Distributed Asynchronous Online Learning for Natural Language Processing

Kevin Gimpel Dipanjan Das Noah A. Smith

Introduction

- Two recent lines of research in speeding up large learning problems:
  - Parallel/distributed computing
  - Online (and mini-batch) learning algorithms:

    stochastic gradient descent, perceptron, MIRA, stepwise EM

- How can we bring together the benefits of parallel computing and online learning?

Introduction

- We use **asynchronous** algorithms
  (Nedic, Bertsekas, and Borkar, 2001;
  Langford, Smola, and Zinkevich, 2009)

- We apply them to structured prediction tasks:
  - Supervised learning
  - Unsupervised learning with both convex and non-convex objectives

- Asynchronous learning speeds convergence and works best with small mini-batches

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Problem Setting

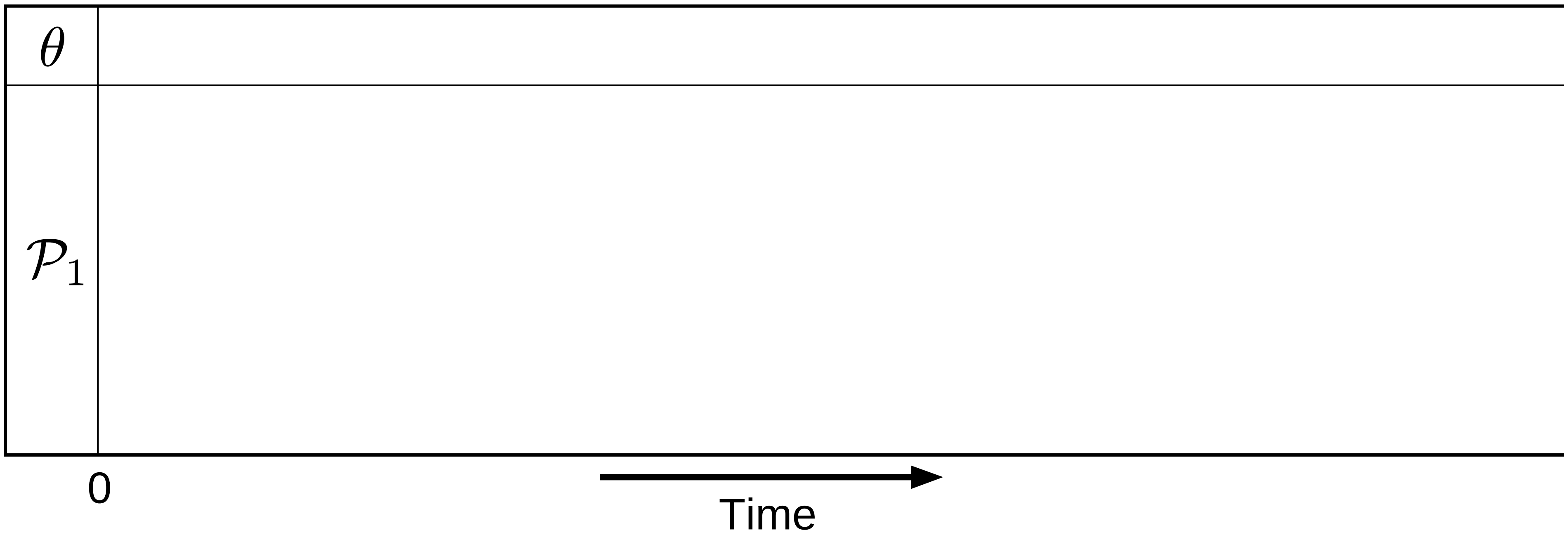
- Iterative learning
  - Moderate to large numbers of training examples
  - Expensive inference procedures for each example
  - For concreteness, we start with gradient-based optimization

- Single machine with multiple processors
  - Exploit shared memory for parameters, lexicons, feature caches, etc.
  - Maintain one master copy of model parameters

Single-Processor Batch Learning

Parameters:	θ_t
Processors:	$\mathcal{P}_i$
Dataset:	$\mathcal{D}$

Single-Processor Batch Learning



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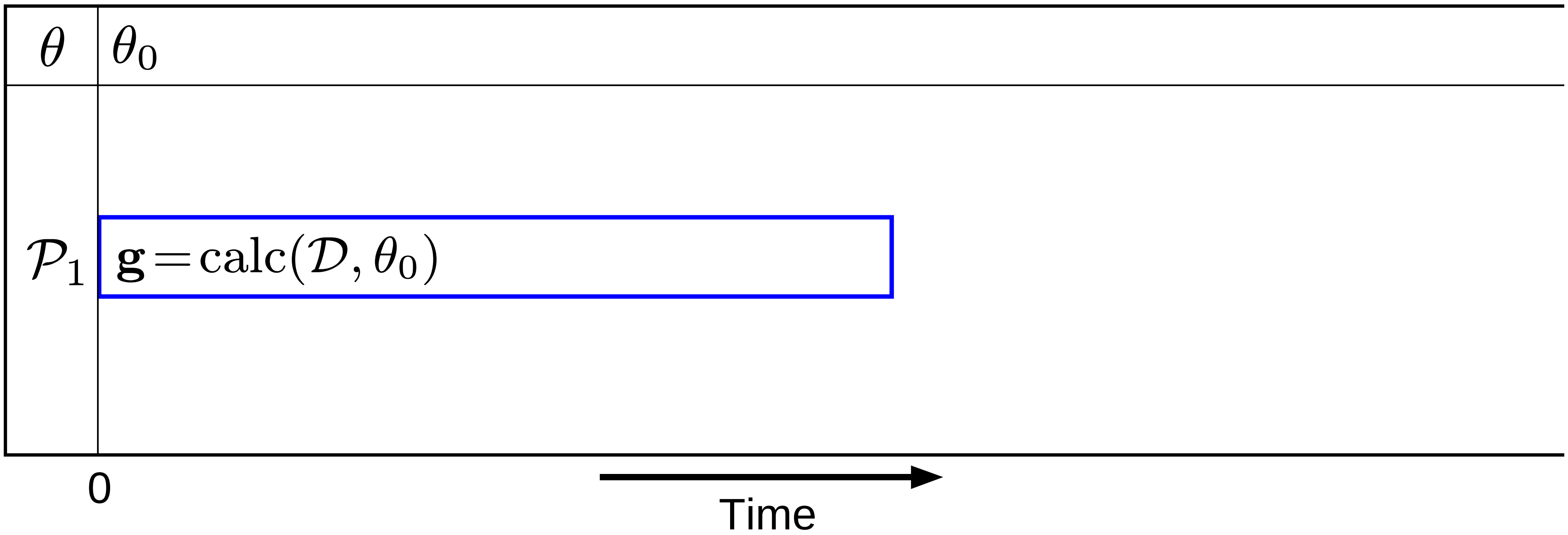

$\mathbf{g} = \text{calc}(\mathcal{D}, \theta)$:

