Joint Scheduling of Overlapping Phases in the MapReduce Framework

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Road Map

1. Introduction
2. Model and Formulation
3. General Greedy Solutions
4. Experiment
5. Conclusion

1. Introduction

Map-Shuffle-Reduce: a popular computation paradigm

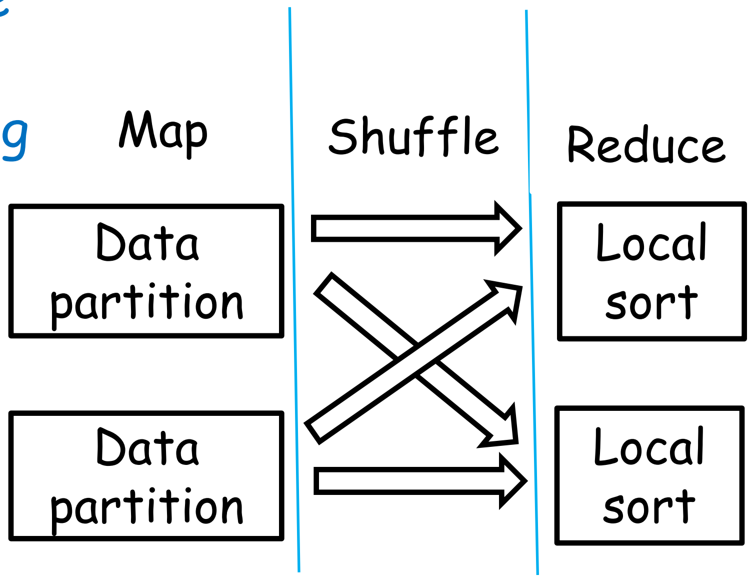
- Map and Reduce: CPU-intensive
- Shuffle: I/O-intensive

Master node: pipeline scheduling

Data node: data parallelism

E.g., TeraSort

- Map: sample & partition data
- Shuffle: move data
- Reduce: locally sort data



Scheduling of Multiple Jobs

- Multiple jobs
  - Terasort, wordcount, ...
- Reduce is not significant (Zaharia, OSDI 2008)
  - 7% of jobs are reduce-heavy

Centralized scheduler

- Determines a sequential order for jobs on the map and shuffle pipeline

Job Classification

Dependency relationship

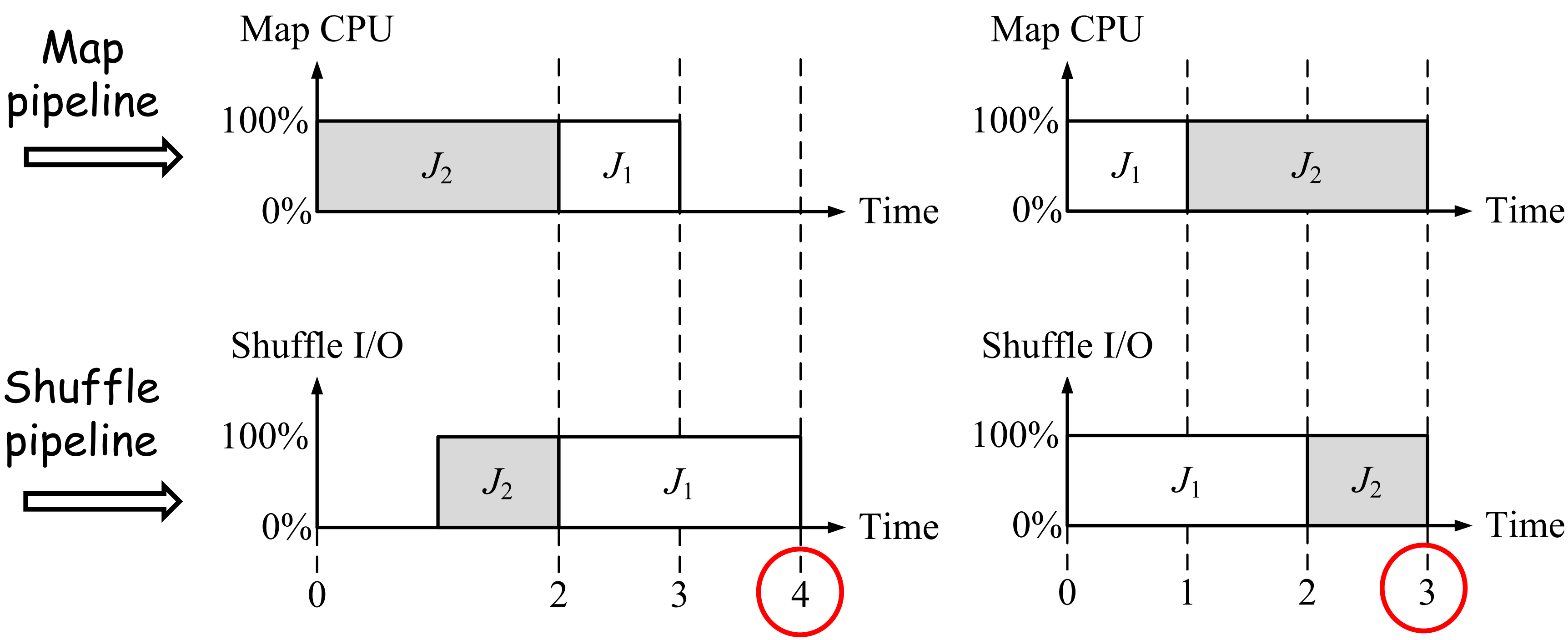
- Map emits data at a certain rate
- Shuffle waits for the map data

Job classification

Map-heavy:	map ≥ shuffle	($m \geq s$)
Shuffle-heavy:	map ≤ shuffle	($m \leq s$)

Execution Order

Impact of overlapping map and shuffle



WordCount (map-heavy) TeraSort (shuffle-heavy)

2. Model and Formulation

Schedule objective:

Minimize the average job completion time for all jobs;
J_i includes the wait time before the job starts.

