Distributed Matrix Completion

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informatik

Matrix Completion

	Avatar	The Matrix	Up
Alice		4	2
Bob	3	2	
Charlie	5		3

Matrix Completion

	Avatar	The Matrix	Up
Alice	?	4	2
Bob	3	2	?
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Matrix Completion

- Discover (rank=1)
  - User factors
  - Movie factors

H

	W	Avatar	The Matrix	Up
		2.24	1.92	1.18
Alice	1.98	?	4	2
Bob	1.21	3	2	?
Charlie	2.30	5	?	3

V

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		Avatar	The Matrix	Up
	H	2.24	1.92	1.18
Alice	1.98	?	4 3.8	2 2.3
Bob	1.21	3 2.7	2 2.3	?
Charlie	2.30	5 5.2	?	3 2.7

W V

- Minimize loss

$$\min_{\mathbf{W},\mathbf{H}} \sum_{(i,j)\in Z} (\mathbf{V}_{ij} - [\mathbf{WH}]_{ij})^2$$

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+ Bias
+ Regularization
+ ...

Distributed Matrix Completion

- Real applications can be large
  - Millions of users, Millions of items, Billions of rating
    e.g., Netflix: >20M users, >20k movies, ≅4B ratings (projected)

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- Existing MapReduce algorithms
  e.g., DALS, DSGD-MR
- Strength
  - Faster than sequential algorithms
  - Can handle large datasets
- Drawbacks
  - Slow
  - Synchronous
  - No use of shared memory

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- New algorithms
  ASGD, DSGD++
- Strength
  - In-memory processing
  - Exploit multi-core
  - Asynchronous

Outline

- Motivation
- Algorithms
  - **Distributed Alternating Least Squares**
  - Distributed SGD-based algorithms
    - Asynchronous SGD
    - DSGD-MR
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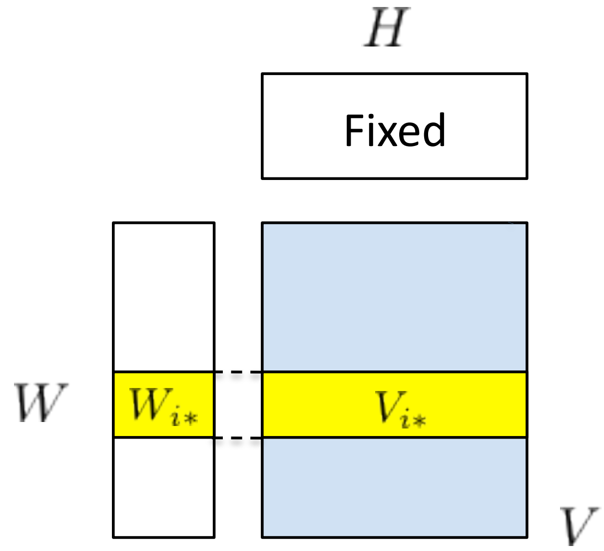
Alternating Least Squares (ALS)

Alternate

- Fix H – optimize for W



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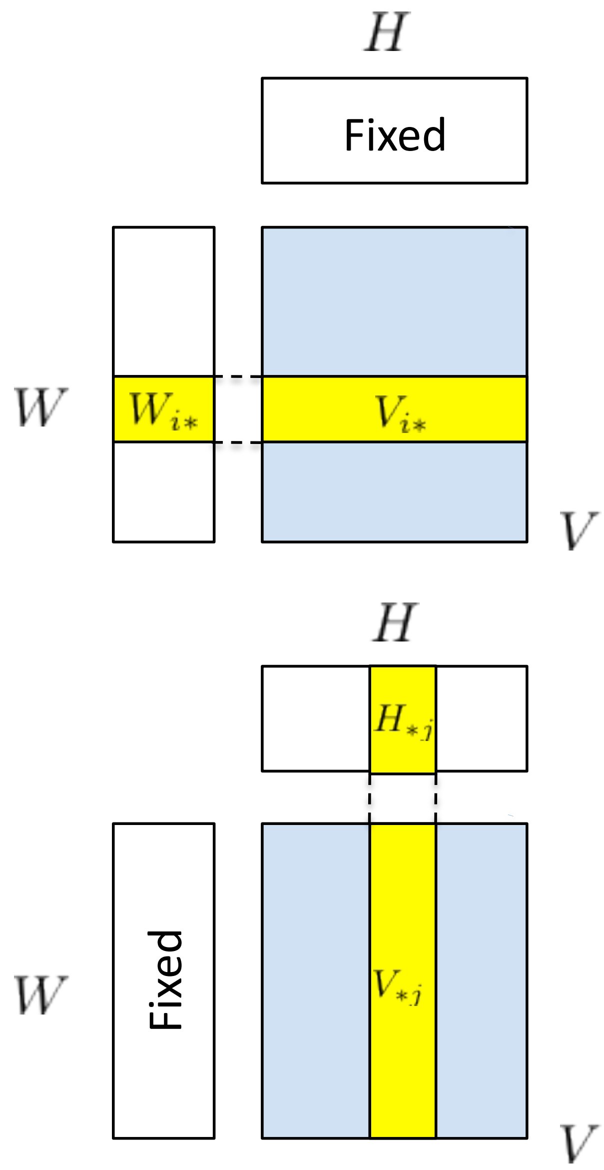

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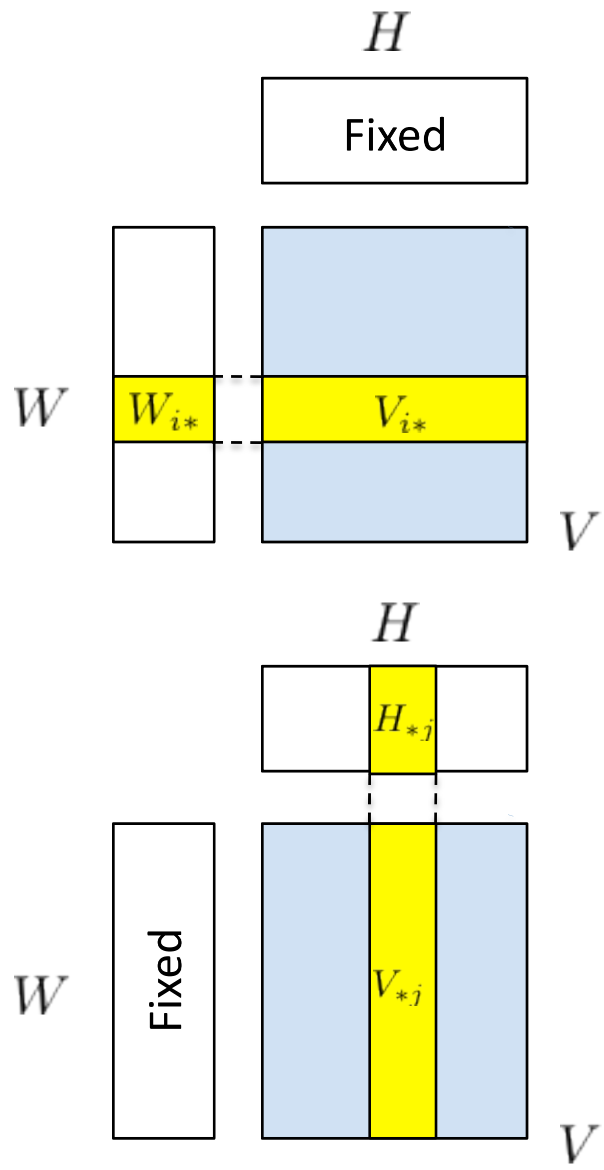
For each user/movie: solve a least squares problem



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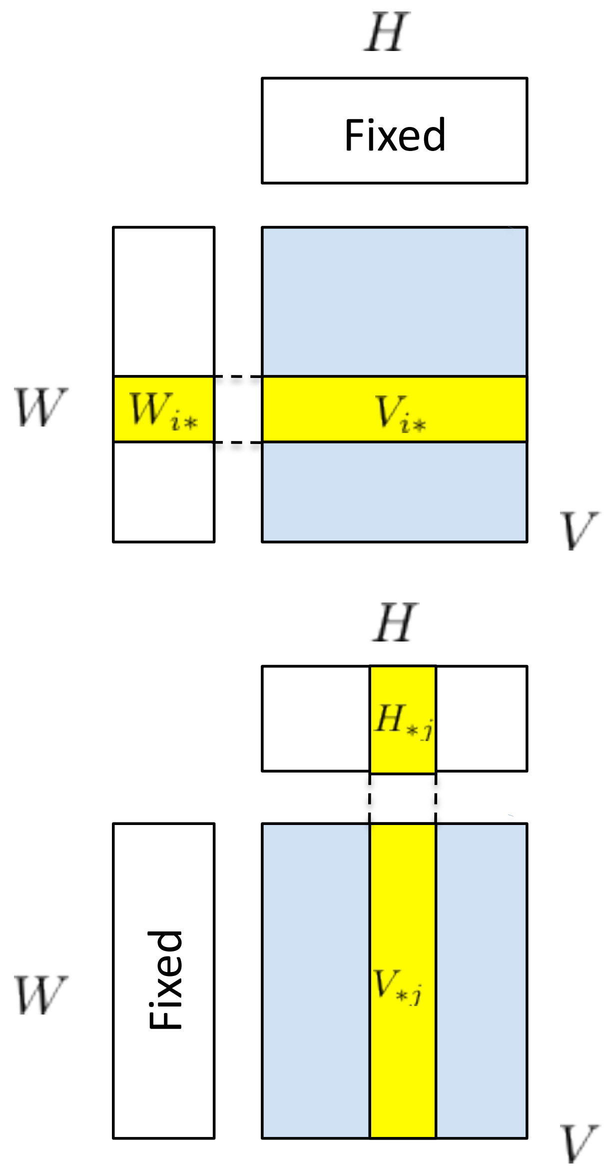

Distributed ALS similar to [Zhou08]
Difference: on each node multiple threads
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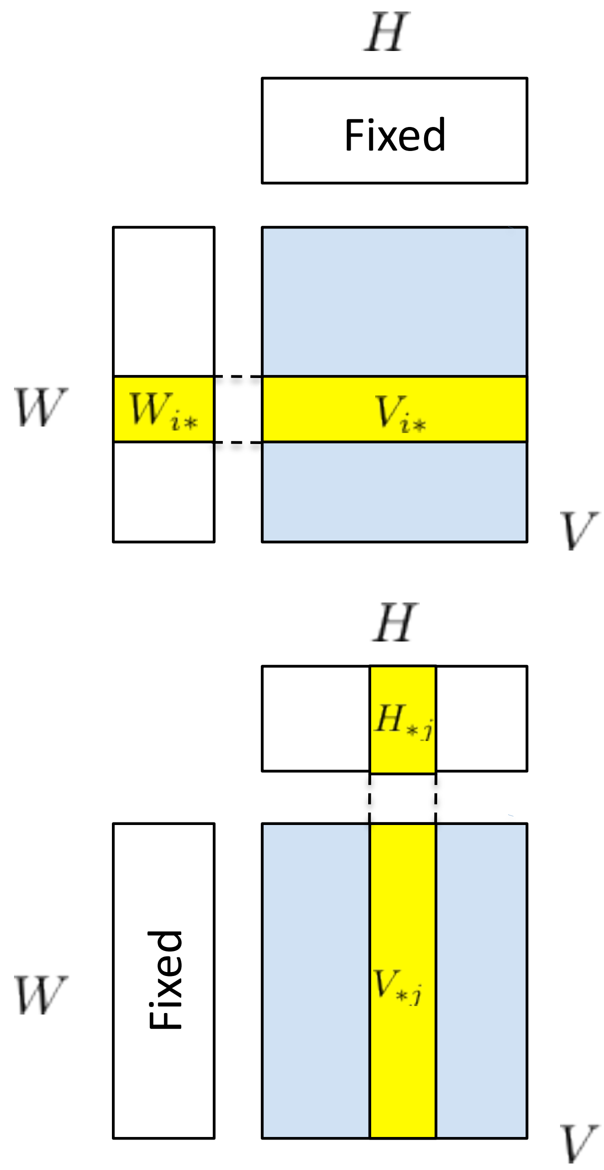

