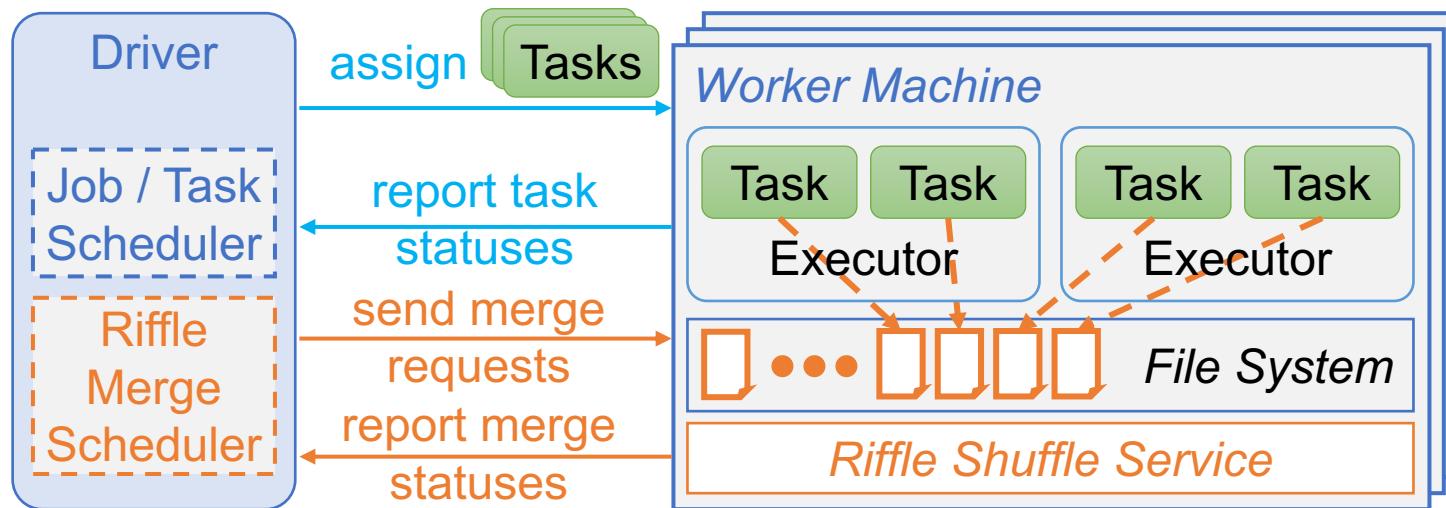
Strawman: tune number of tasks in a job



- Need to retune when input data volume changes for each individual job
- Bulky tasks can be detrimental [Dolly NSDI 13] [SparkPerf NSDI 15] [Monotask SOSP 17]
 - straggler problems, imbalanced workload, garbage collection overhead