Schedule is NP-hard offline and APX-hard online (Lin 2013)

Offline

All jobs arrive at the beginning (and wait for schedule)

Related Work: Flow Shop

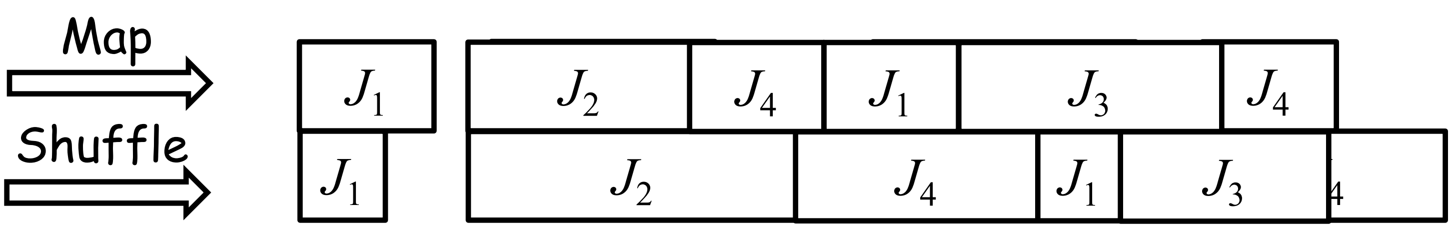
Minimize last job completion time

l-phase flow shop is solvable when l=2

G_s: shuffle-heavy jobs sorted in decreasing order of shuffle load

G_m: map-heavy jobs sorted in increasing order of map load

Optimal schedule: G_s followed by G_m



S. M. Johnson, Optimal two-and three-stage production schedules with setup times included, *Naval Research Logistics Quarterly*, 1954.

Related Work: Strong Pair

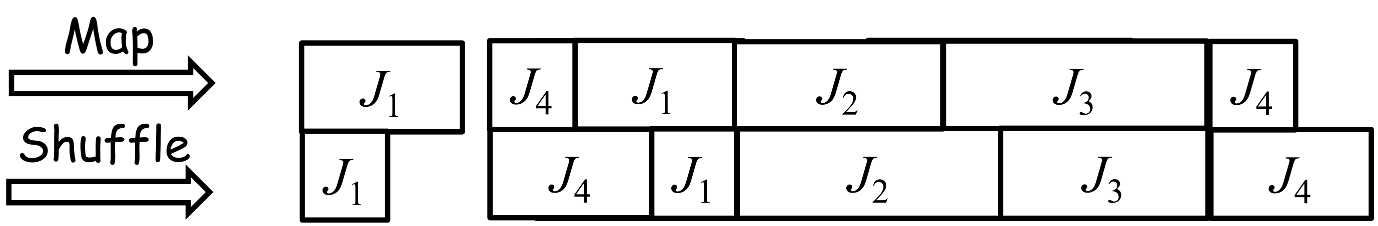
Minimize average job completion time

Strong pair

J_1 and J_2 are a strong pair if $m_1 = s_2$ and $s_1 = m_2$

Optimal schedule: jobs are strong pairs

Pair jobs and rank pairs by total workloads



H. Zheng, Z. Wan, and J. Wu, Optimizing MapReduce framework through joint scheduling of overlapping phases, *Proc. of IEEE ICCCN*, 2016.

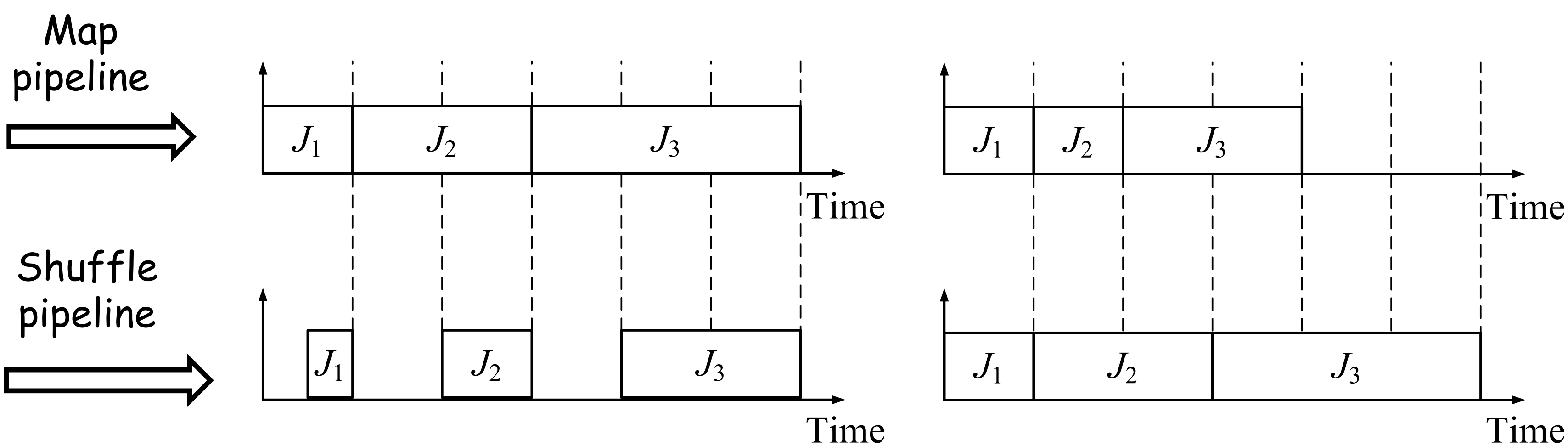
First Special Case

When all jobs are map-heavy, balanced, or shuffle-heavy

Optimal schedule O(n log n):