Calculate gradient $\mathbf{g}$ on data $\mathcal{D}$ using parameters θ

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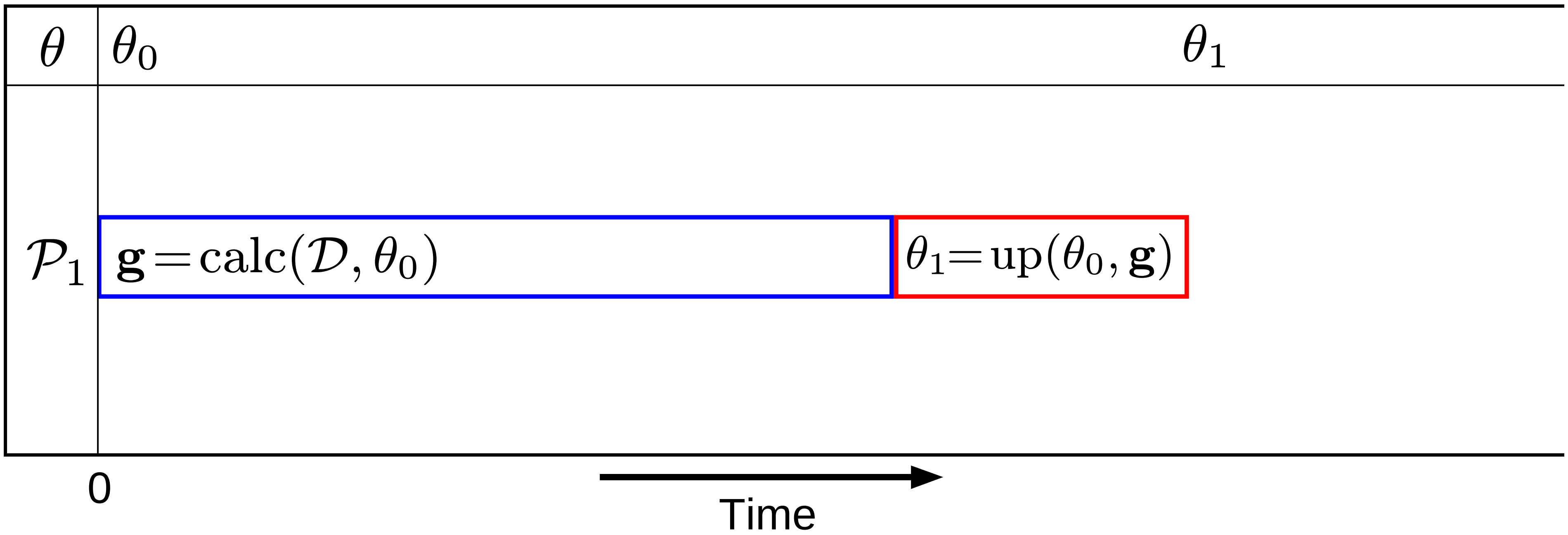

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Update θ_0 using gradient $\mathbf{g}$ to obtain θ_1

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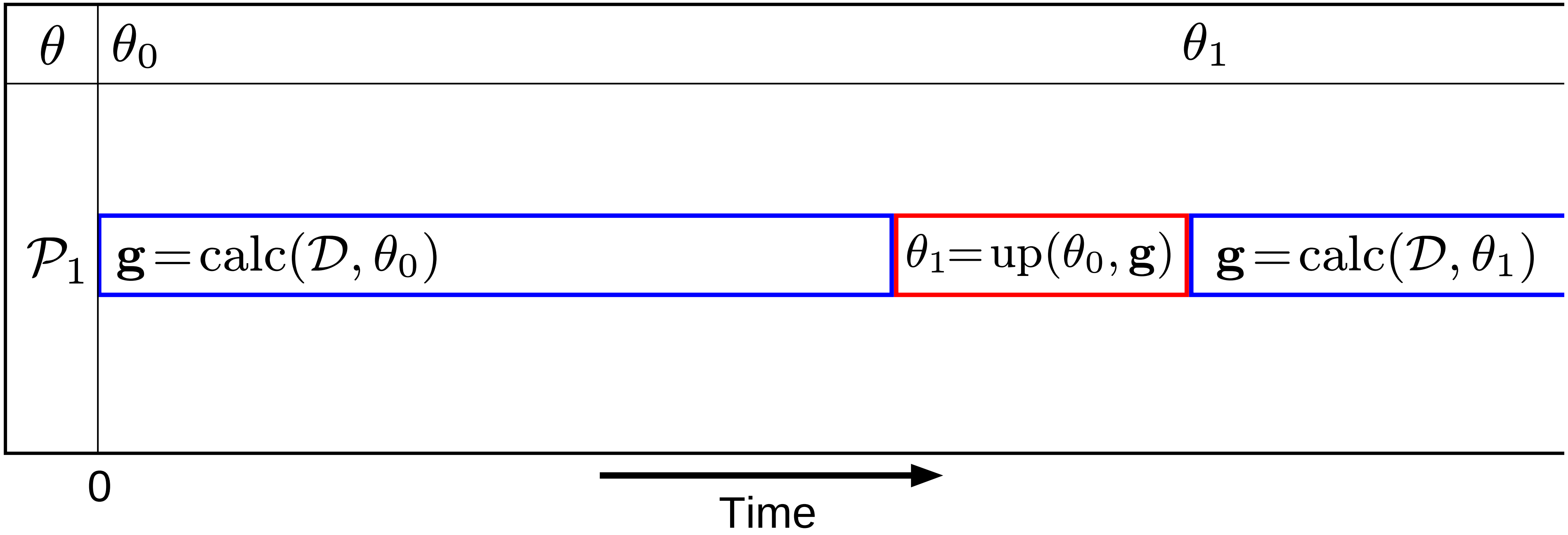

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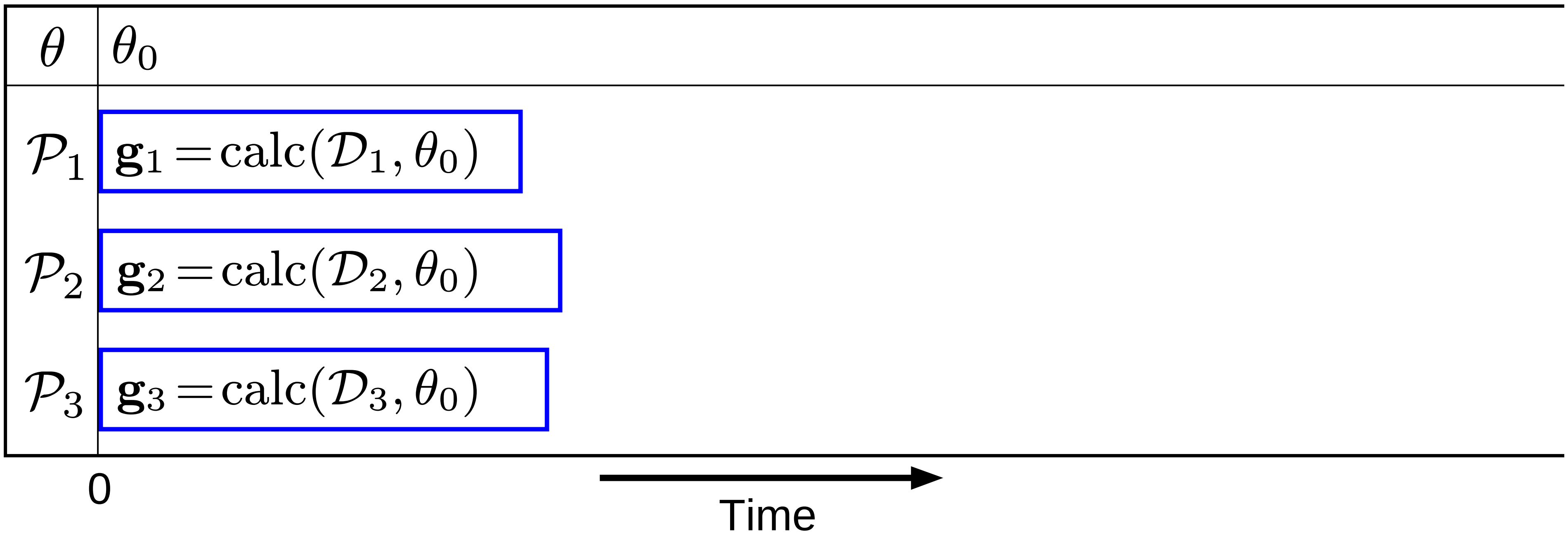
Parallel Batch Learning