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Difference: on each node multiple threads instead of multiple processes

- Slow (cubic in rank)
- Memory intensive (stores data matrix twice)

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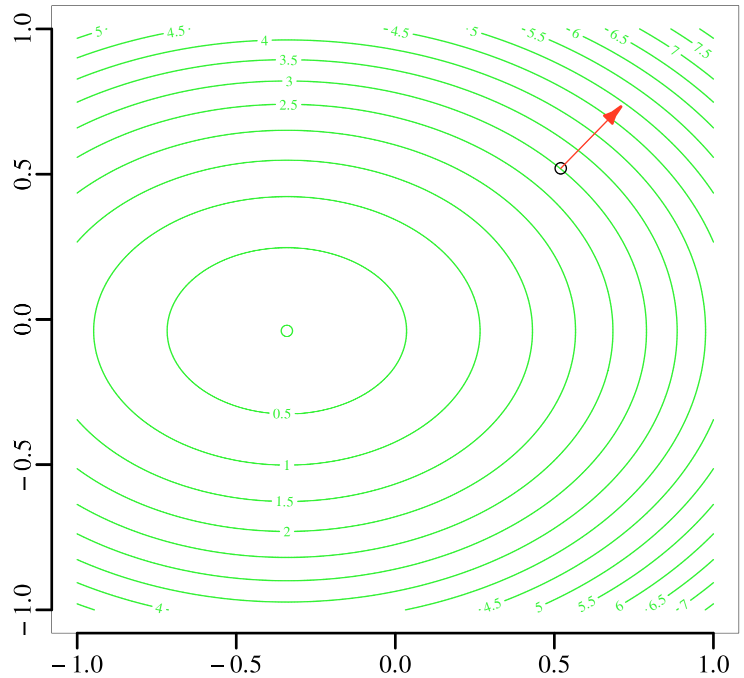
Stochastic Gradient Descent(SGD)

Goal: Find minimum θ^* of function L

- Pick a starting point θ_0



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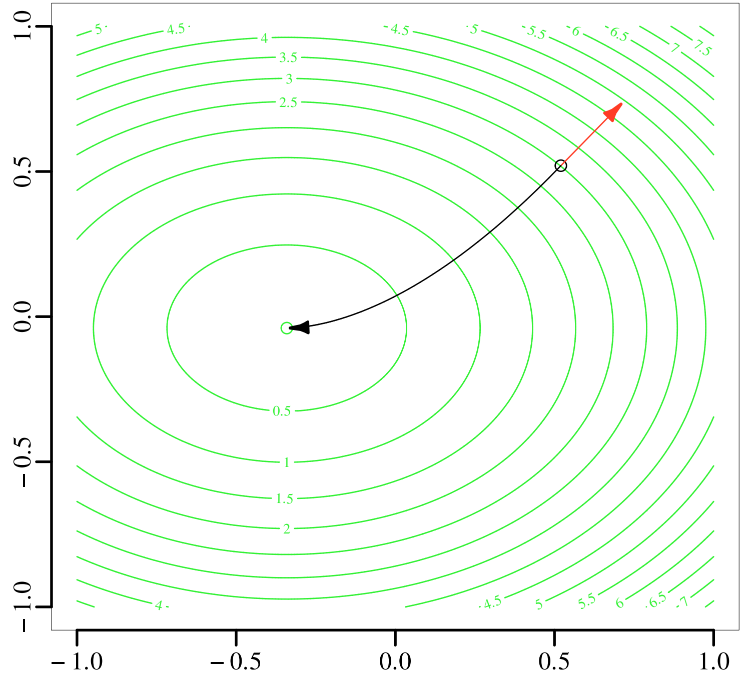

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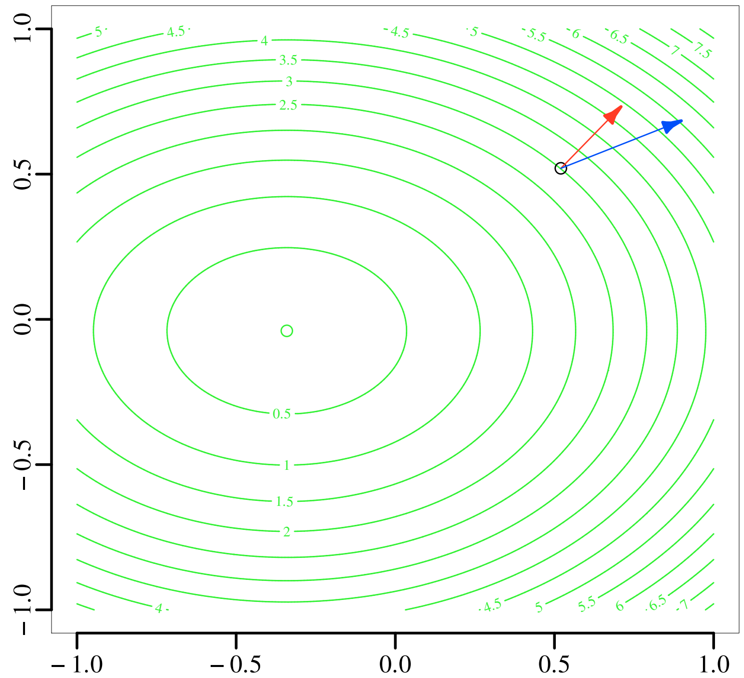

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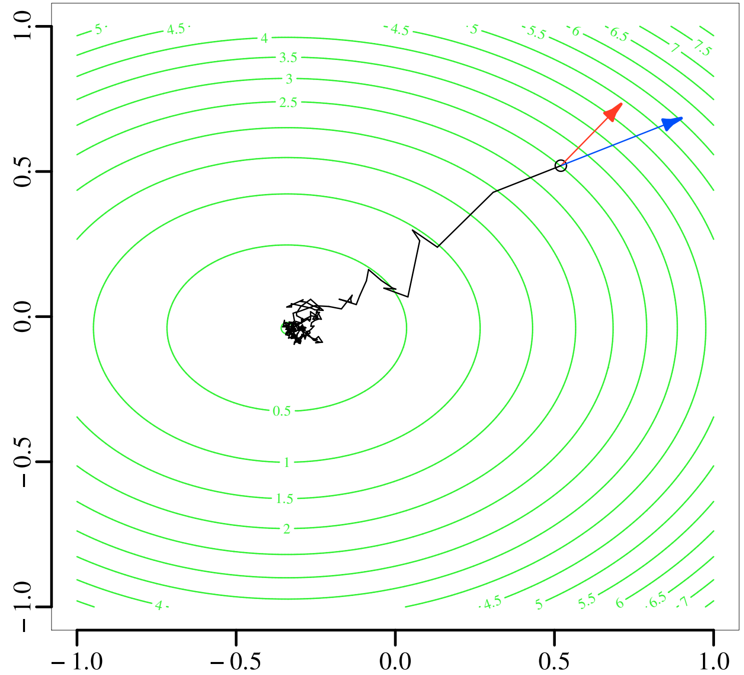

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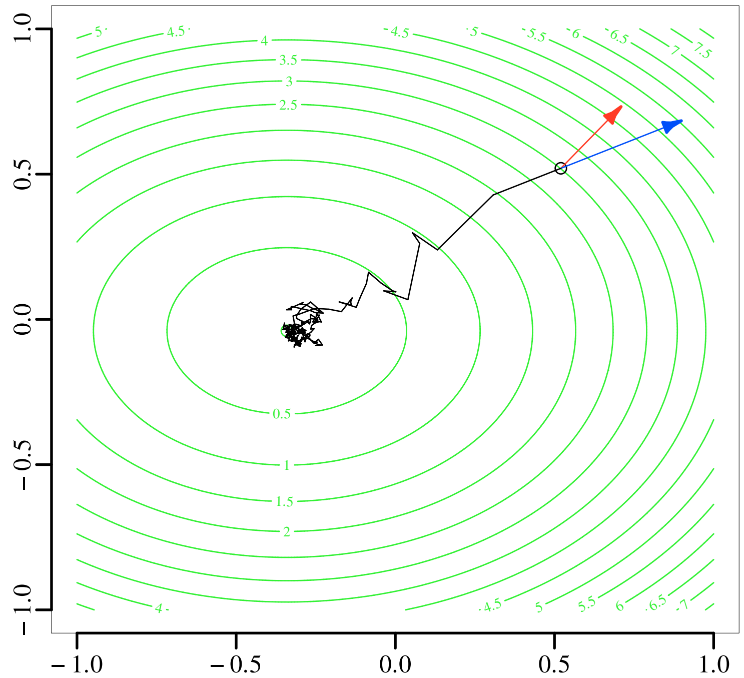
$$\theta_{n+1} = \theta_n - \varepsilon_n \widehat{L}'(\theta_{n+1})$$



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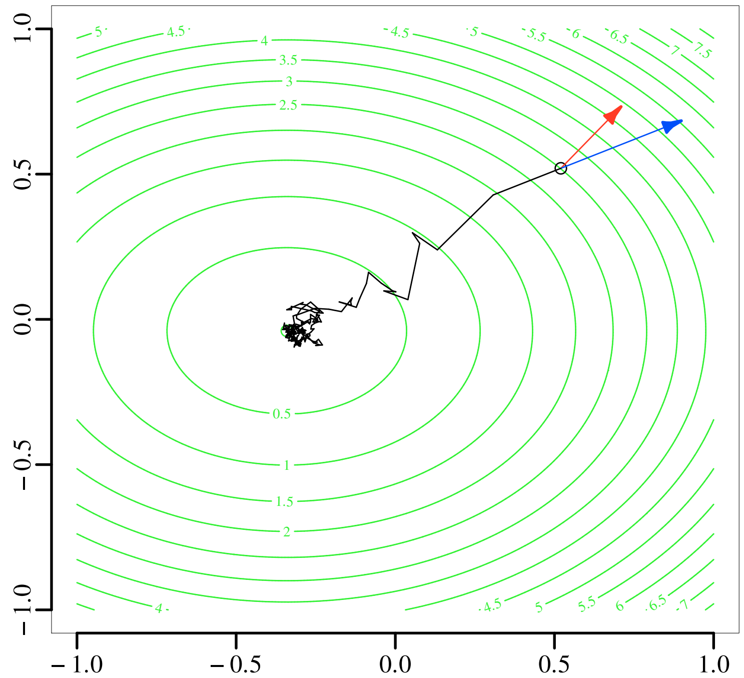
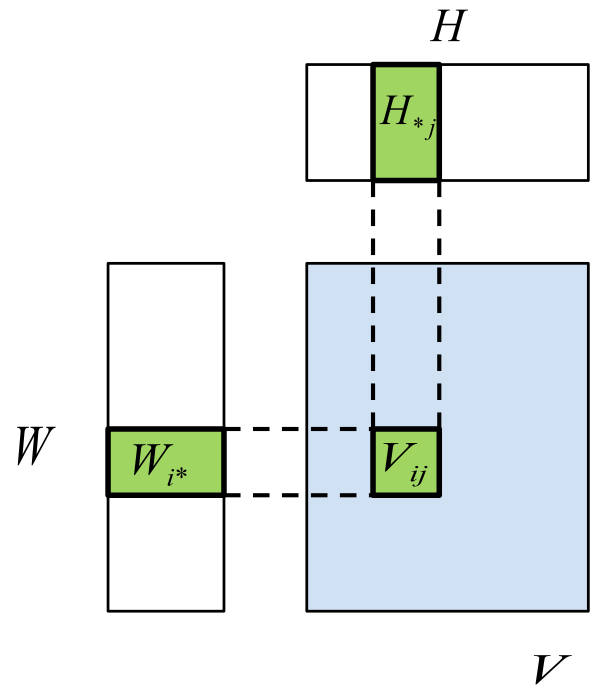
- Under certain conditions, asymptotically approximates (continuous) gradient descent