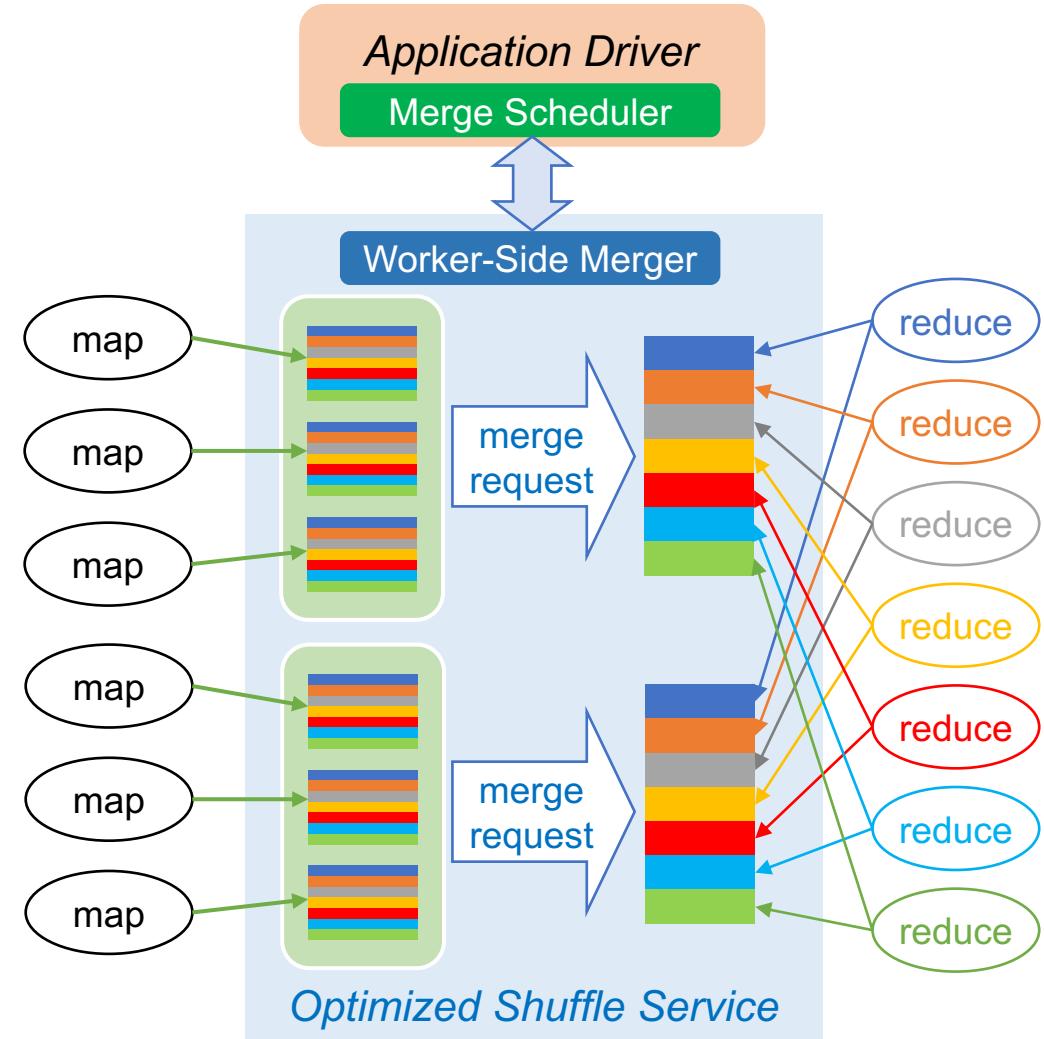
Riffle: optimized shuffle service



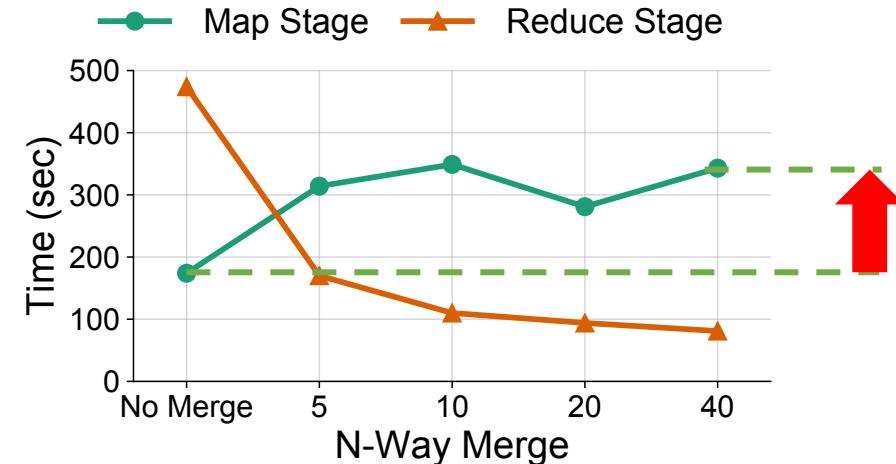
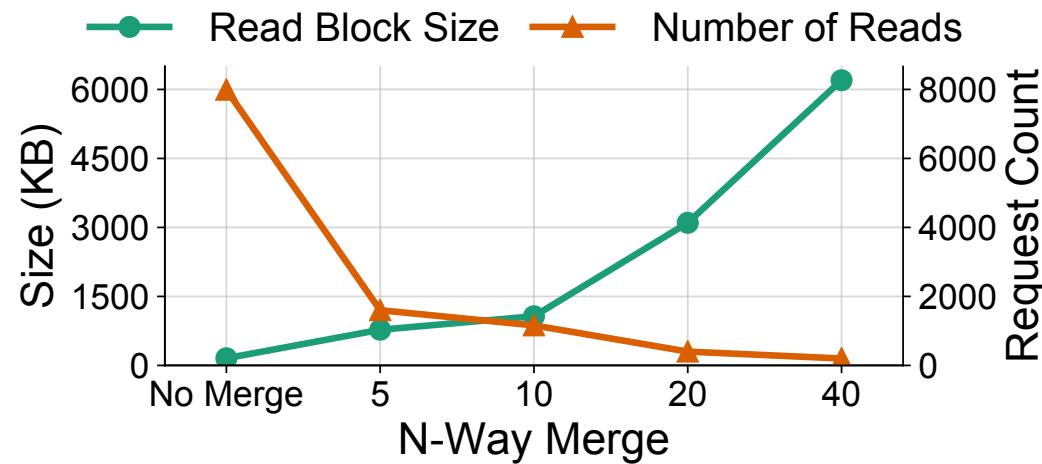
- Riffle shuffle service: a long running instance on each physical node
- Riffle scheduler: keeps track of shuffle files and issues merge requests