- Divide data into parts, compute gradient on parts in parallel

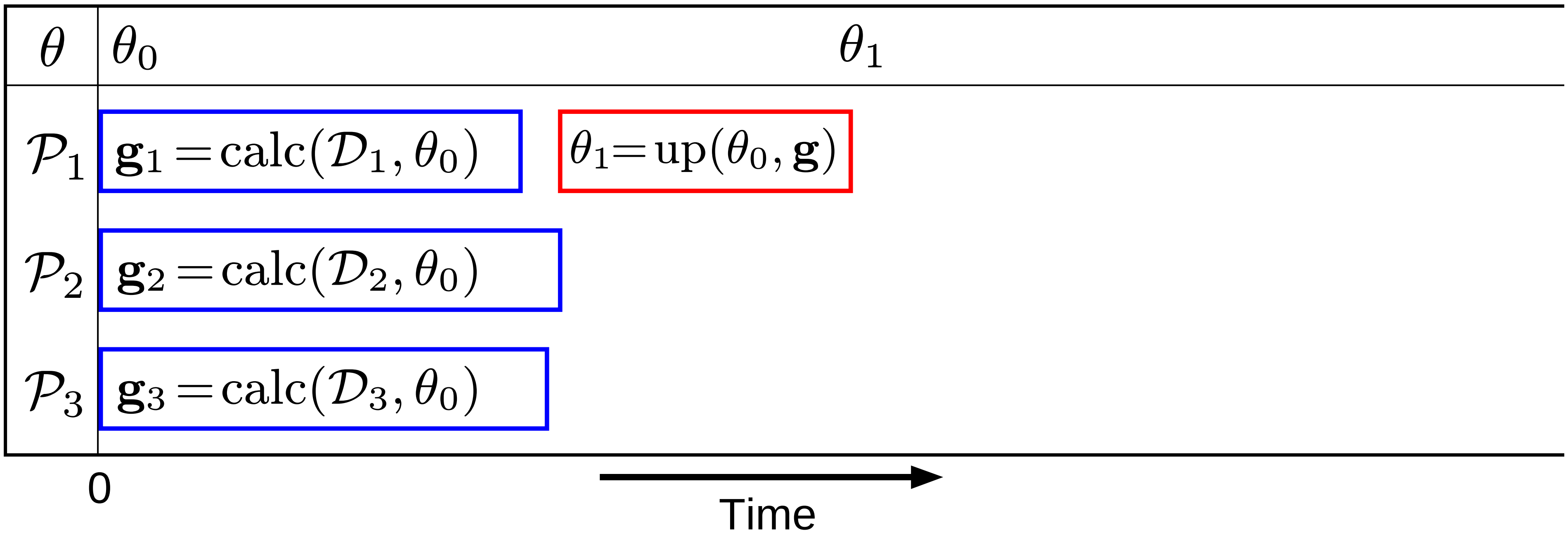
Parameters: θ_t

Processors: $\mathcal{P}_i$

Dataset: $\mathcal{D} = \mathcal{D}_1 \cup \mathcal{D}_2 \cup \mathcal{D}_3$

Gradient: $\mathbf{g} = \mathbf{g}_1 + \mathbf{g}_2 + \mathbf{g}_3$

Parallel Batch Learning



- Divide data into parts, compute gradient on parts in parallel
- One processor updates parameters

Parameters: θ_t

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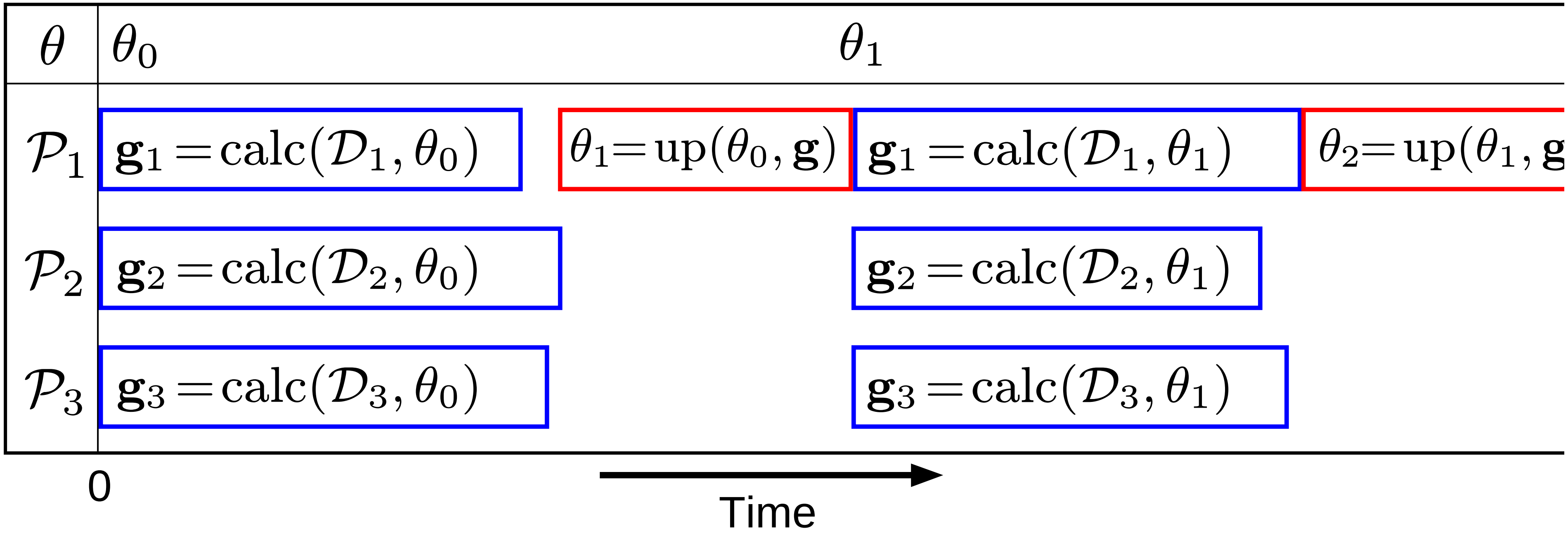