Sort jobs ascendingly by dominant workload max{m, s}

Execute small jobs first

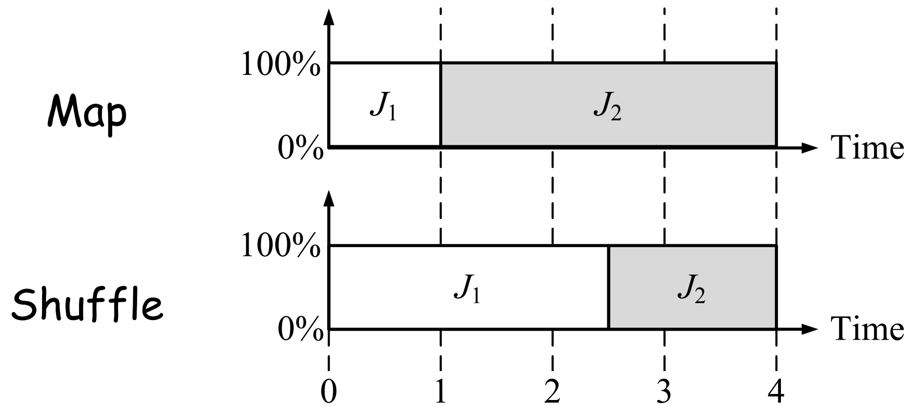


Finishing times J_1, J_2, J_3: 1, 3, 6 vs. J_3, J_2, J_1: 3, 5, 6

Second Special Case

Jobs J_1 and J_2 can be "paired"

if $m_1 \le m_2$, $s_1 \ge s_2$ (non-dominance), and $m_1+m_2=s_1+s_2$ (balance)

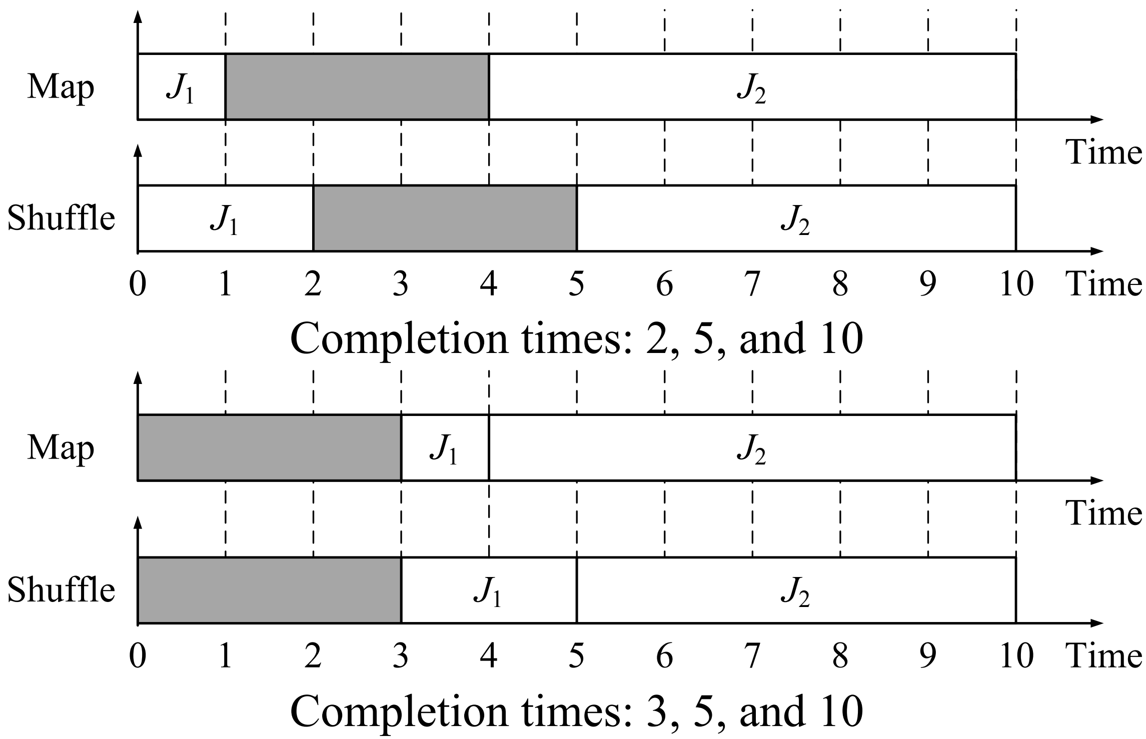


Optimal schedule O(n log n):

- Pair jobs: head to tail pairing on sorted jobs based on m-s
- Sort job pairs: by total workload m+s
- Execute sorted job pairs: smallest pair first

Why Non-dominance?

Cannot pair small and large jobs J_1 and J_2



Theorem

If jobs can be paired, paired job scheduling is optimal if
(1) job pairs with smaller workloads are executed earlier and
(2) all pairs are executed together (with shuffle-heavy first).

In each pair, shuffle-heavy job is executed before map-heavy job
Otherwise a swap leads to a better result