Riffle: optimized shuffle service

- When receiving a merge request
 1. Combines small shuffle files into larger ones
 2. Keeps original file layout
- Reducers fetch fewer, large blocks instead of many, small blocks

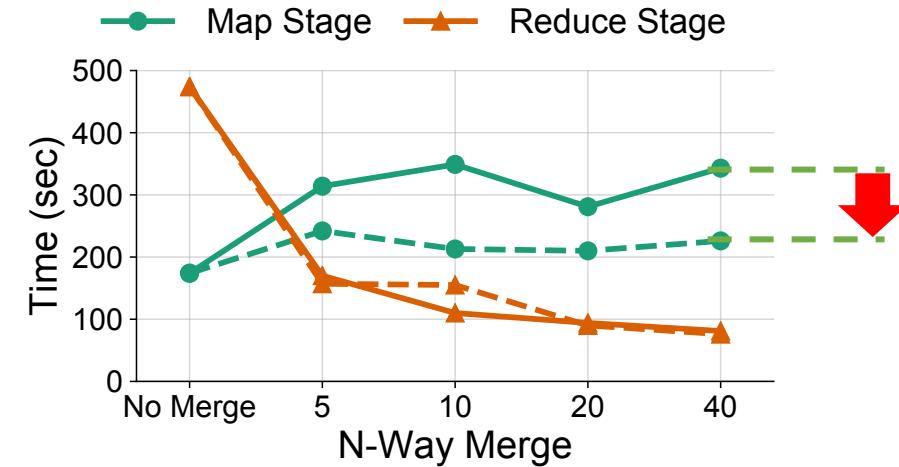
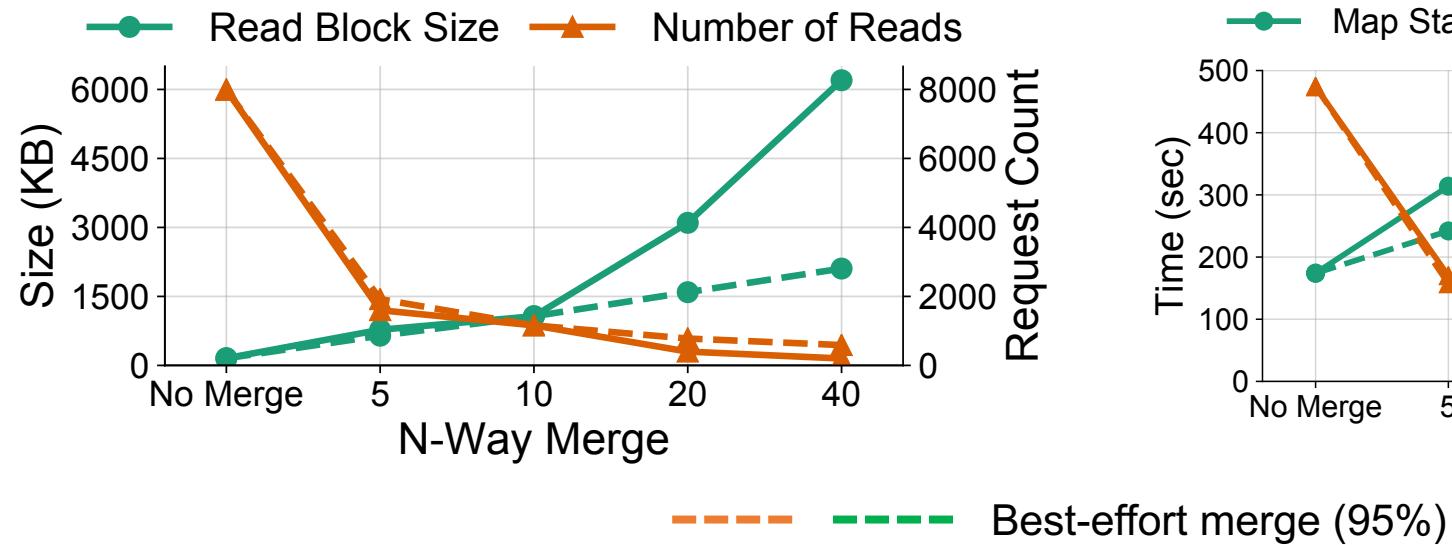