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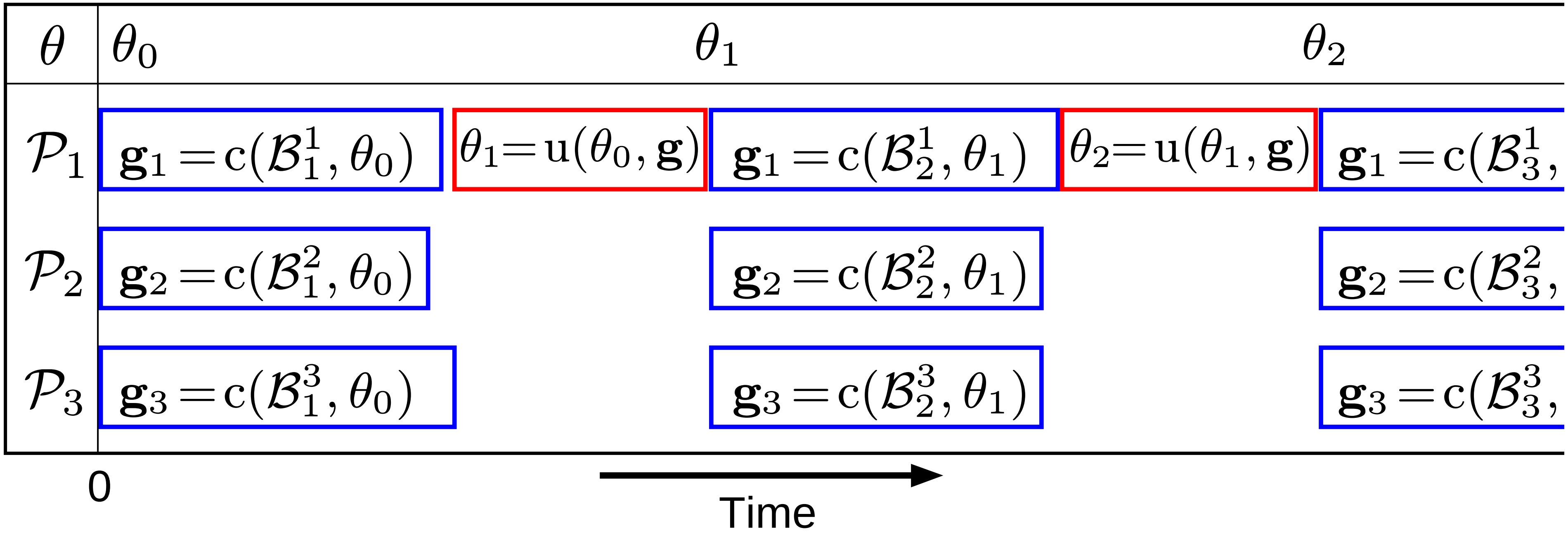
Parallel Synchronous Mini-Batch Learning

Finkel, Kleeman, and Manning (2008)



- Same architecture, just more frequent updates

Parameters: θ_t

Processors: $\mathcal{P}_i$

Mini-batches: $\mathcal{B}_t = \mathcal{B}_t^1 \cup \mathcal{B}_t^2 \cup \mathcal{B}_t^3$

Gradient: $\mathbf{g} = \mathbf{g}_1 + \mathbf{g}_2 + \mathbf{g}_3$

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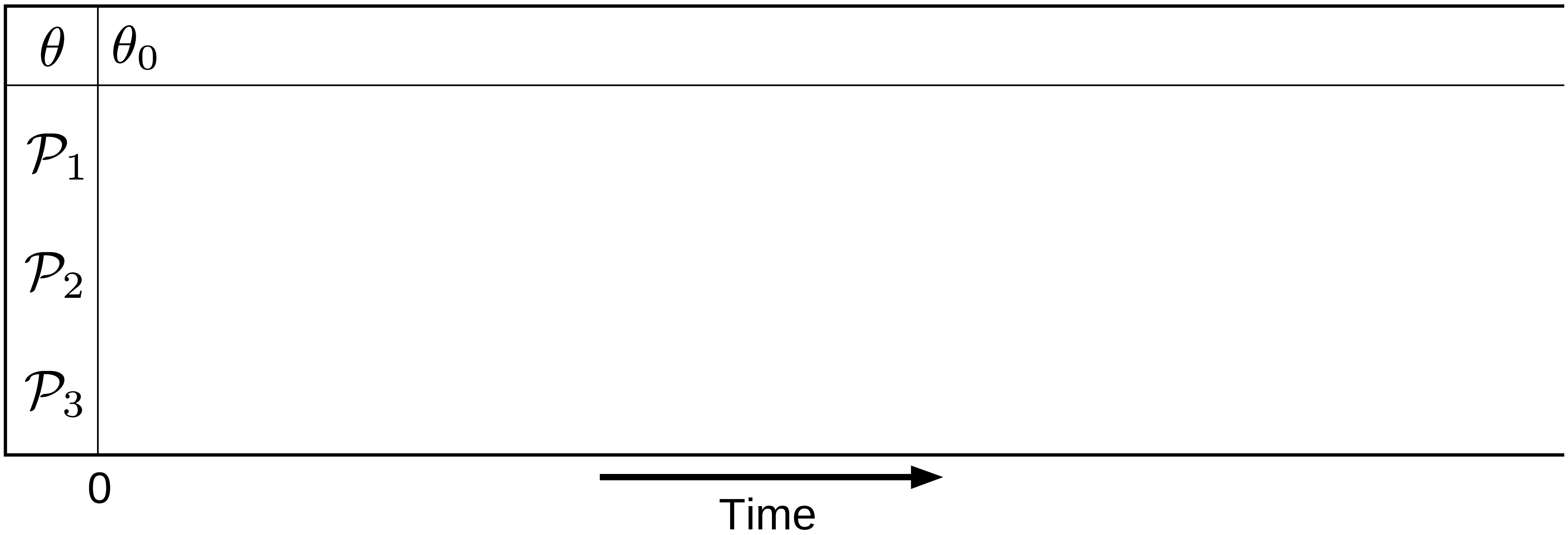
Parallel Asynchronous Mini-Batch Learning

Nedic, Bertsekas, and Borkar (2001)