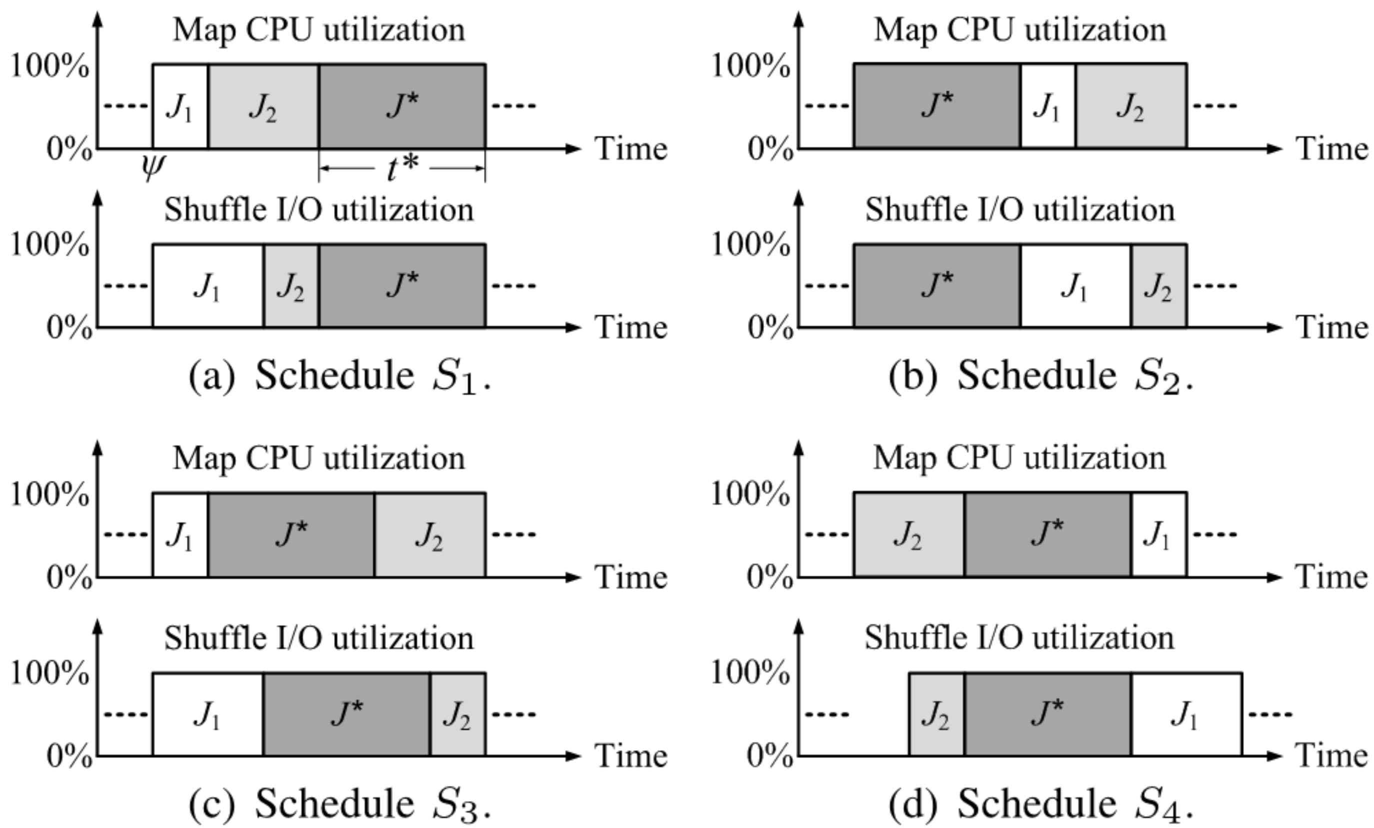
Job pairs with smaller total workloads are executed earlier
Otherwise a swap leads to a better result

Paired jobs should not be separately executed
A bit more involved

Proof

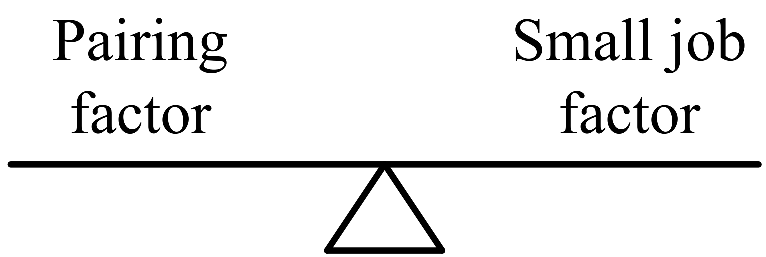
S_1 is better than S_3 and S_4 when J^* is large

S_2 is better than S_3 and S_4 when J^* is small



3. General Greedy Solutions

A delicate balance for general cases



Map-dominant (shuffle-dominant)

more map (shuffle)-heavy than shuffle (map)-heavy

First Greedy Algorithm

Sort jobs based on their sizes ("workload")

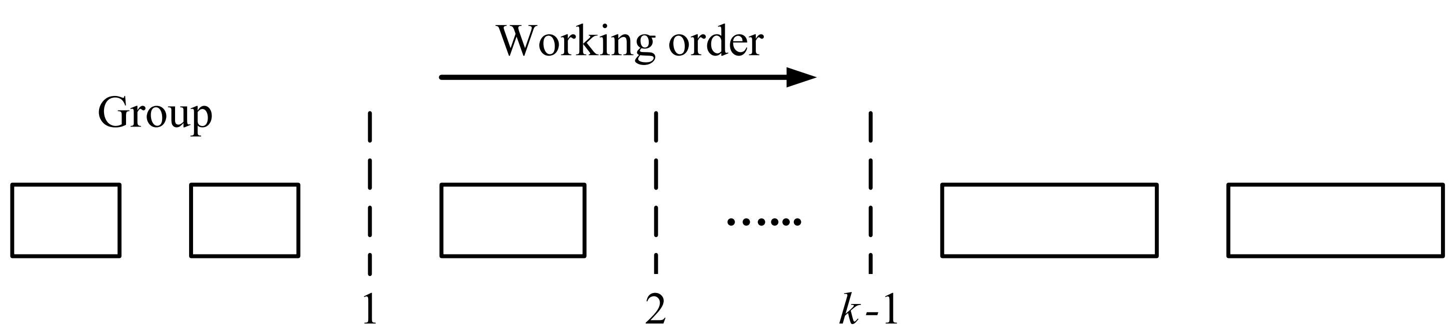
Partition sorted list in k (group factor) groups

Execute each group in order based on workload

- Order matters for inter-group!