SGD for Matrix Completion

$$L = \sum_{(i,j)\in Z} \boxed{(V_{ij} - [WH]_{ij})^2}$$

Local loss



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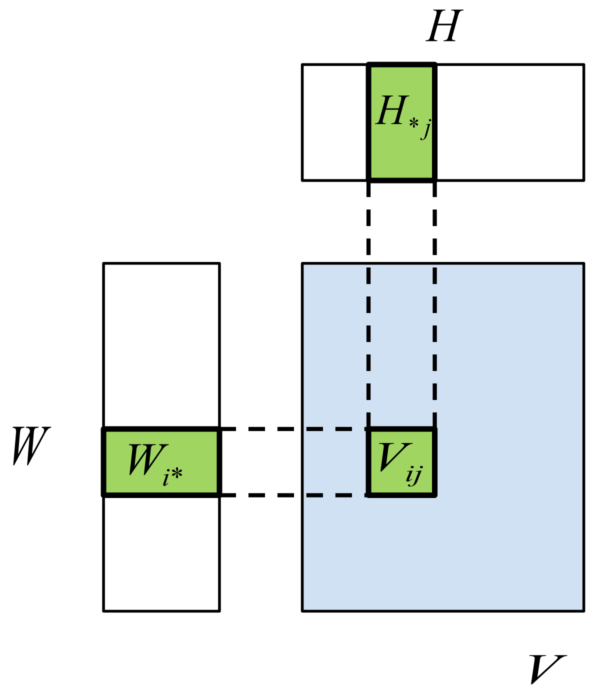
Local loss

- Estimate gradient based on **single** training point
- Scale up by # training points N



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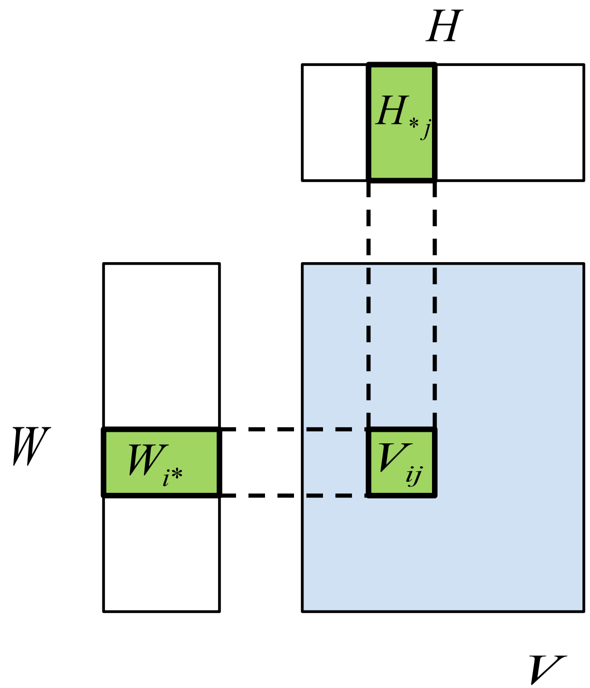
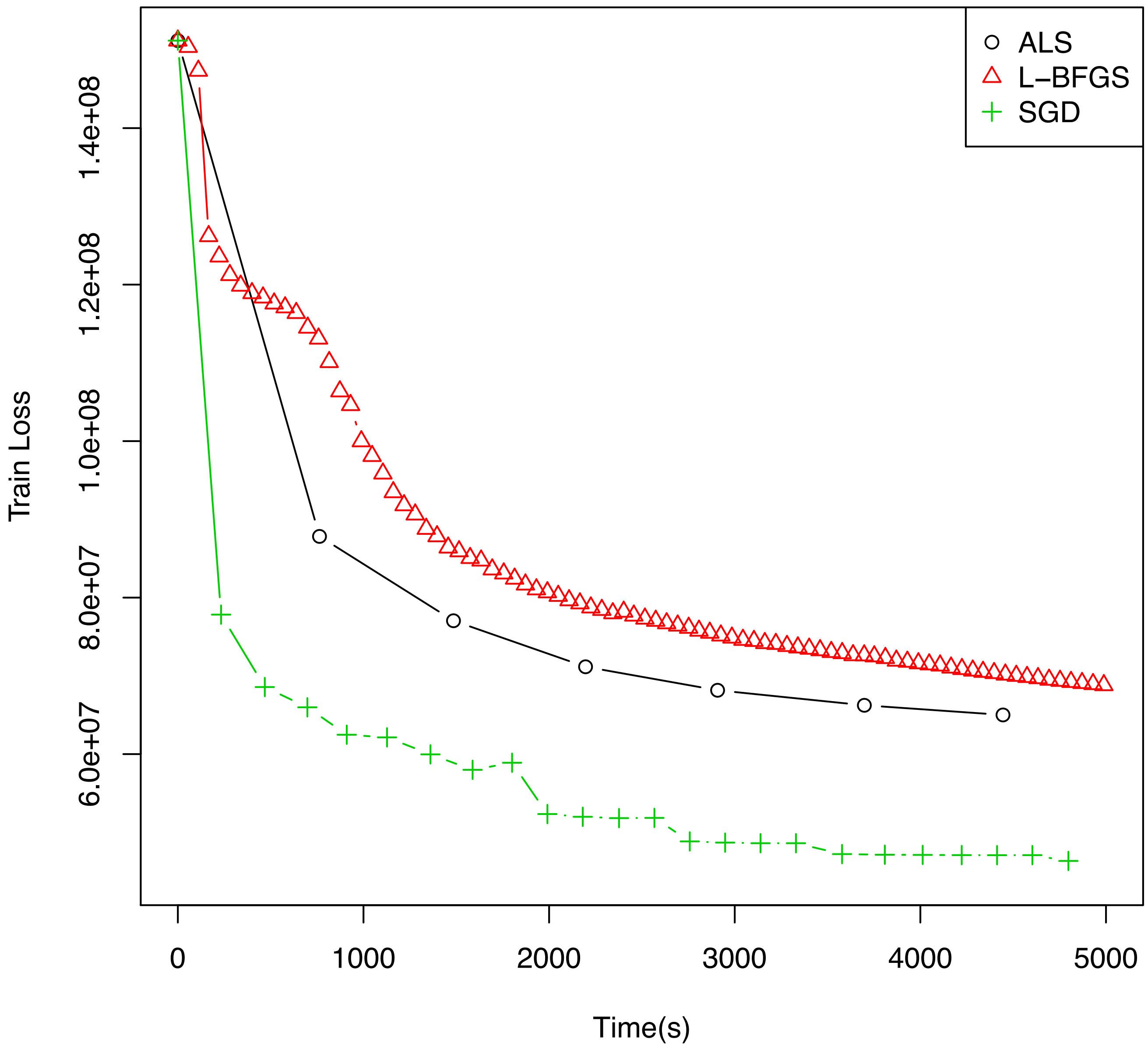


- Estimate gradient based on **single** training point
- Scale up by # training points N

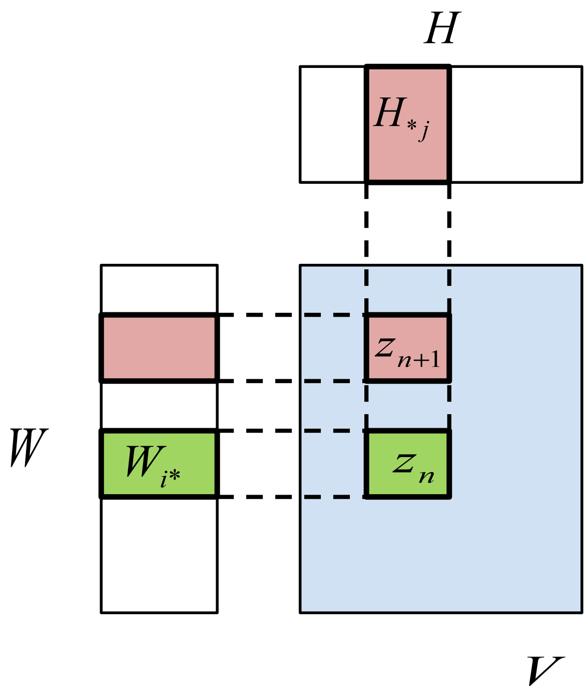
- SGD epoch:
  1. Pick a random training point
  2. Compute approximate gradient
  3. Update W_{i*} and H_{*j}
  4. Repeat N times

Netflix Single-Core



Problem Structure

SGD steps depend on each other



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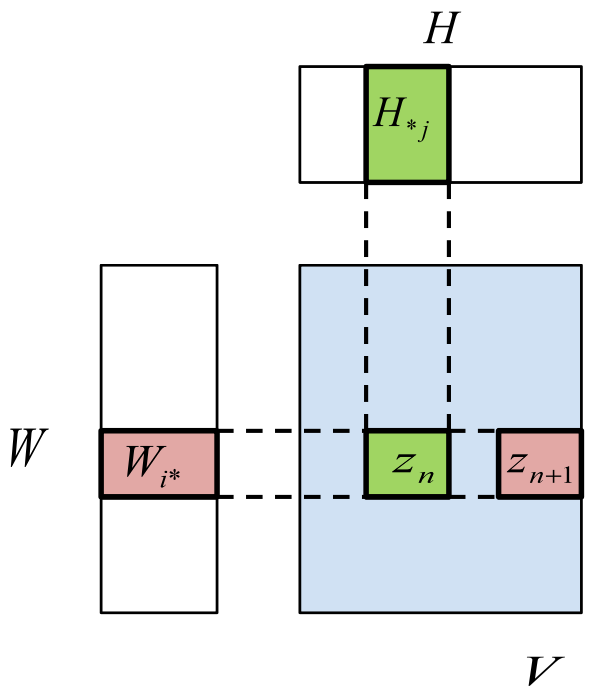

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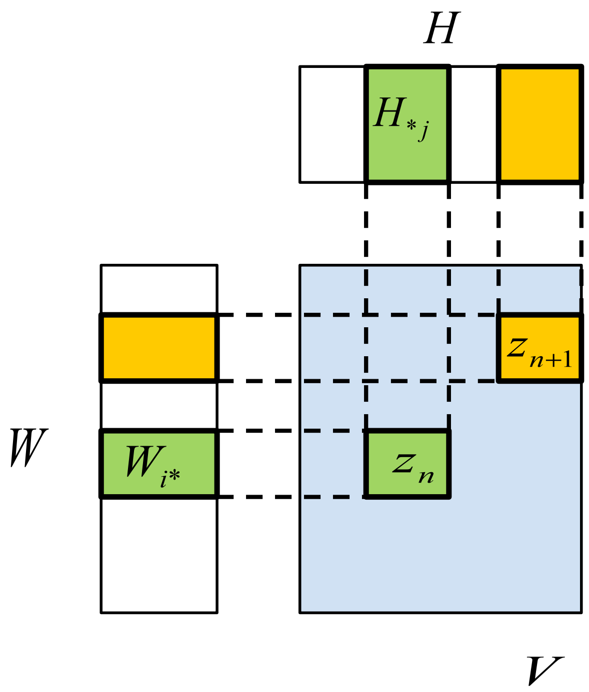

But not all steps are dependent

Shared-memory, parallel SGD:
Efficient and simple

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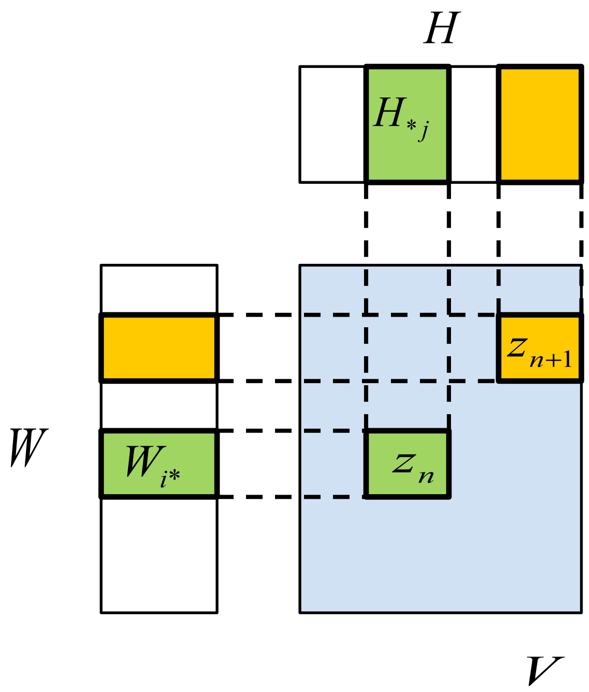

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Shared-memory, parallel SGD:
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Parallel SGD slow for larger problems.