Parameters: θ_t

Processors: $\mathcal{P}_i$

Mini-batches: $\mathcal{B}_j$

Gradient: $\mathbf{g}_k$

Parallel Asynchronous Mini-Batch Learning

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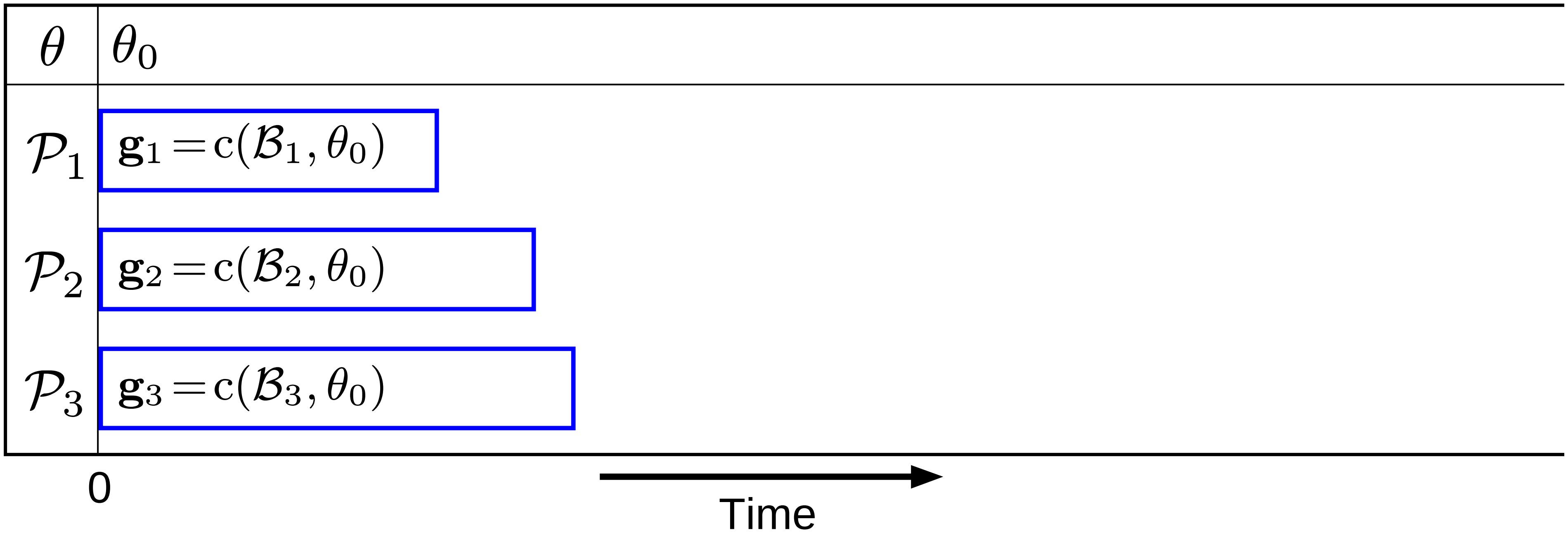

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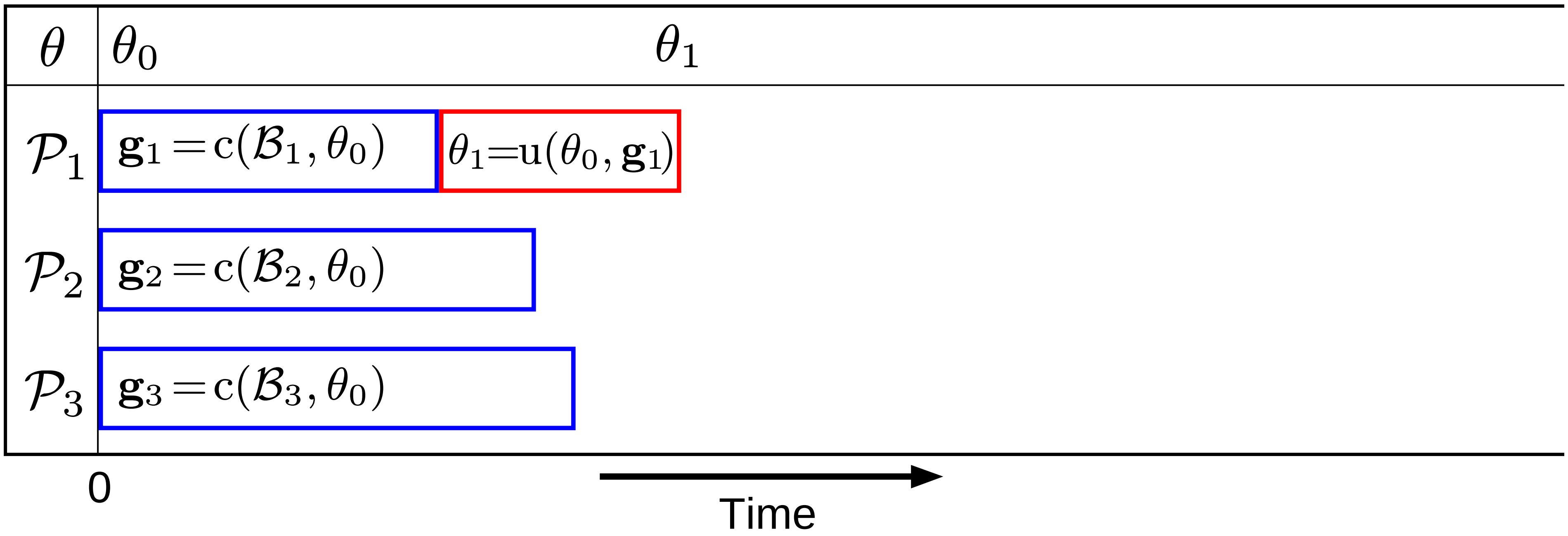

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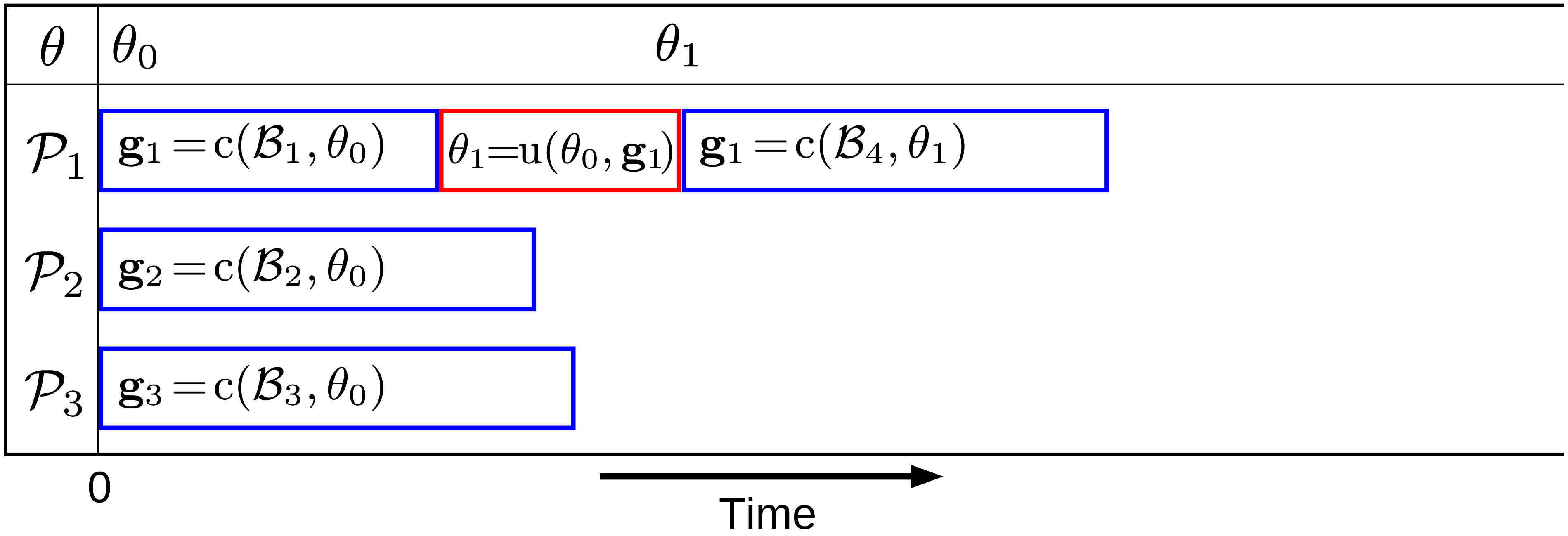