Pair jobs in each group

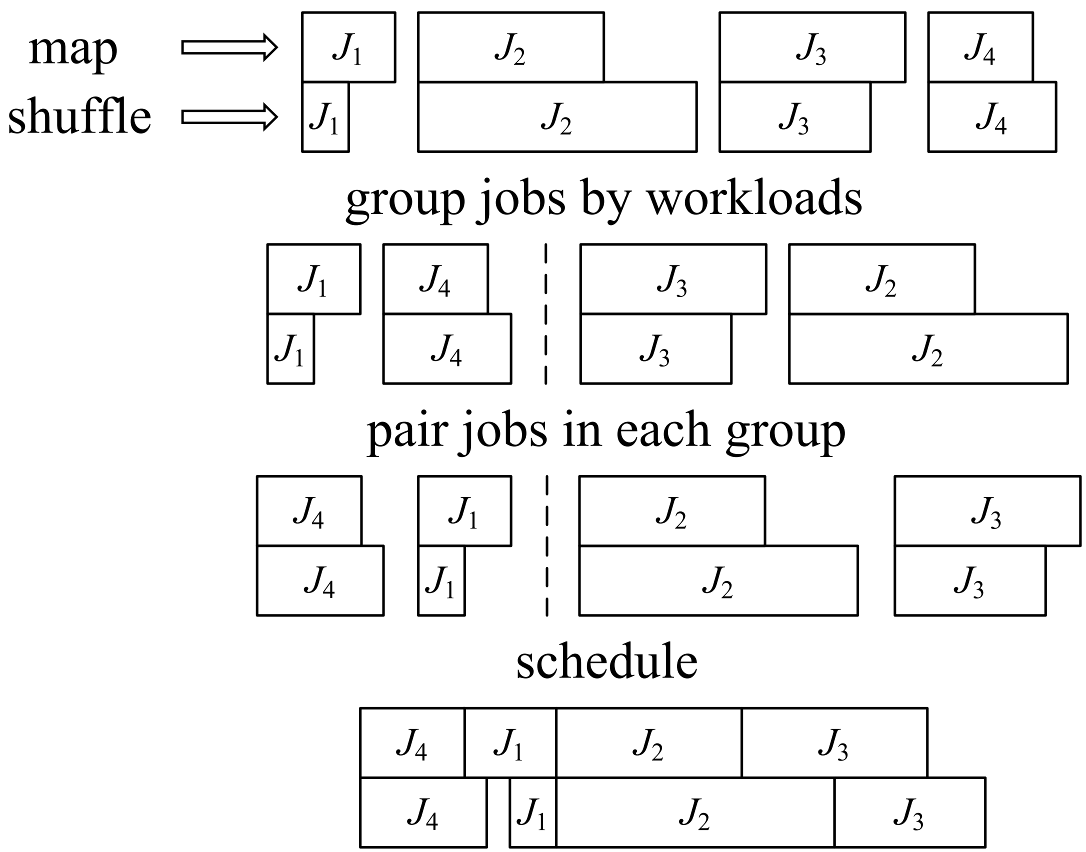
- Pairing matters for intra-group!



Group-Based Scheduling Policy (GBSP)

- Group jobs by their workloads (first factor)
  - Optimally divide jobs into k groups
    - minimize the sum of maximum job workload difference in each group
  - Execute the group of smaller jobs earlier
- Pair jobs in each group (second factor)
  - Jobs in each group have similar workloads
  - Pair shuffle-heaviest and map-heaviest jobs
- Time complexity is $O(n^2k)$

Example 1: GBSP



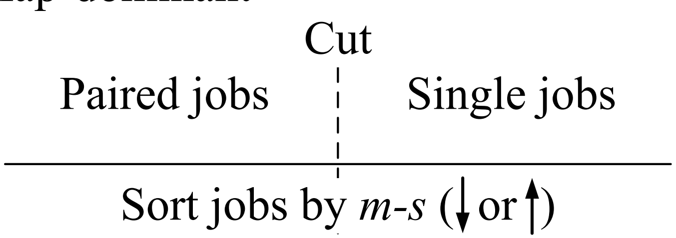
Workload Definition

- Dominant workload scheduling policy (DWSP)
  - Groups jobs by dominant workloads, max {m, s}
  - Performs well when jobs are simultaneously map-heavy, balanced, or shuffle-heavy
- Total workload scheduling policy (TWSP)
  - Groups jobs by total workloads, m+s
    - Performs well when jobs can be perfectly paired
- Weighted workload scheduling policy (WWSP)
    - A tradeoff between DWSP and TWSP
  - Groups jobs by weighted workloads , $\alpha * \max\{m,s\} + (1-\alpha) * (m+s)$

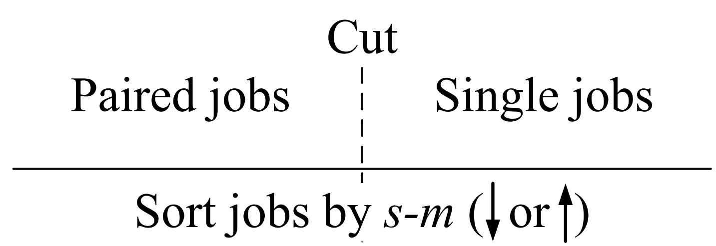
Second Greedy Algorithm

- Sort jobs by map-shuffle workload difference
- Cut jobs into two parts
  - Use minimum weight maximum matching to pair jobs in the first part
  - Exhaust all possible cuts and pick the best cut
- Sort jobs by their workloads after pairing, together with single jobs
  - Paired jobs are regarded as one job

Map-dominant



Shuffle-dominant



Match-Based Scheduling Policy (MBSP)