Results with merge operations on synthetic workload



- Riffle reduces number of fetch requests by **10x**
- Reduce stage **-393s**, map stage **+169s** → job completes **35% faster**

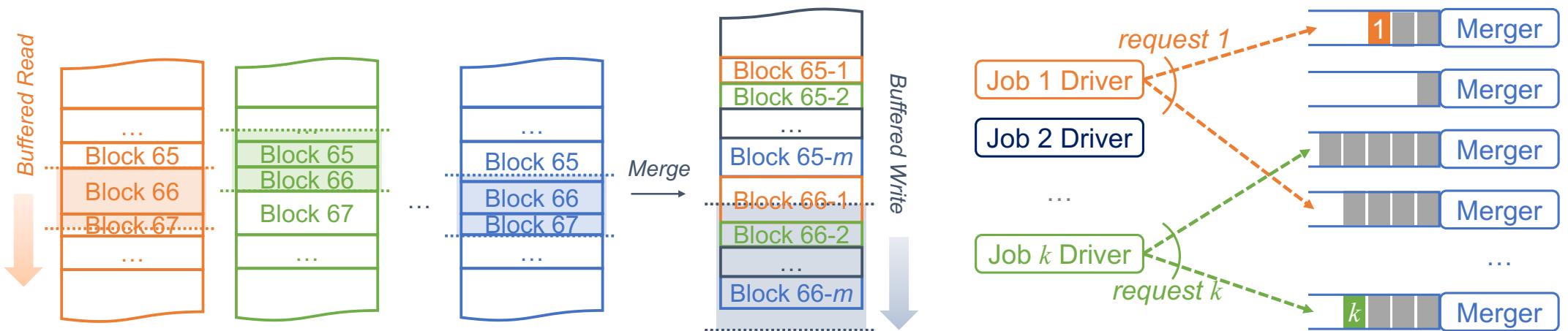
Best-effort merge: mixing merged and unmerged files



- Reduce stage **-393s**, map stage **+52s** → job completes **53% faster**
 - Riffle finishes job with only ~50% of cluster resources!

Additional enhancements

- Handling merge operation failures
- Efficient memory management
- Balance merge requests in clusters