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    - DSGD-MR
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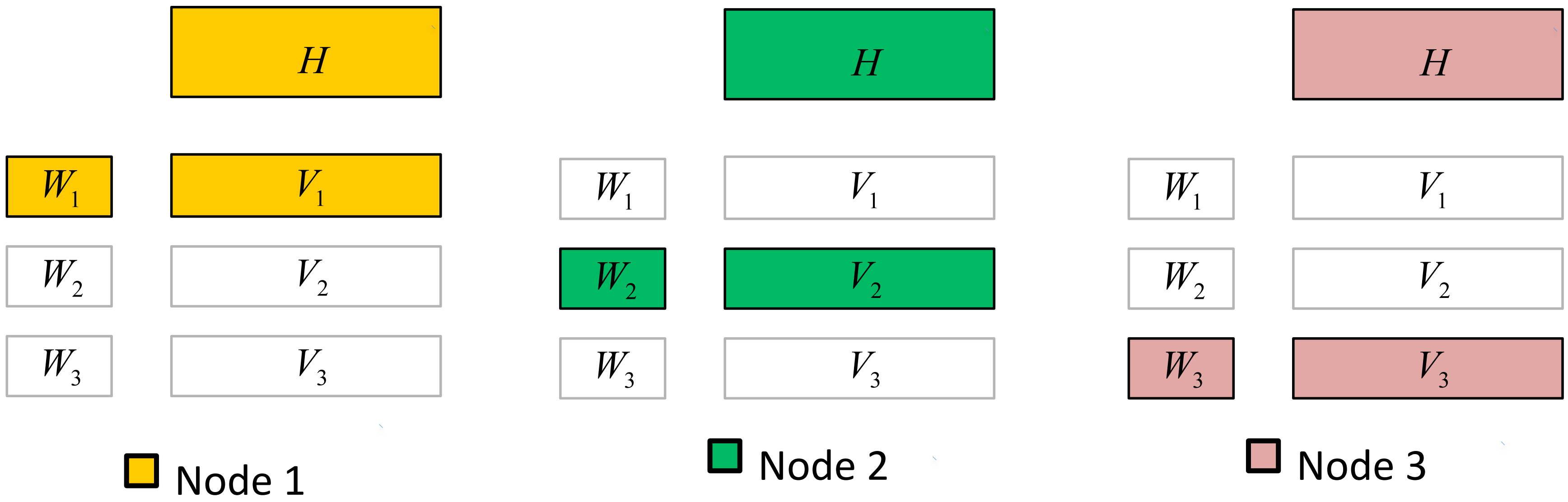
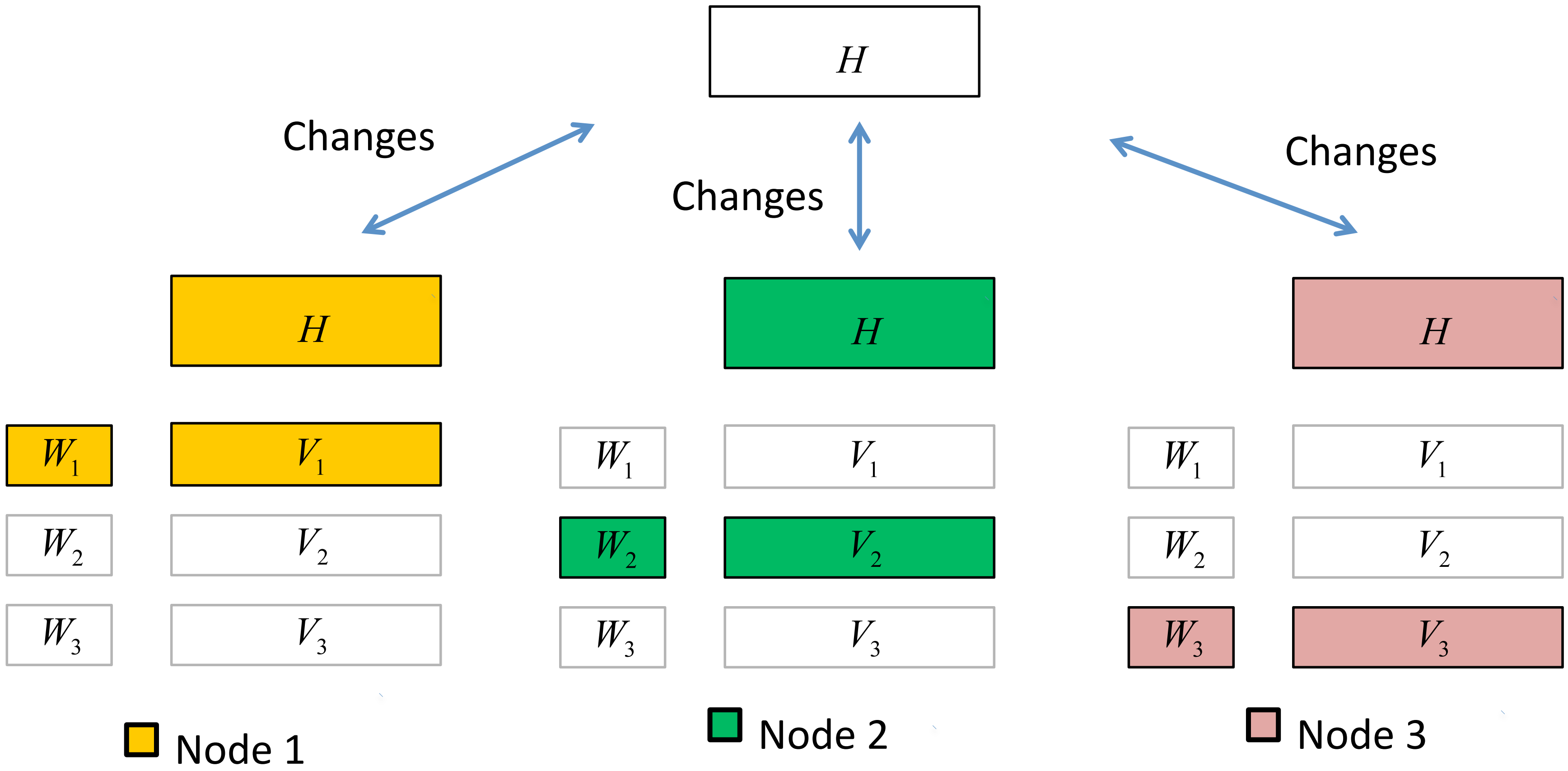
Asynchronous SGD (ASGD)

Each node works on a local copy of the movies matrix H.



Asynchronous SGD (ASGD)

Each node works on a local copy of the movies matrix H.
Local copies are synchronized continuously.



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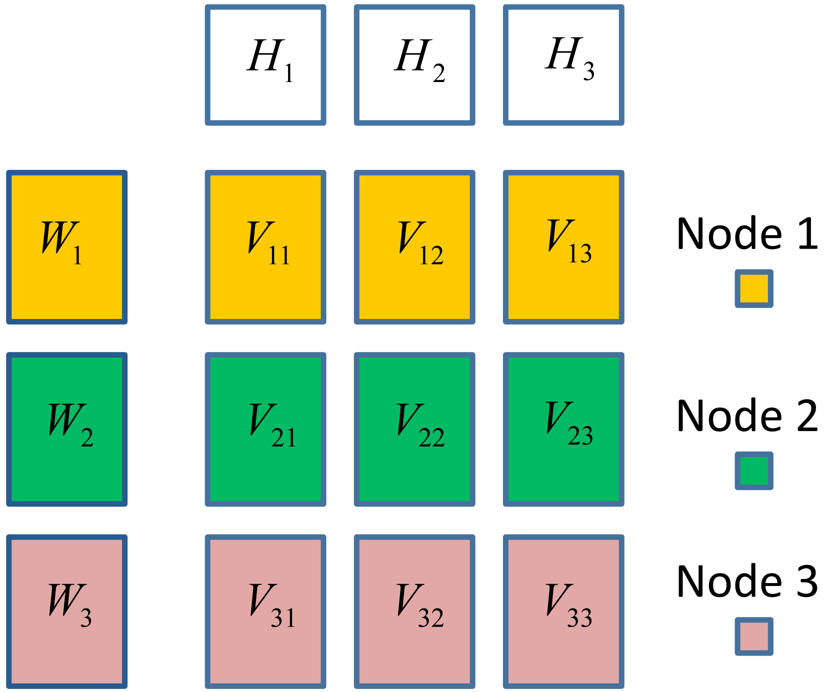
Distributed SGD-MapReduce

Block and distribute V



Distributed SGD-MapReduce

Block and distribute V

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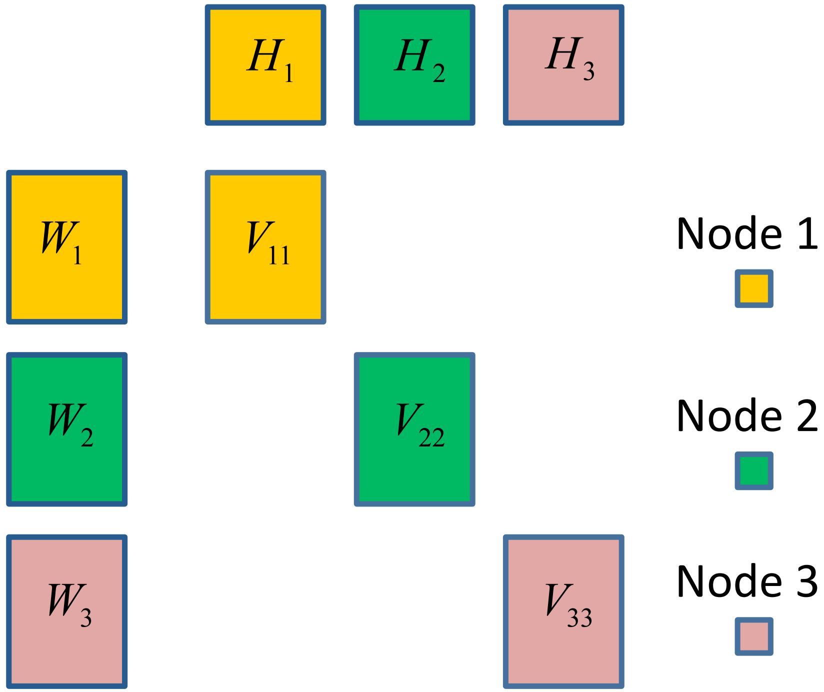