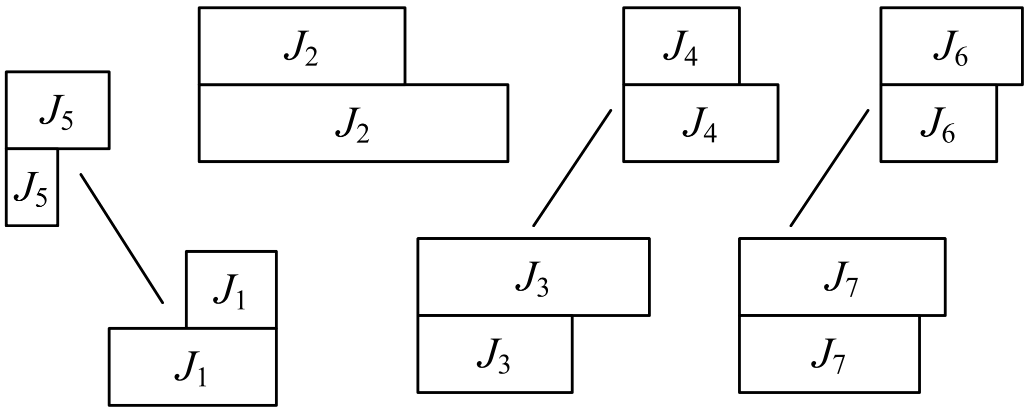
Pair jobs through minimum weight maximum matching

Matching weight for J_1 and J_2:

(1-β) * non-dominance factor +β * balance factor

Non-dominance factor: $\mathbb{1}_{(m_1-m_2)(s_1-s_2)\geq 0}$

Balance factor: $\frac{|m_1+m_2-s_1-s_2|}{m_1+m_2+s_1+s_2}$



Theorem

MBSP has an approximation ratio of 2 if

(1) some jobs can be perfectly paired,

(2) all remaining jobs are map-heavy or shuffle-heavy,

(3) dominant workload is used to sort jobs.

Time complexity is $O(n^{3.5})$

Exhausting all cuts takes $O(n)$ iterations

Matching in each iteration takes $O(n^{2.5})$

(Blossom algorithm, 1961)

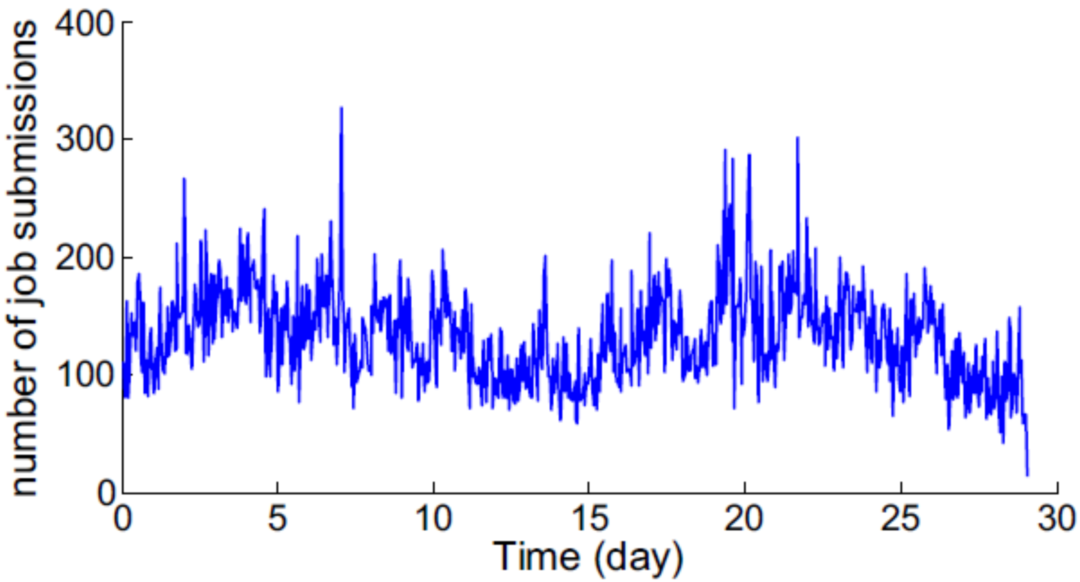
4. Experiment

Google Cluster Simulation

About 11,000 machines

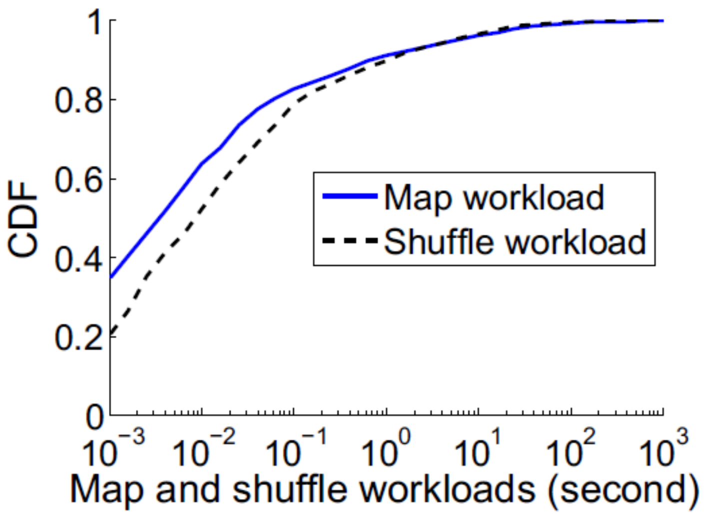
96,182 jobs over 29 days in May 2011

Number of job submissions per hour (arrival rate)

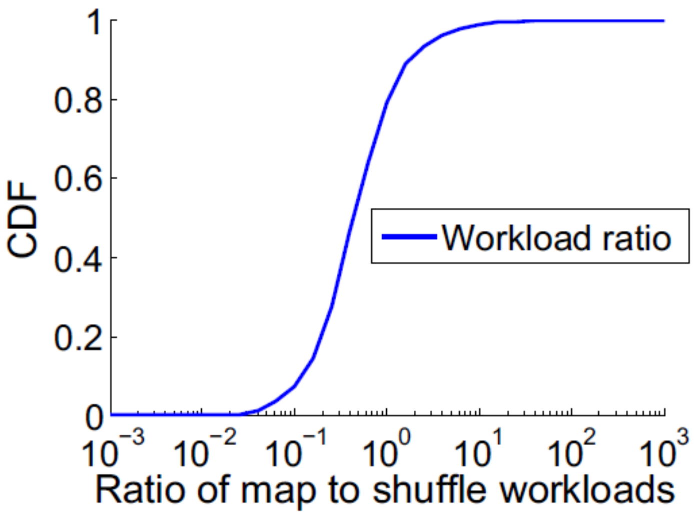


Google Cluster Dataset

Distribution of map and shuffle time



(a) Map and shuffle workloads.