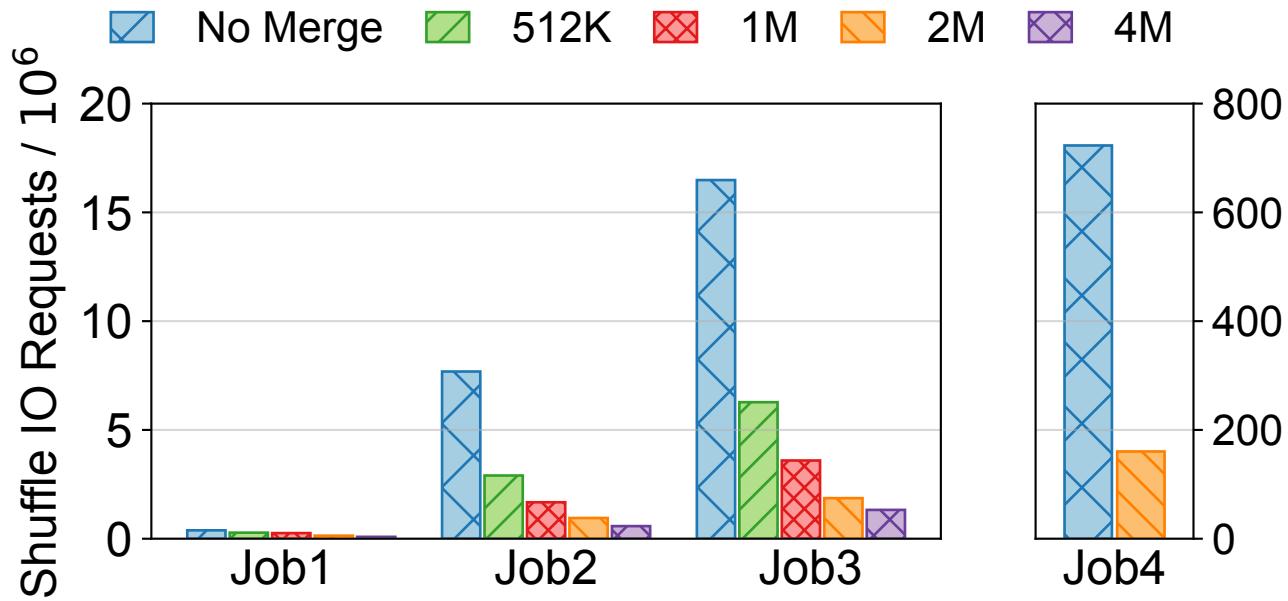


Experiment setup

- Testbed: Spark on a 100-node cluster
 - 56 CPU cores, 256GB RAM, 10Gbps Ethernet links
 - Each node runs 14 executors, each with 4 cores, 14GB RAM
- Workload: 4 representative production jobs at Facebook

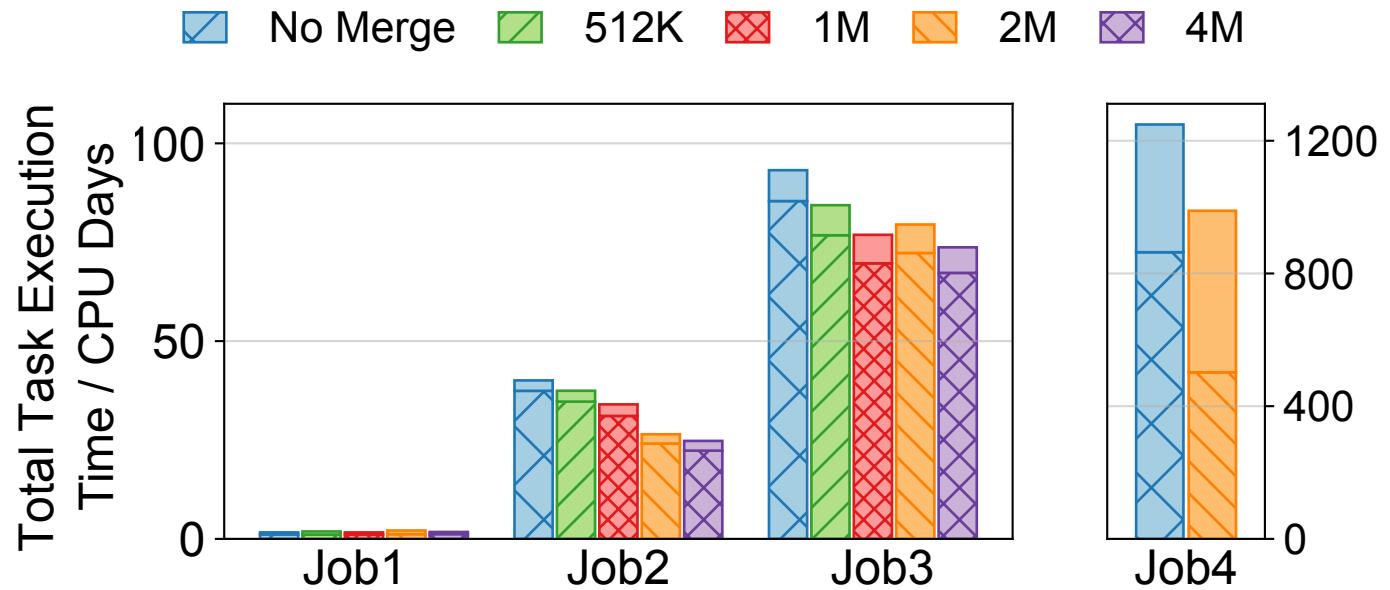
	Data	Map	Reduce	Block
1	167.6 GB	915	200	983 K
2	1.15 TB	7,040	1,438	120 K
3	2.7 TB	8,064	2,500	147 K
4	267 TB	36,145	20,011	360 K