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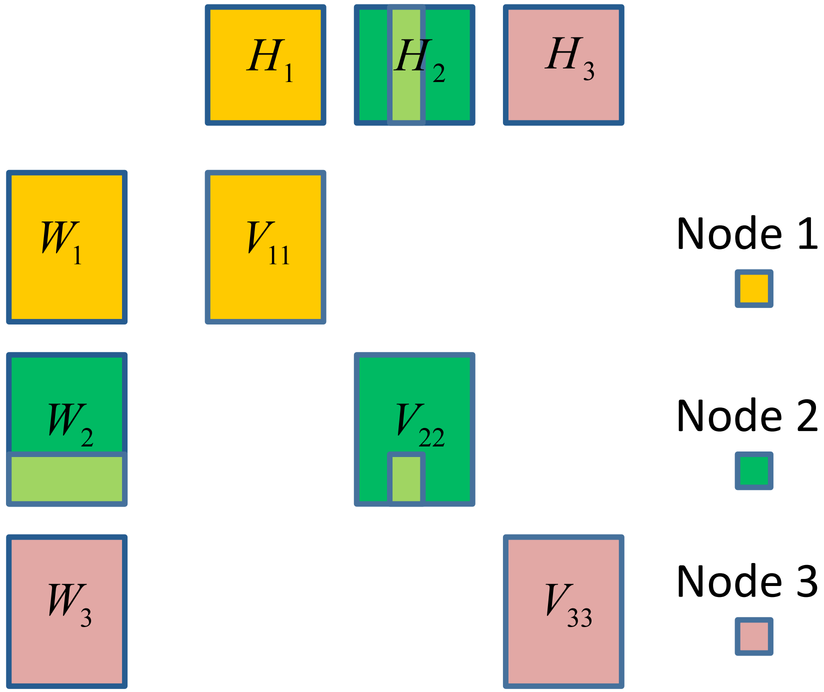

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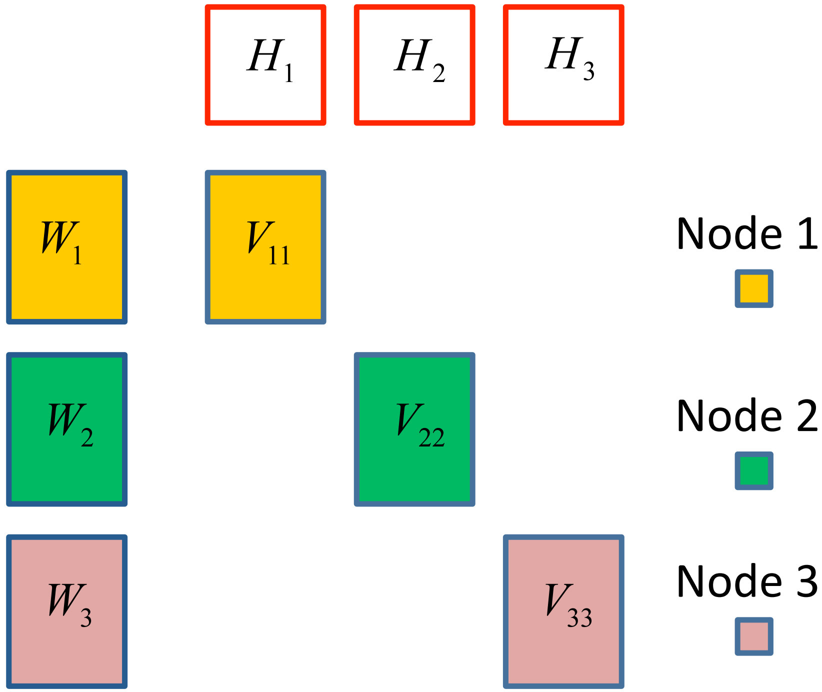

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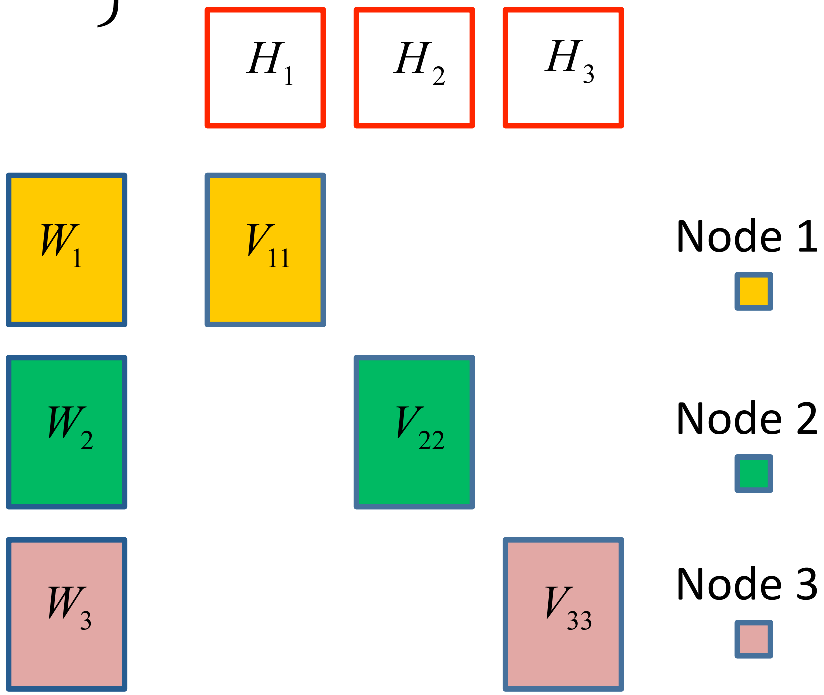
1 subepoch
1 Map Job



Distributed SGD-MapReduce

Block and distribute V

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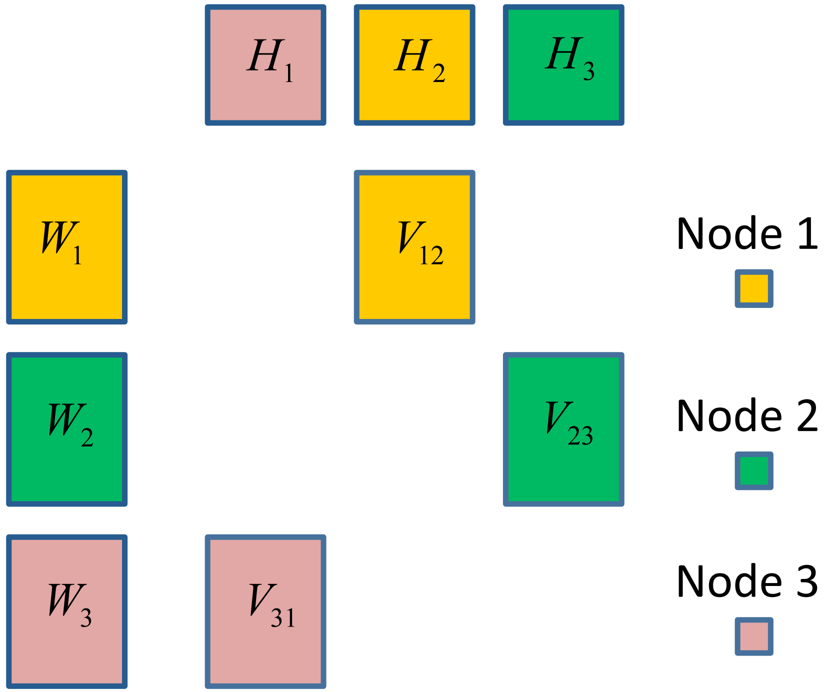

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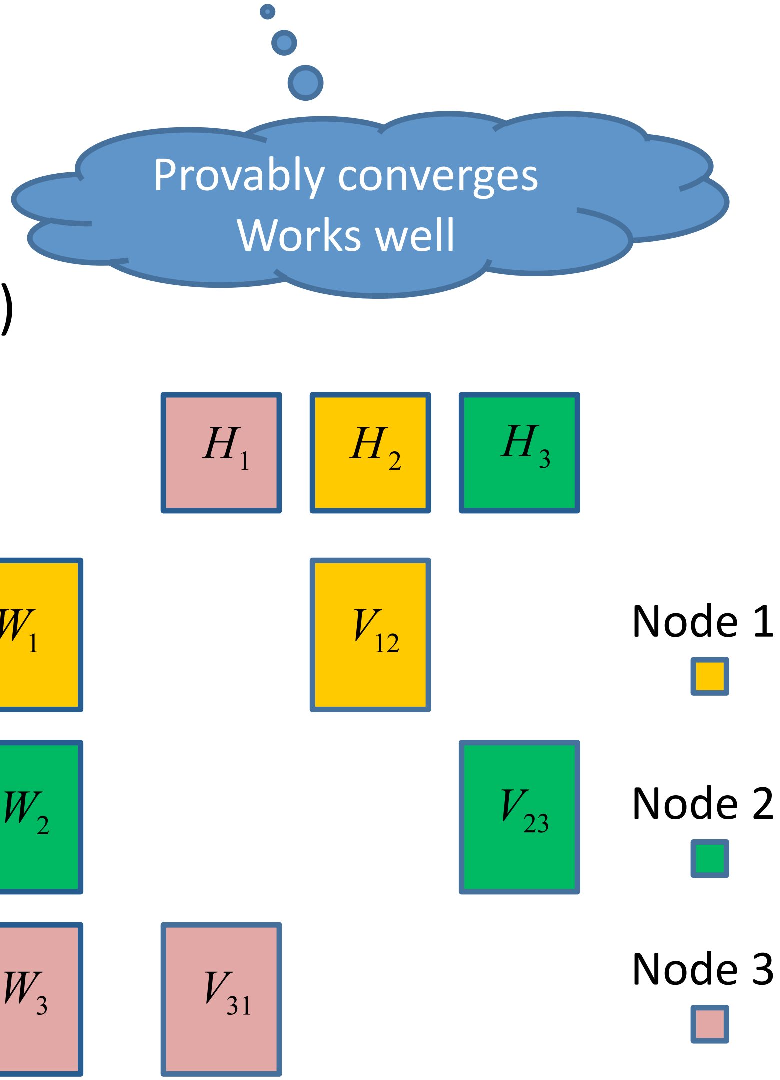

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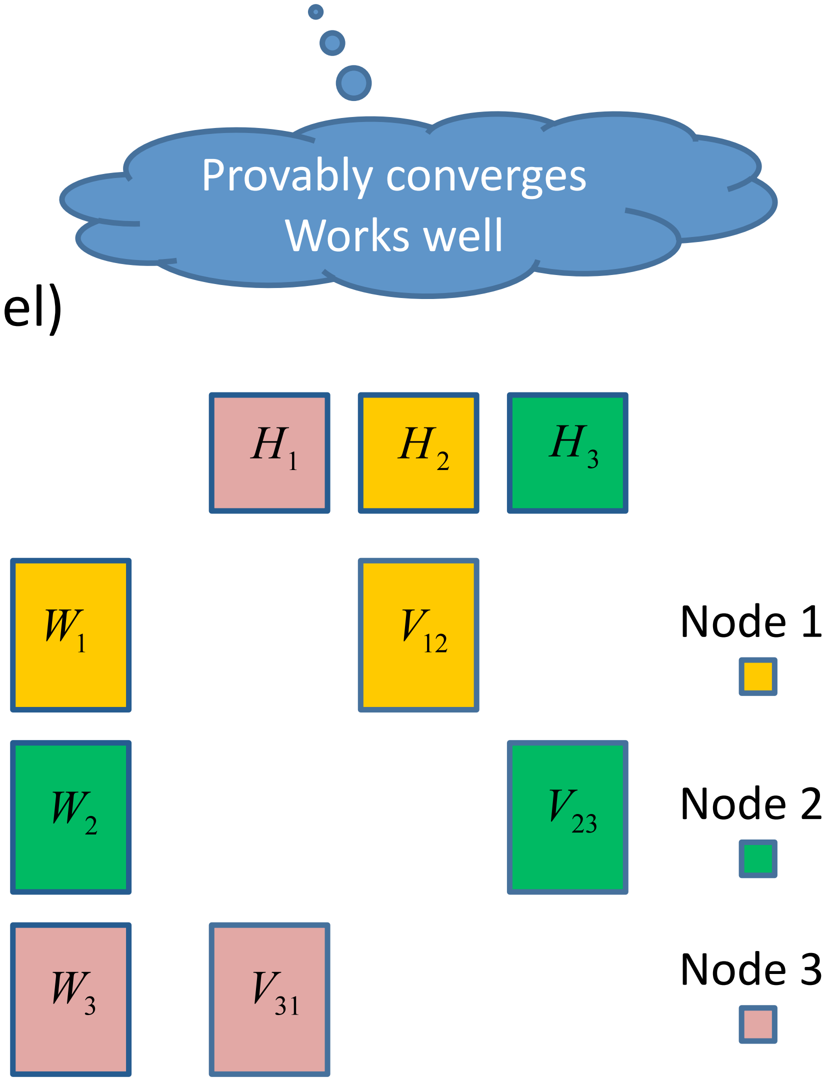

DSGD-MR drawbacks:

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- Synchronous
- No overlapping of communication and computation
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DSGD++: Direct communication between nodes

How to do better in a shared-nothing environment?