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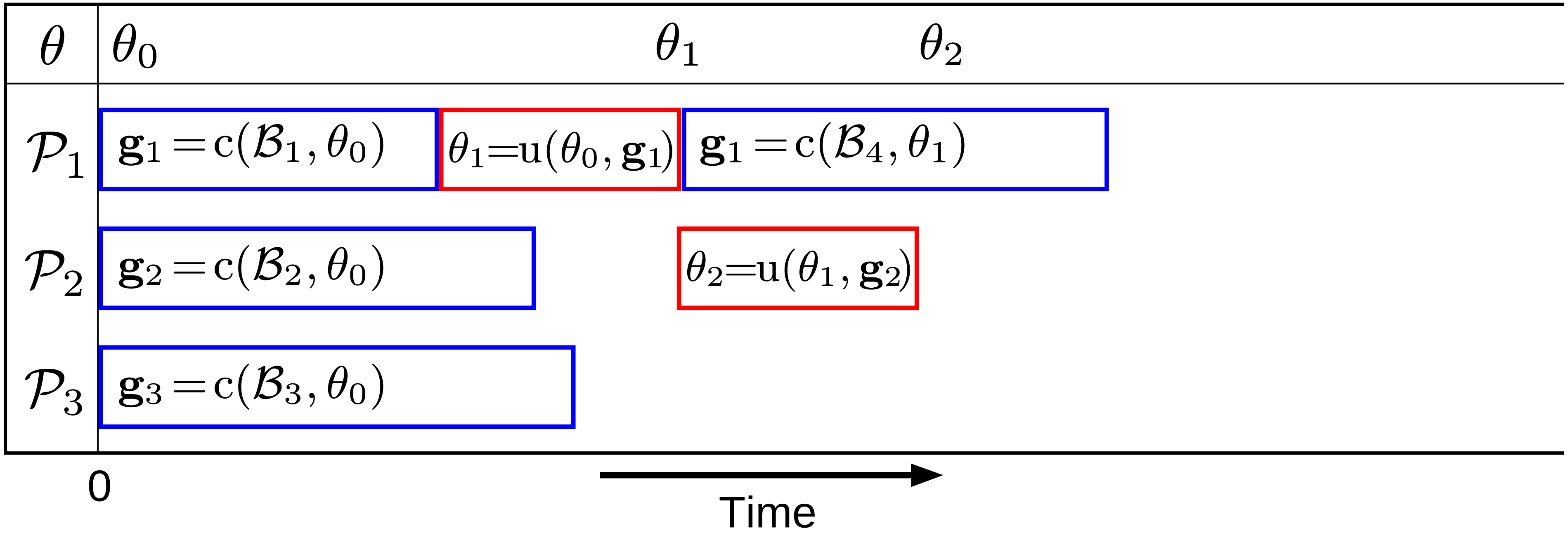

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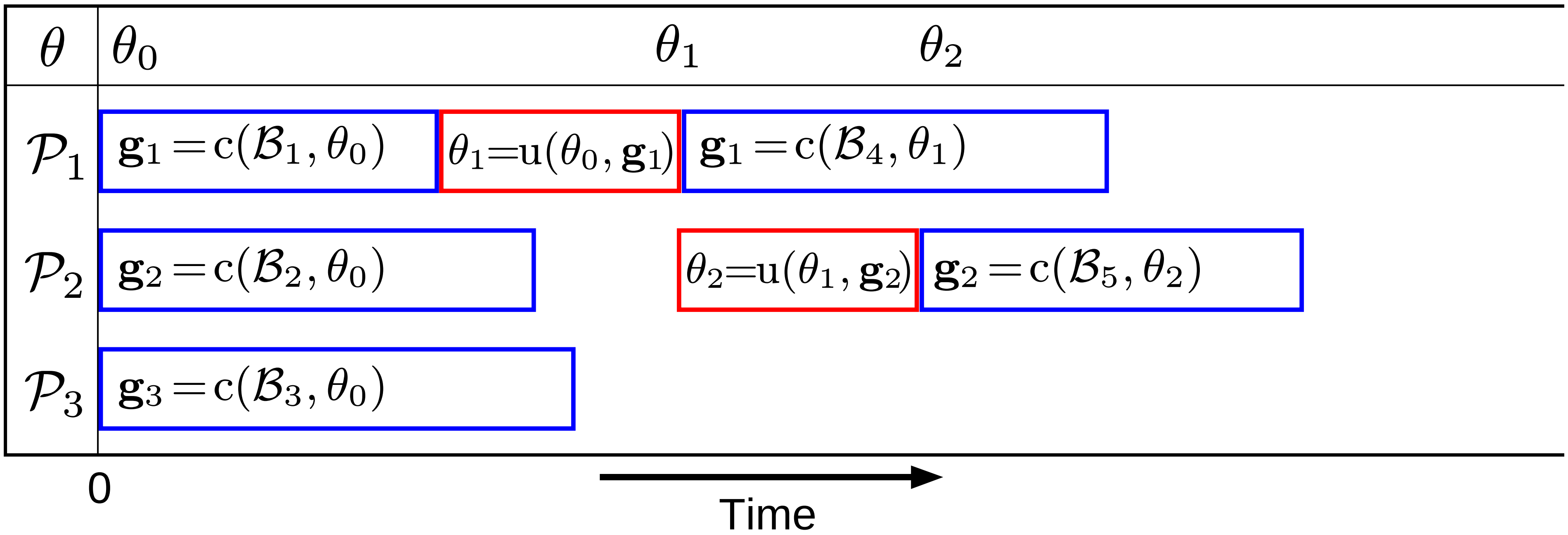