Reduction in shuffle I/O requests



- Riffle reduces # of I/O requests by 5--10x for medium / large scale jobs

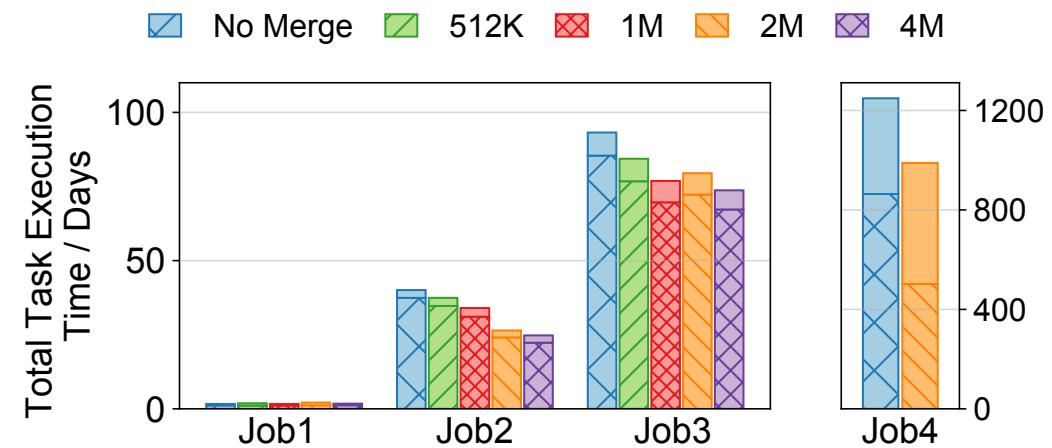
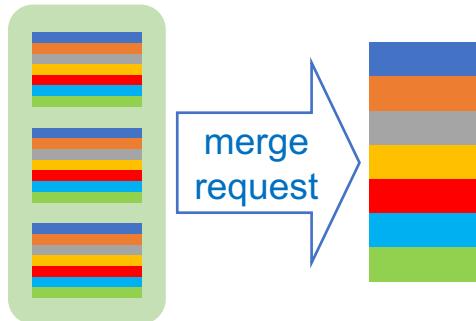
Savings in end-to-end job completion time



- Map stage time is almost not affected (with best-effort merge)
- Reduces job completion time by 20--40% for medium / large jobs

Conclusion

- Shuffle I/O becomes scaling bottleneck for multi-stage jobs
- Efficiently schedule merge operations, mitigate merge stragglers