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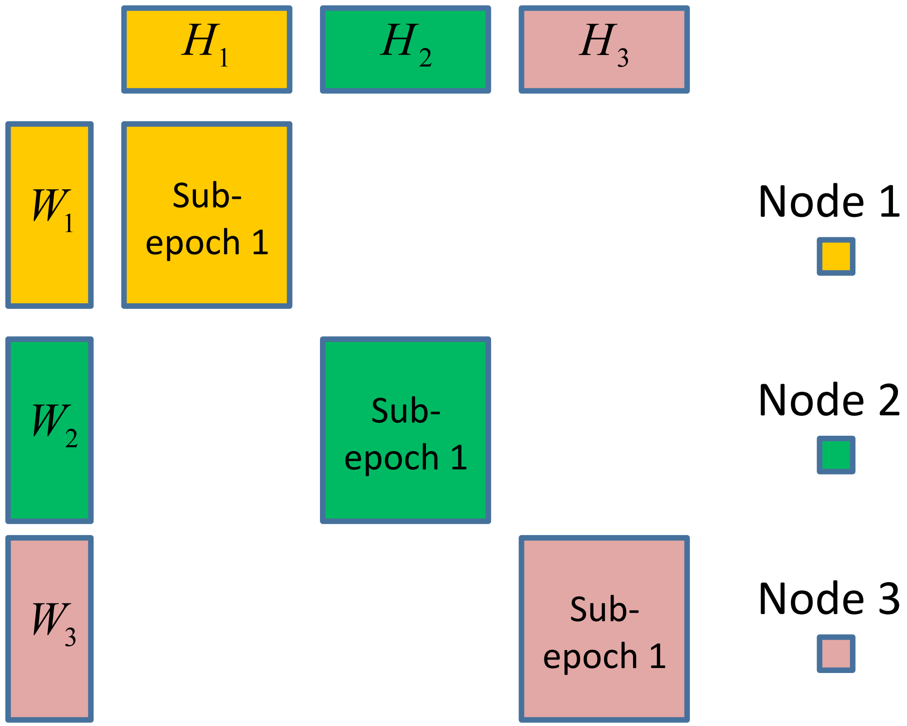

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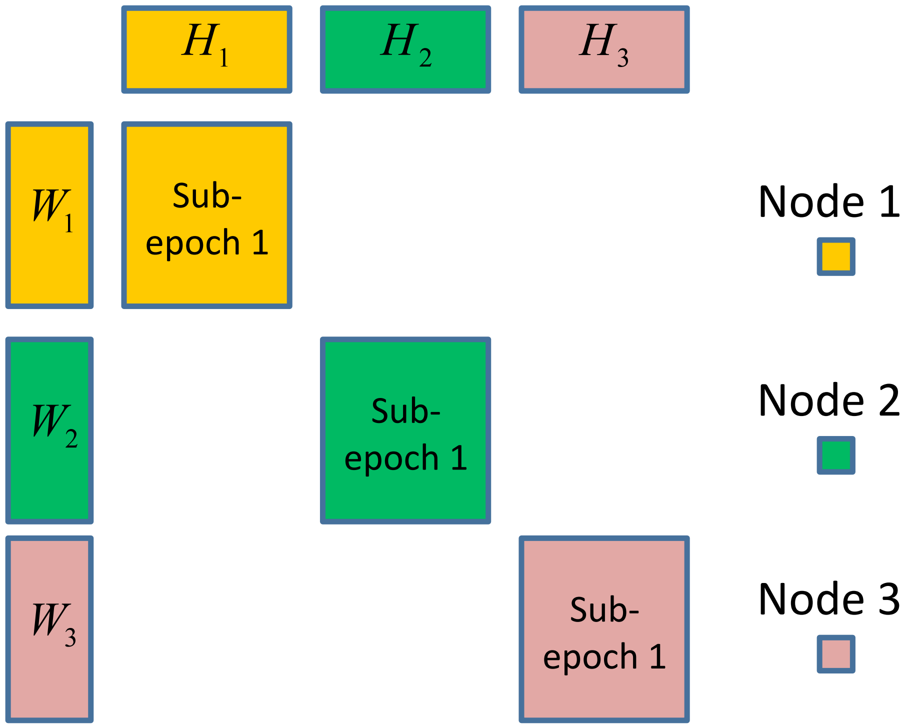

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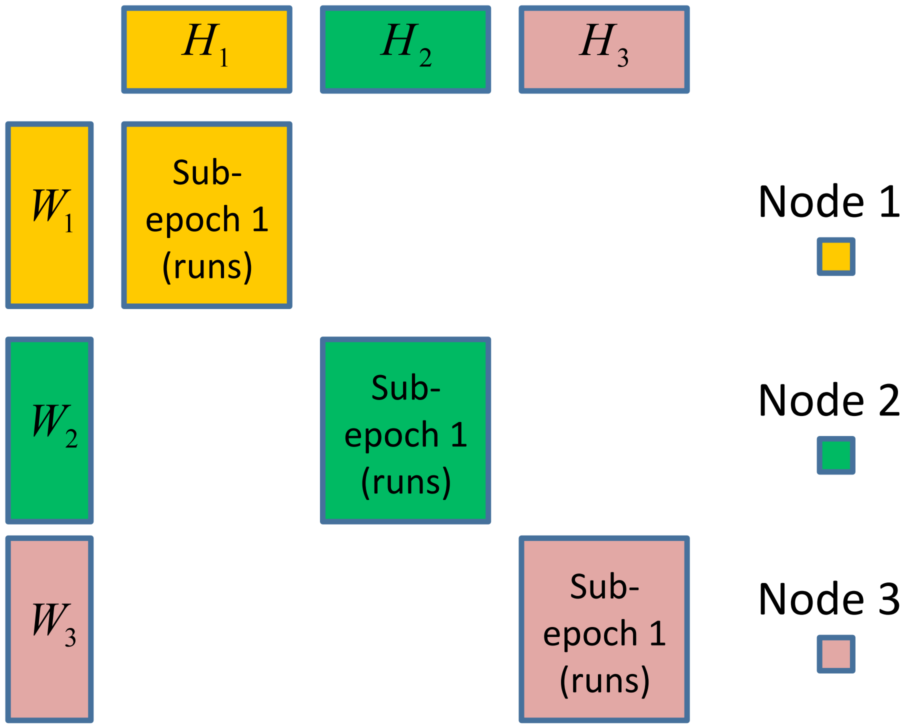

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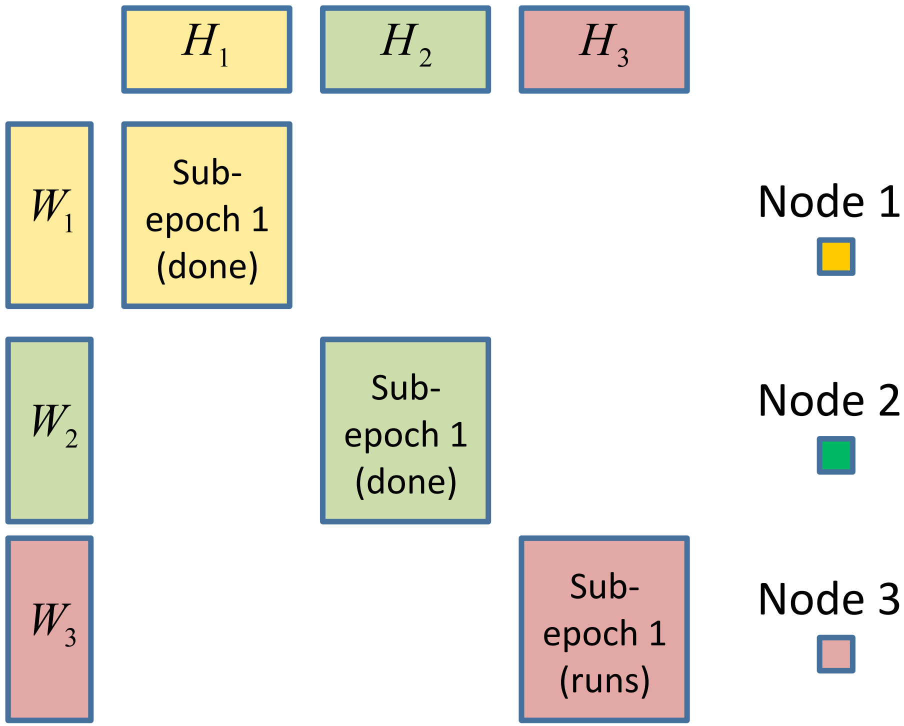

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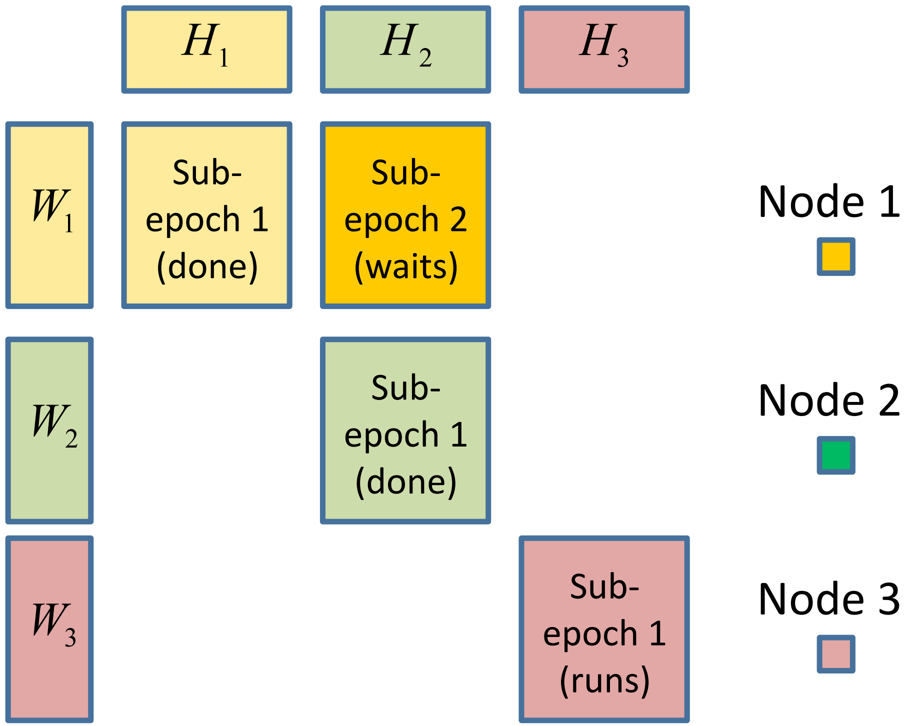