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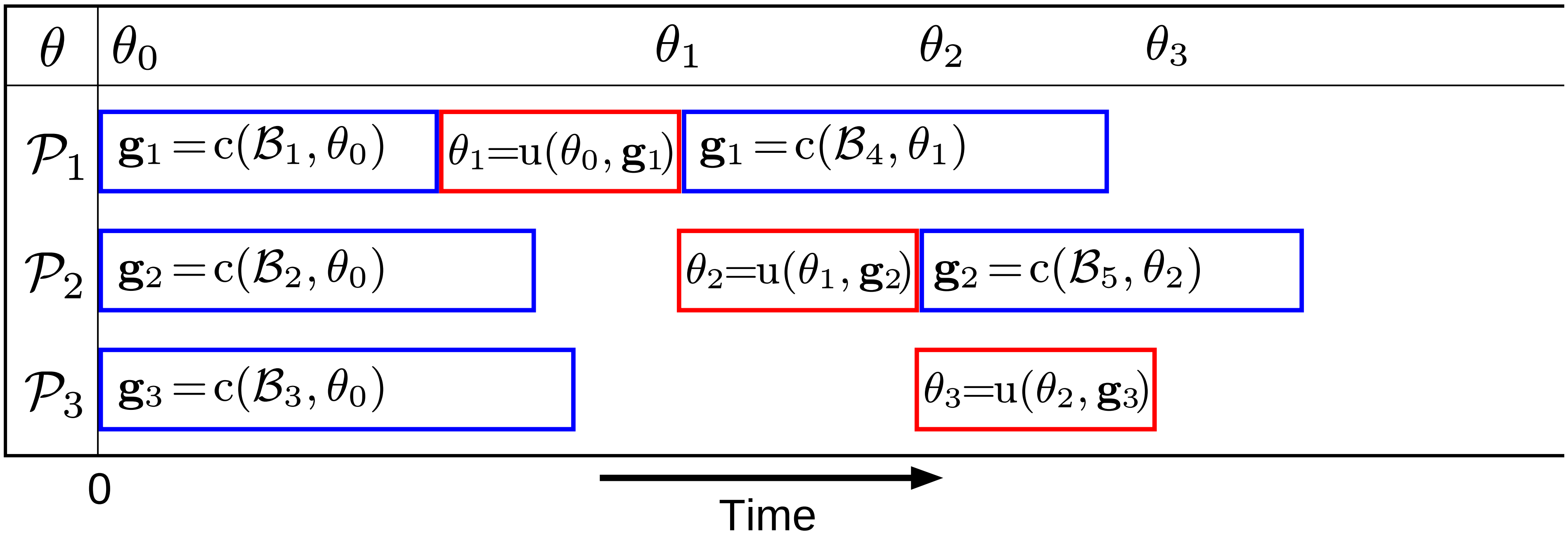

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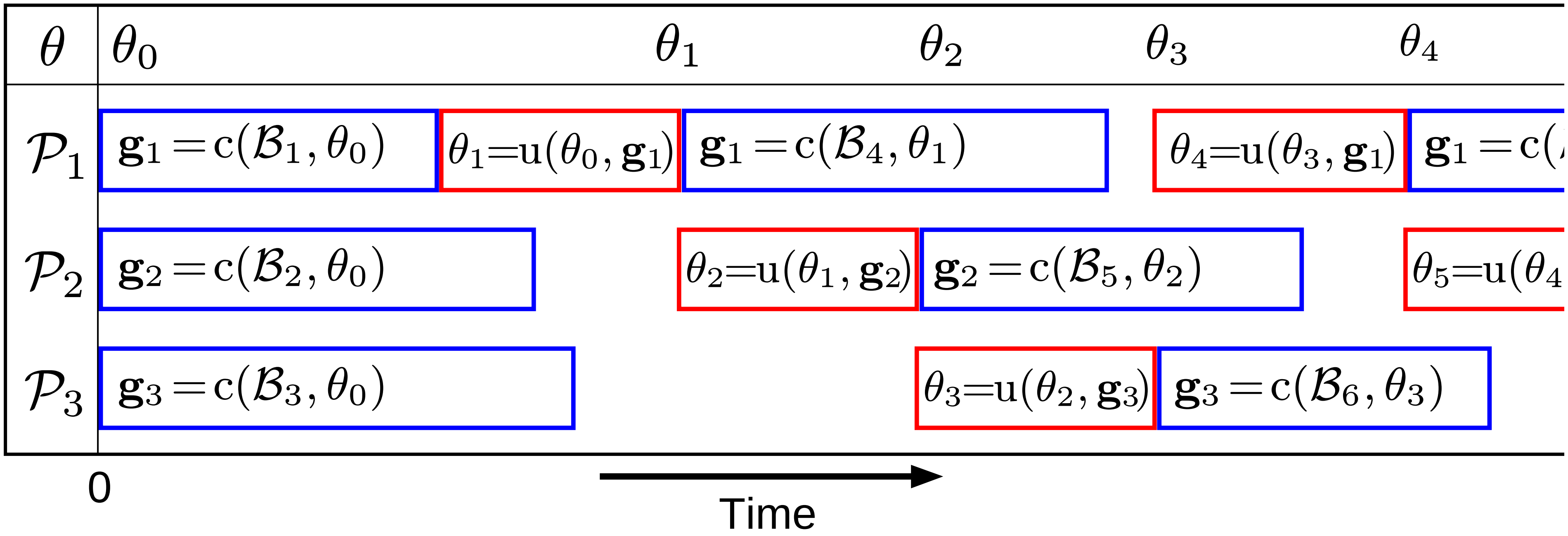

- Gradients computed using stale parameters
- Increased processor utilization
- Only idle time caused by lock for updating parameters

Parameters:	θ_t
Processors:	$\mathcal{P}_i$
Mini-batches:	$\mathcal{B}_j$
Gradient:	$\mathbf{g}_k$

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Theoretical Results

- How does the use of stale parameters affect convergence?

- Convergence results exist for convex optimization using stochastic gradient descent
  - Convergence guaranteed when max delay is bounded (Nedic, Bertsekas, and Borkar, 2001)
  - Convergence rates linear in max delay (Langford, Smola, and Zinkevich, 2009)

Experiments

Task	Model	Method	Convex?	$\|\mathcal{D}\|$	$\|\theta\|$	m
Named-Entity Recognition	CRF	Stochastic Gradient Descent	Y	15k	1.3M	4
Word Alignment	IBM Model 1	Stepwise EM	Y	300k	14.2M	10k
Unsupervised Part-of-Speech Tagging	HMM	Stepwise EM	N	42k	2M	4

- To compare algorithms, we use wall clock time (with a dedicated 4-processor machine)
- m = mini-batch size

Experiments

Task	Model	Method	Convex?	$\lvert\mathcal{D}\rvert$	$\lvert\theta\rvert$	m
Named-Entity Recognition	CRF	Stochastic Gradient Descent	Y	15k	1.3M	4

- CoNLL 2003 English data
- Label each token with entity type (person, location, organization, or miscellaneous) or non-entity
- We show convergence in F1 on development data