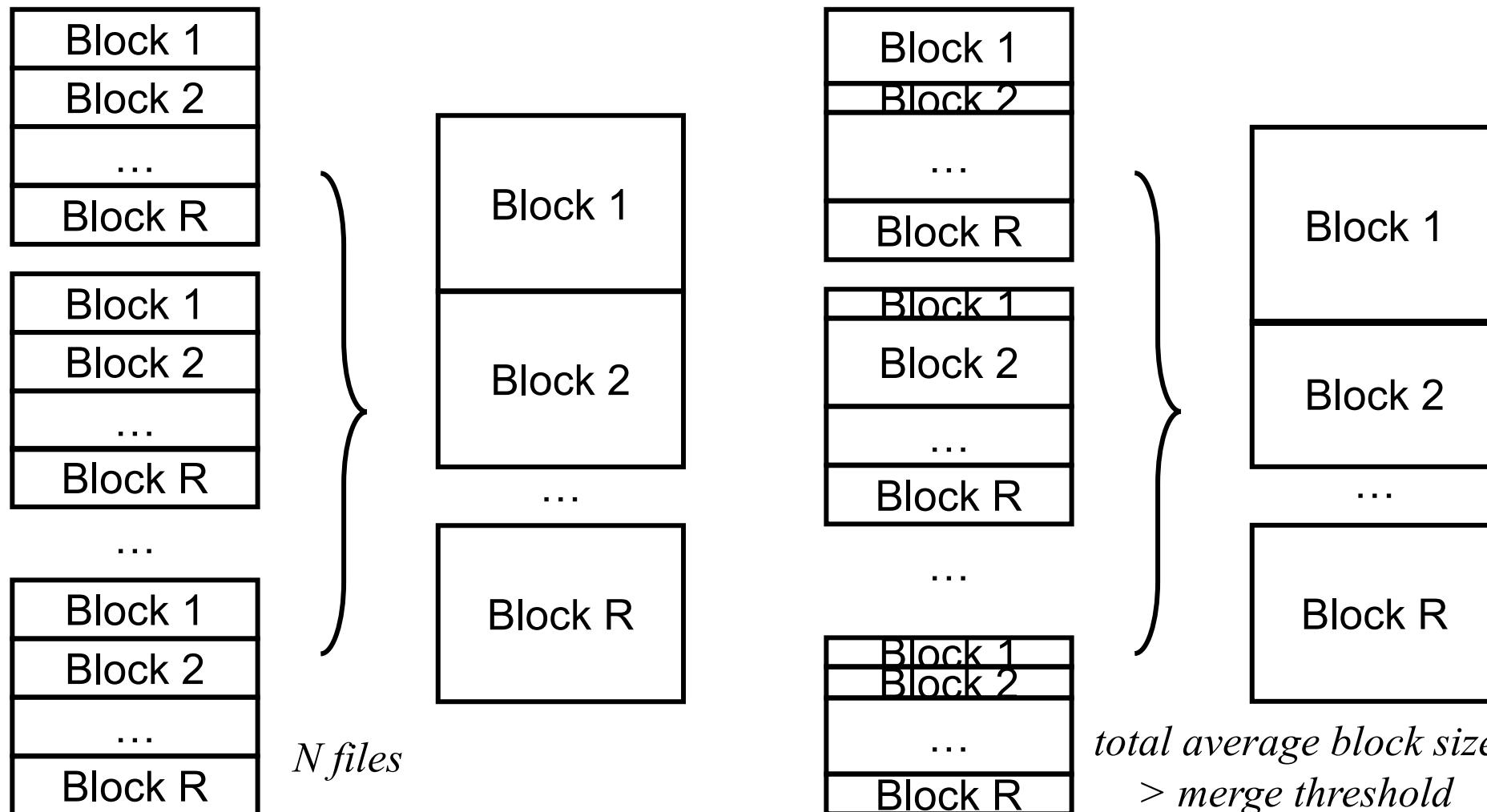


- Riffle is deployed for Facebook's production jobs processing PBs of data

Thanks!

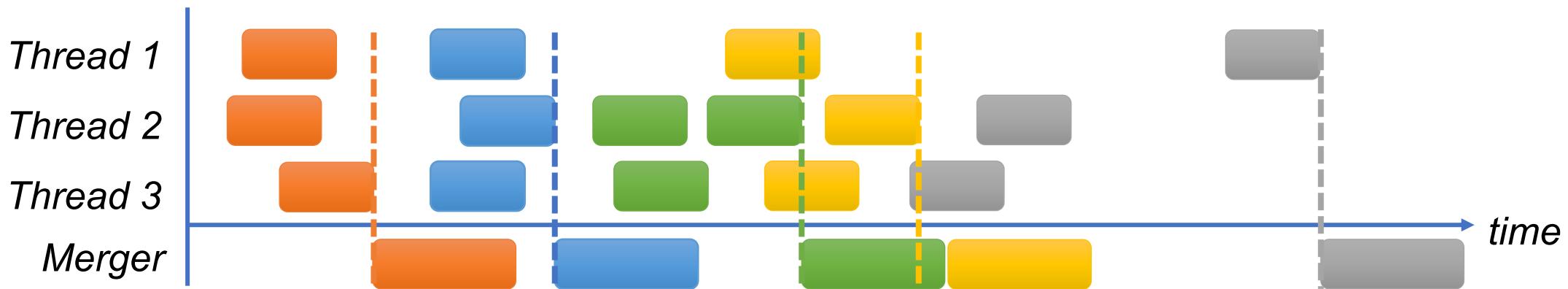
Haoyu Zhang
haoyuz@cs.princeton.edu
<http://www.haoyuzhang.org>

Riffle merge policies



Best-effort merge

- Observation: slowdown in map stage is mostly due to stragglers



- Best-effort merge: mixing merged and unmerged shuffle files
 - When number of finished merge requests is larger than a user specified percentage threshold, stop waiting for more merge results