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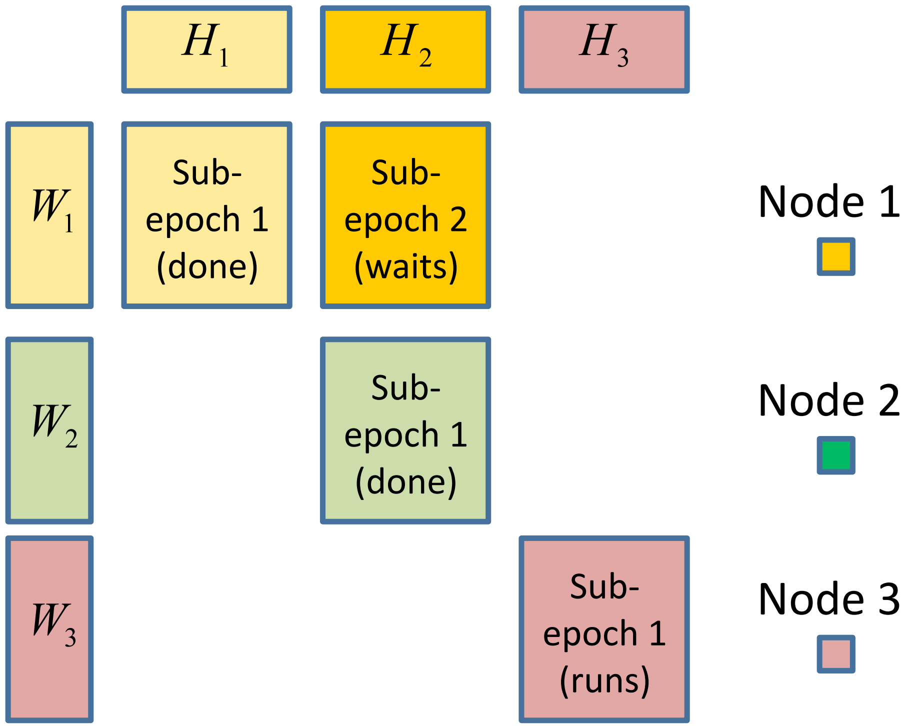

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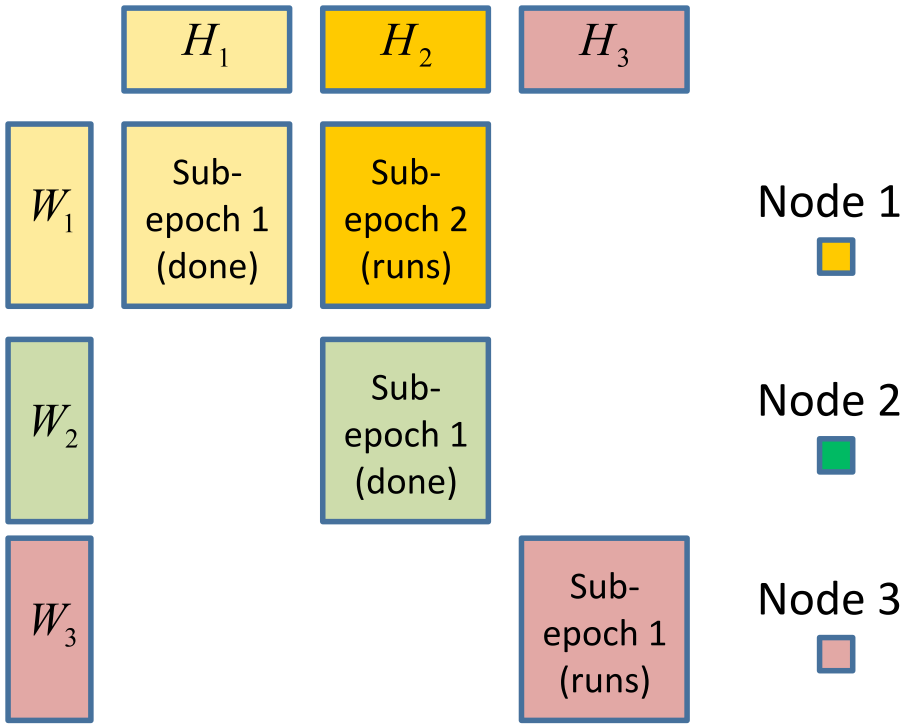

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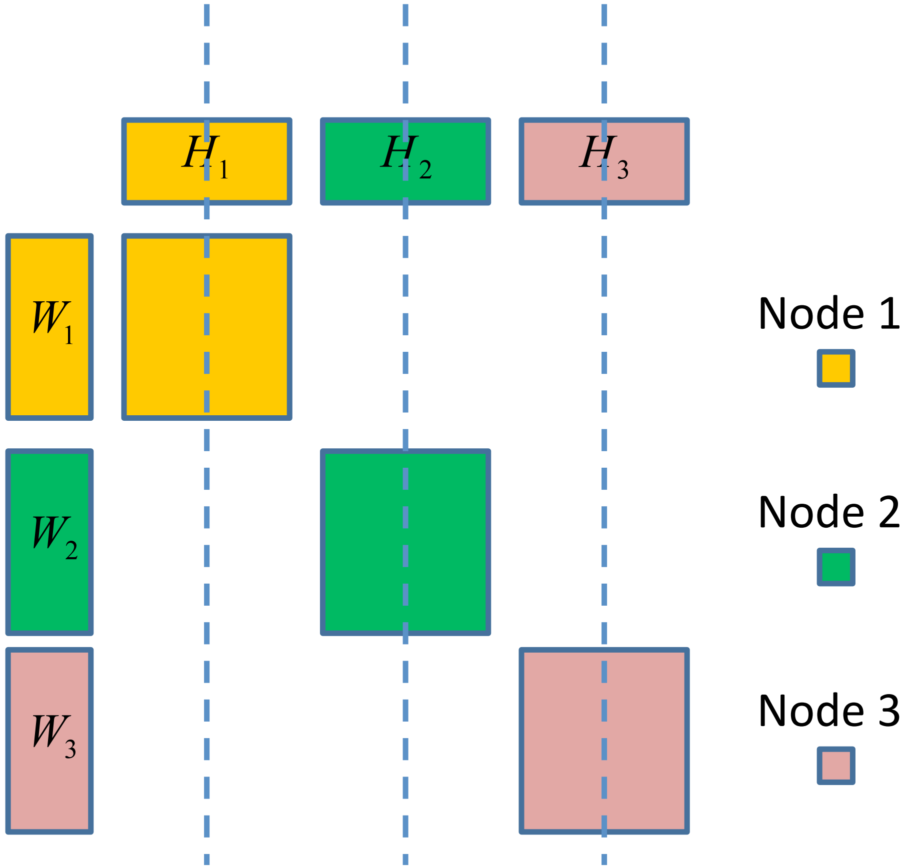

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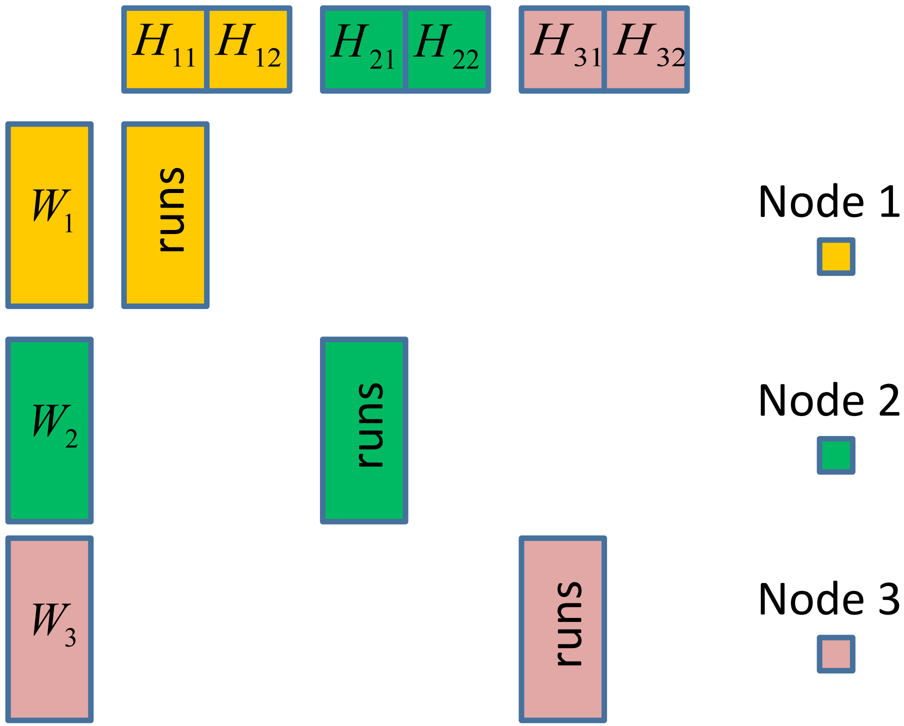

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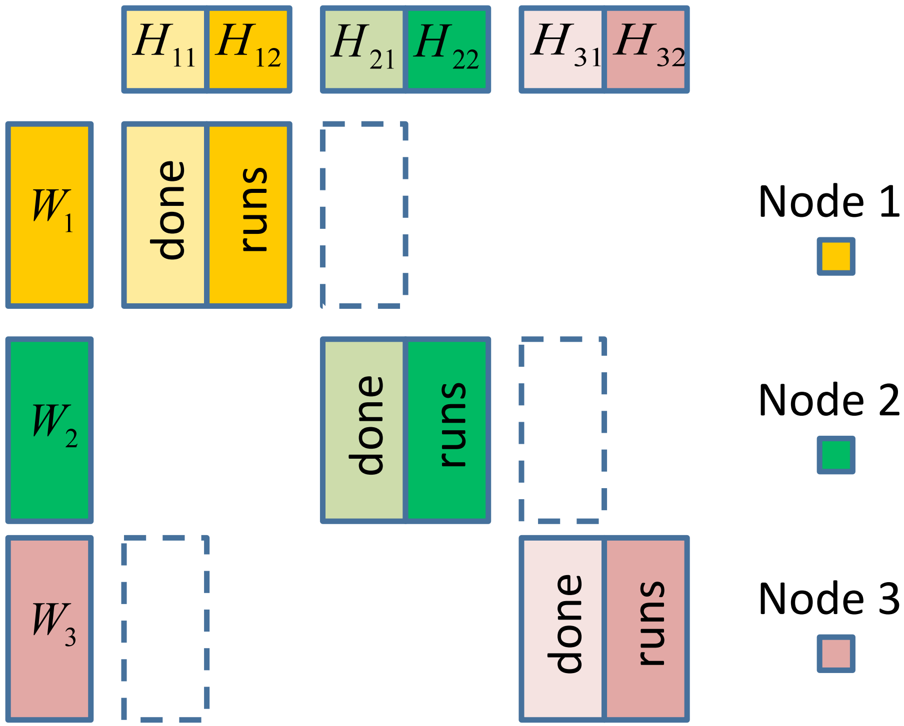

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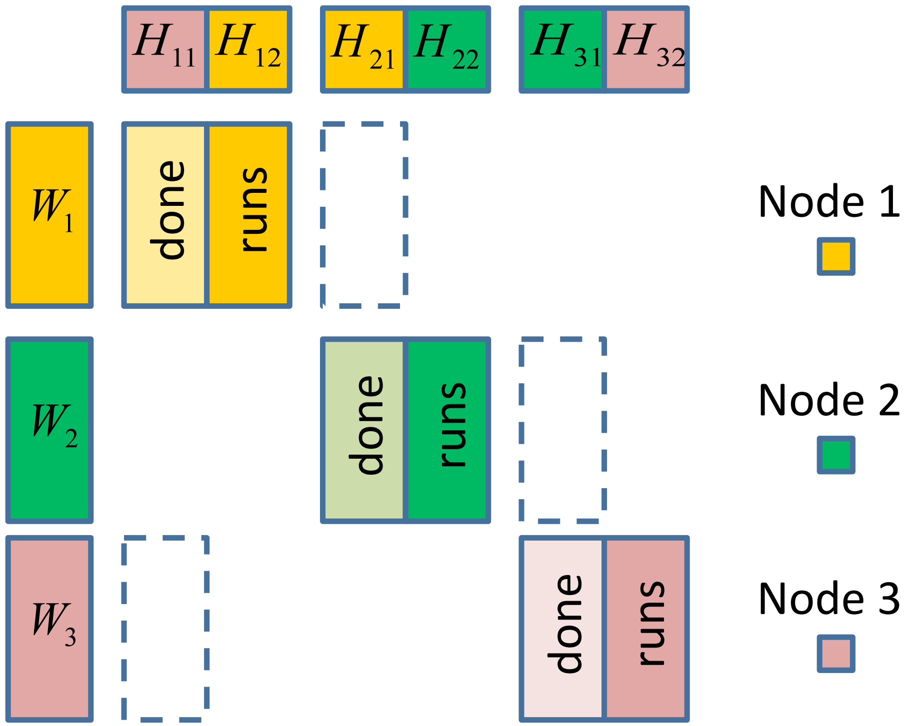