(b) Workload ratio distribution.

Slightly more map-heavy jobs

Comparison Algorithms

Pairwise: has only one group then iteratively pairs the map-heaviest and shuffle-heaviest jobs in the group

MaxTotal: ranks jobs by total workload m+s and executes jobs with smaller total workloads earlier

MaxSRPT: ranks jobs by dominant workload max{m,s} and executes jobs with smaller dominant workloads earlier

Waiting, Execution, and Completion

Group k = 20, α = 0.5, β = 0.5, Col 1st regular, 2nd shuffle half, 3rd map half

	Scheduling algorithms	Average job waiting time			Average job execution time			Average job completion time		
	Pairwise	8289	7652	3609	149	23	28	8438	7675	3637
	MaxTotal	5054	4586	2525	362	32	156	5416	4618	2681
	MaxSRPT	4768	4546	2591	840	32	150	5608	4578	2741
GBSP	DWSP	4809	4519	2545	581	53	85	5390	4572	2630
GBSP	TWSP	4787	4501	2522	563	49	104	5350	4550	2626
GBSP	WWSP	4619	4482	2479	532	45	79	5151	4527	2558
	MBSP	4562	4314	2142	193	26	36	4754	4340	2178

The average job completion time ratio between MBSP and WWSP is 92.3%, 95.8% and 85.1%, respectively.

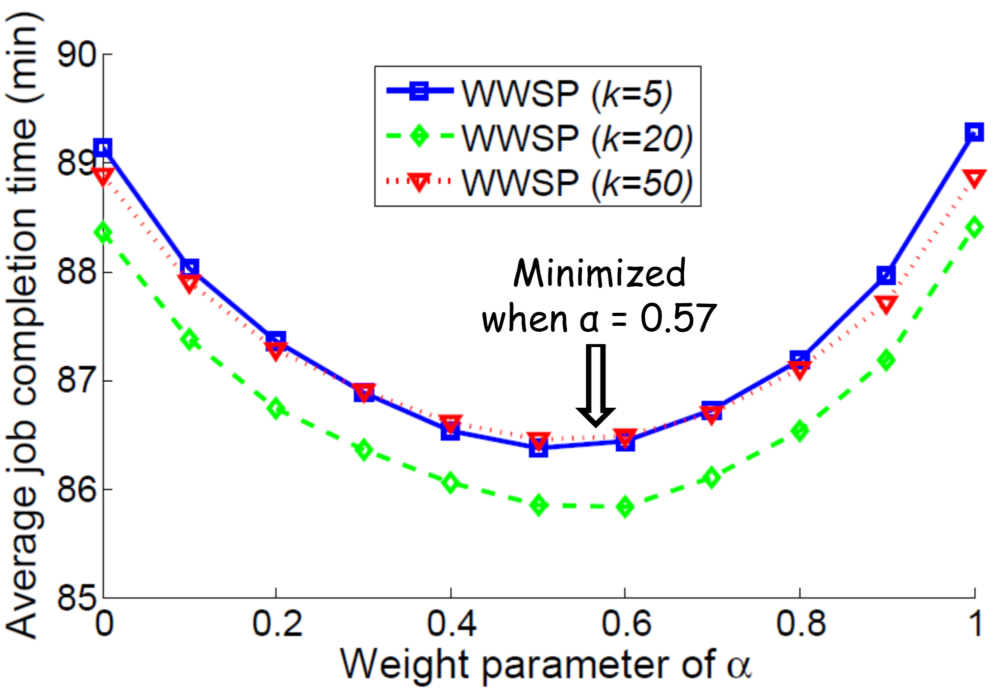
Impact of k and α in WWSP

Group-based scheduling policy with k groups

- Sorts jobs by α*max(m,s) + (1-α)*(m+s)