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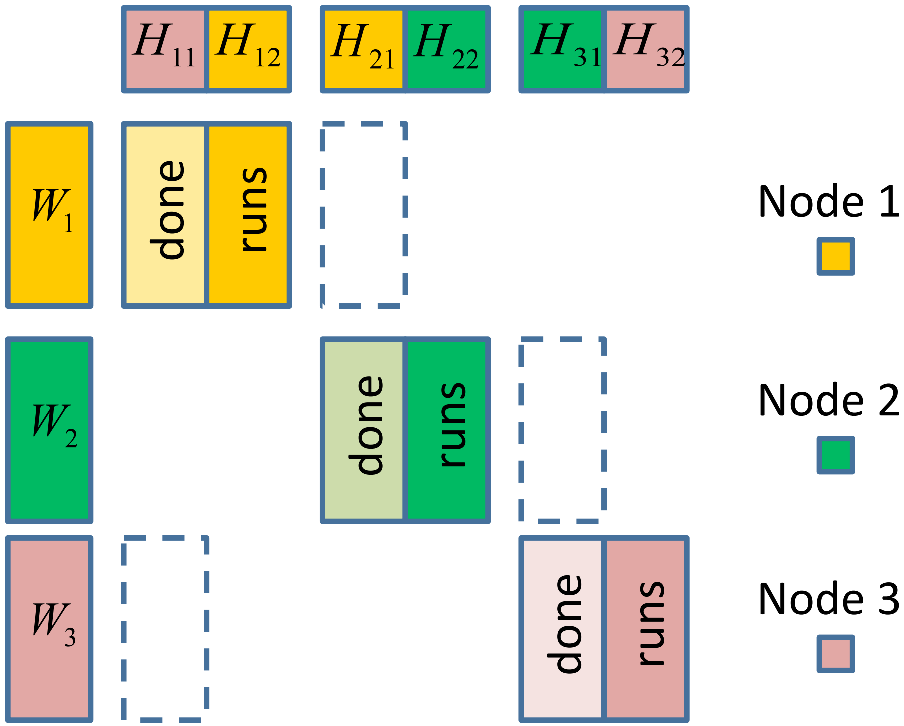

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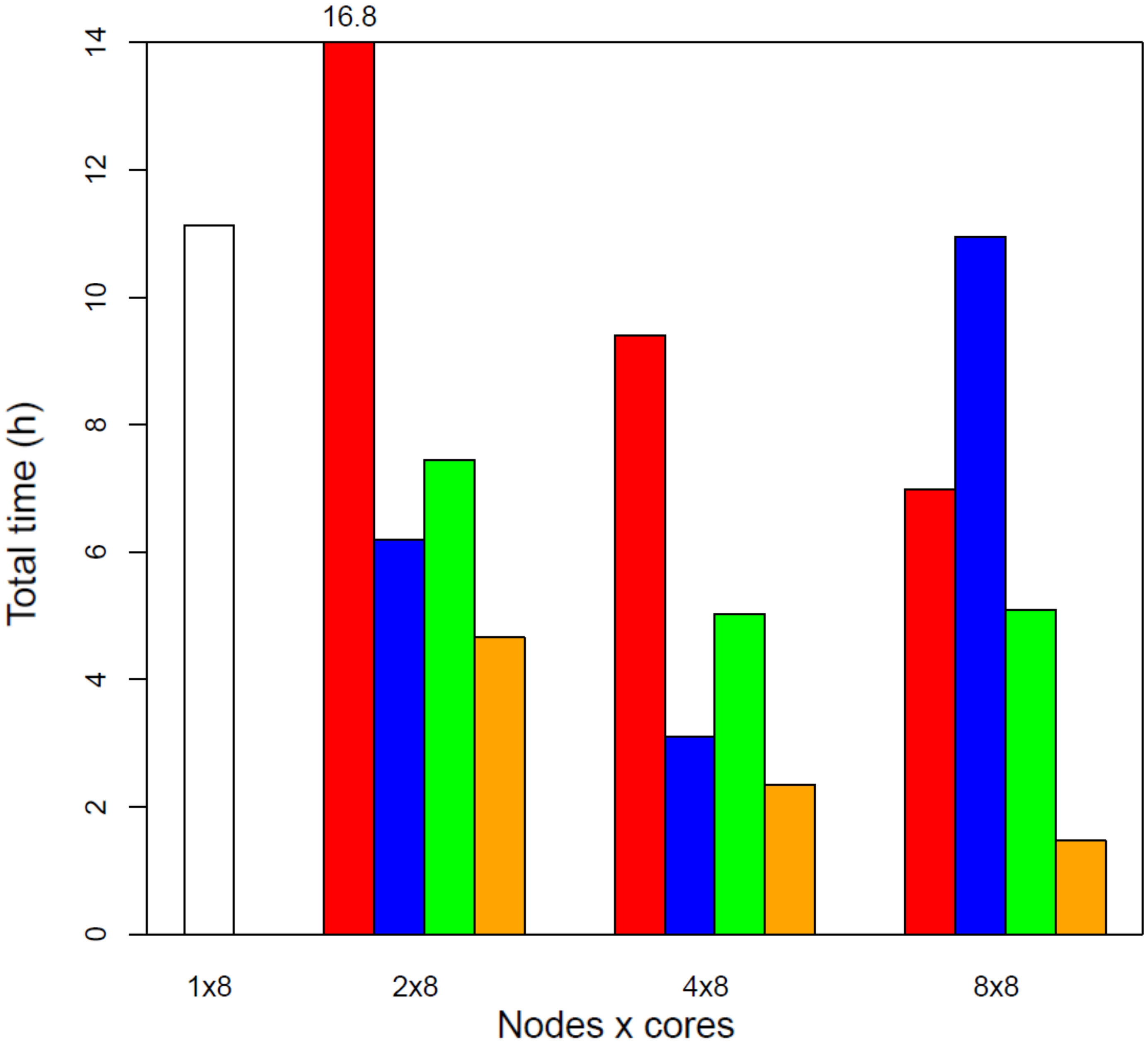
    - Asynchronous SGD
    - DSGD-MR
    - DSGD++
- **Experimental Results**
- Summary

Large Data

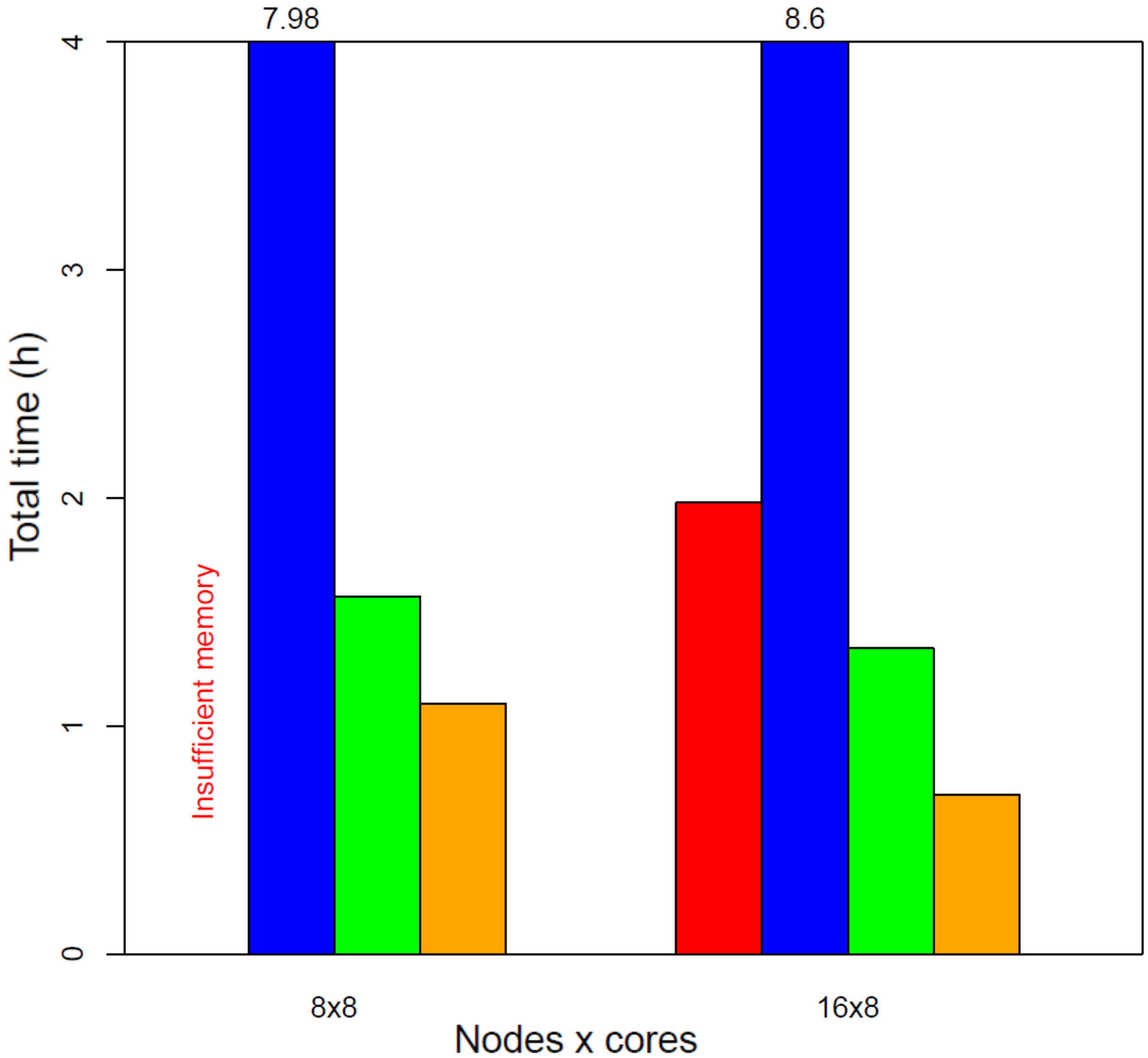


Dataset: 10M x 1M,
1B entries

- Parallel SGD
- Distributed ALS
- Asynchronous SGD
- DSGD−MapReduce
- DSGD++

DSGD++:
- Fastest
- Best scalability

Very Large Data



Dataset: 10M x 1M,
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- Parallel SGD
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- DSGD−MapReduce
- DSGD++

DSGD++:
faster on 8 nodes
than any other
method on 16 nodes

Outline

- Motivation
- Algorithms
  - Distributed Alternating Least Squares
  - Distributed SGD-based algorithms
    - Asynchronous SGD
    - DSGD-MR
    - DSGD++
- Experimental Results
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Summary

- Existing distributed algorithms for matrix completion mainly designed for MapReduce
- Distributed algorithms for a shared-nothing environment :
  - Direct communication of nodes
  - Asynchronous
  - Overlay computation and communication
  - Multi-threading
- DSGD++:
  - Scales better
  - Can reach superlinear speed-ups
  - Low memory footprint
  - 10M x 1M with 10B entries: ~40min on 16 nodes

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Thank you
Questions?