Small/large group k

Small/large weight α

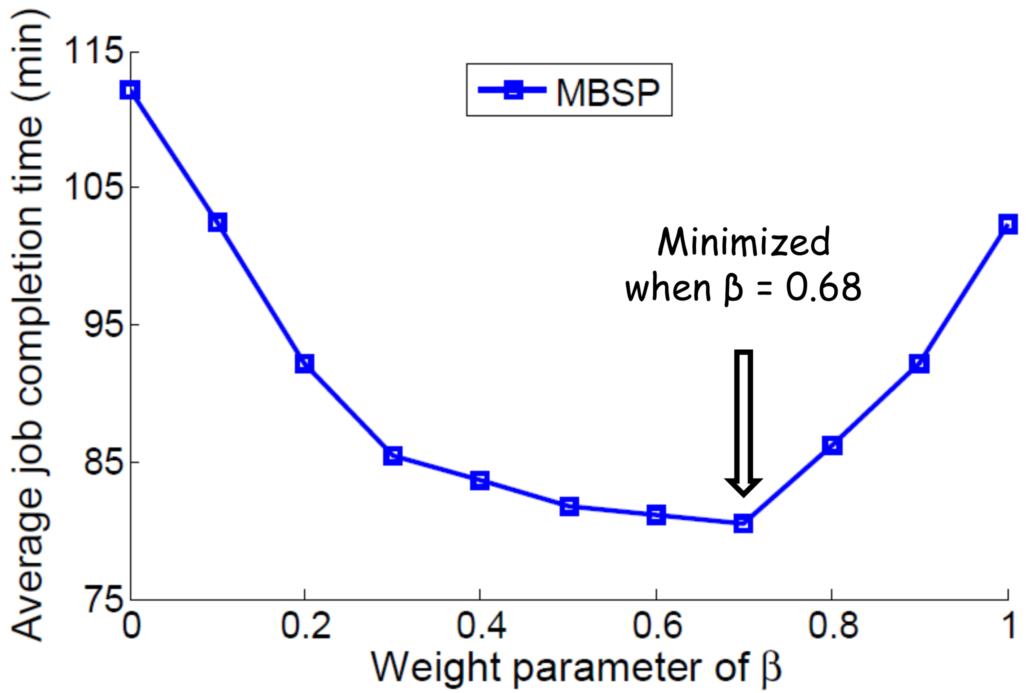


Impact of β in MBSP

Match-based scheduling policy matches J_1 and J_2 by

β * balance factor + $(1-\beta)$ * non-dominance factor

Small/large weight β



Hadoop Testbed on Amazon EC2

Testbed

- Ubuntu Server 14.04 LTS (HVM)
- Single core CPU and 8G SSD memory

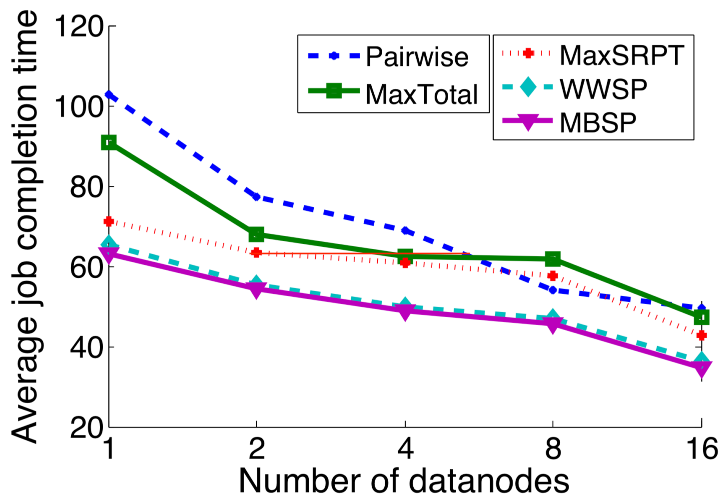
Jobs: WordCount jobs and TeraSort jobs

- 6 WordCount use books of different sizes
  - 2MB, 4MB, 6MB, 8MB, 10MB, 12MB
- 6 TeraSort use instances of different sizes
  - 1KB, 10KB, 100KB, 1MB, 10MB, 100MB

Completion Time

Hadoop: one master node + several data nodes

Number of data nodes: 1, 2, 4, 8, 16



MBSP and WWSP have the best results

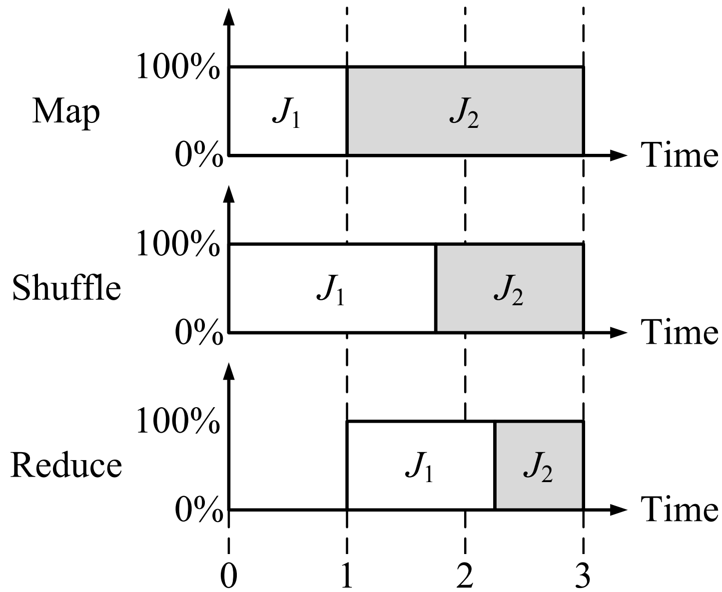
5. Conclusion

- Map and Shuffle phases can overlap
  - CPU and I/O resource
- Objective: minimize average job completion time
- Group-based and match-based schedules
  - Optimality under certain scenarios
  - Pairing factor
  - Small jobs factor

Future Work

3-phase example

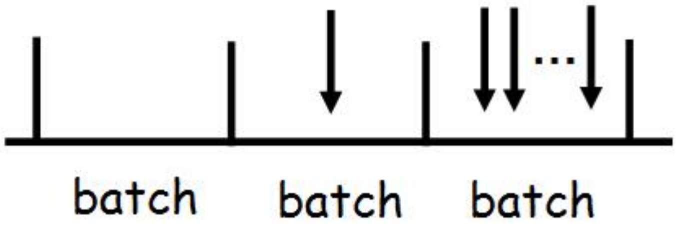
- More simulations
  - Imbalanced map and shuffle
  - impact of k, α, and β
- Multiple phases
  - Beyond 2-phase
- Other computation paradigms
  - Map-collective



Future Work

Online scheduling

- Batched
  - Batch size



- Duration-based batching
  - Low-job rate: time out
  - High-job rate: probabilistic
  - Δ: efficient, but slow; 1-Δ: inefficient, but fast
- Counting-based batching
  - Low-job rate: time out
  - High-job rate: credit
  - Scheduling time vs. execution time