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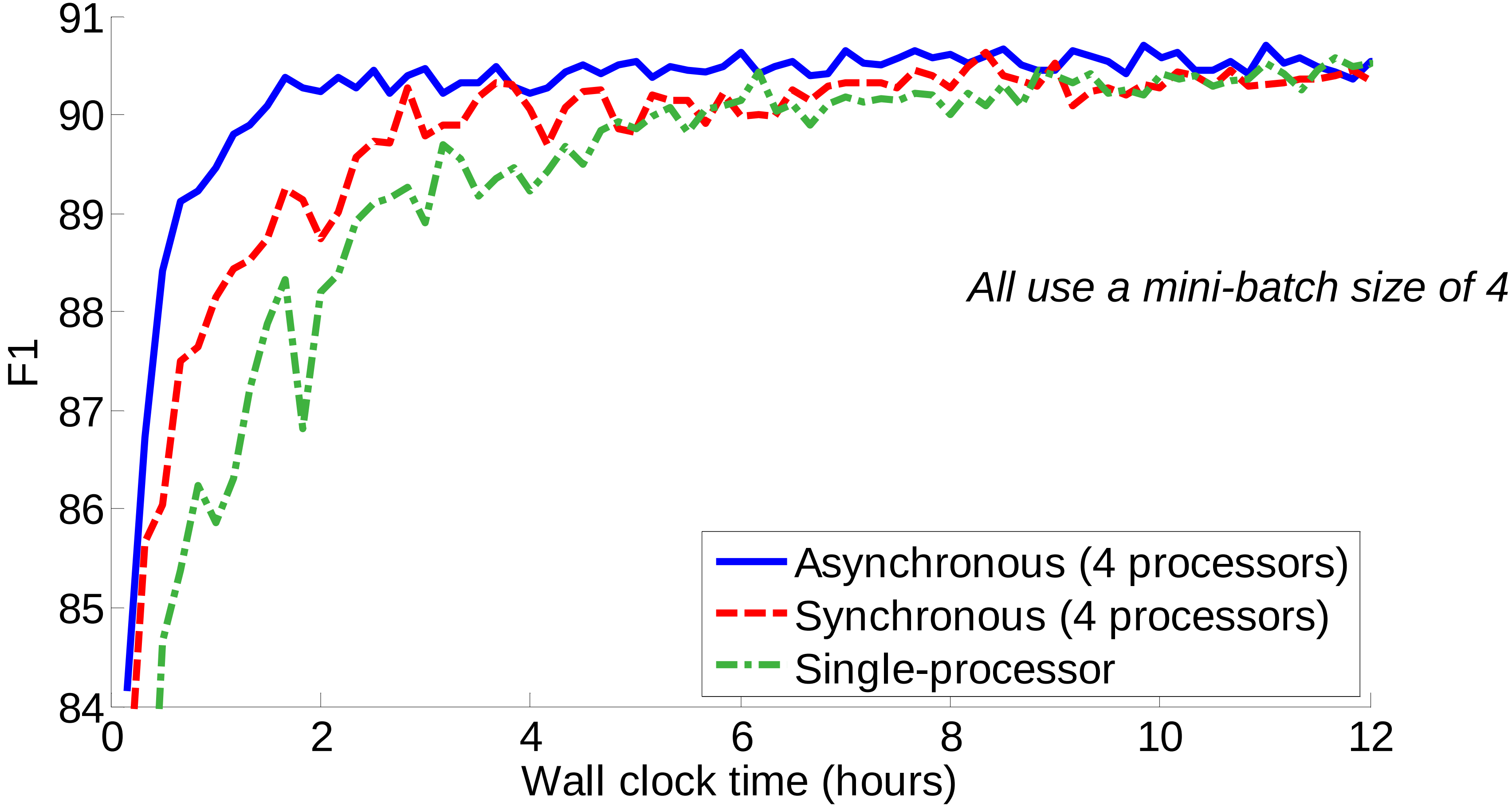
Asynchronous Updating Speeds Convergence



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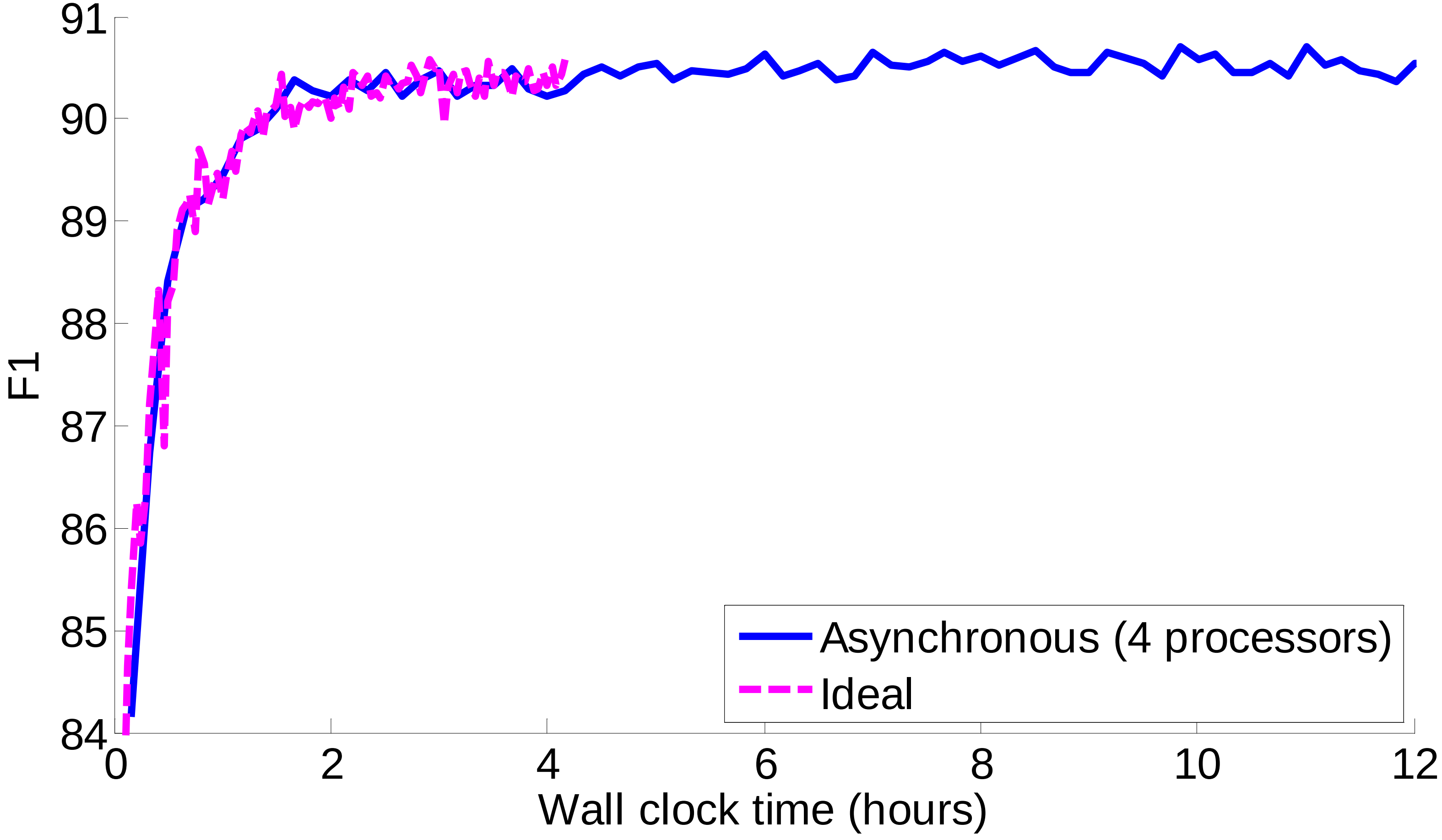
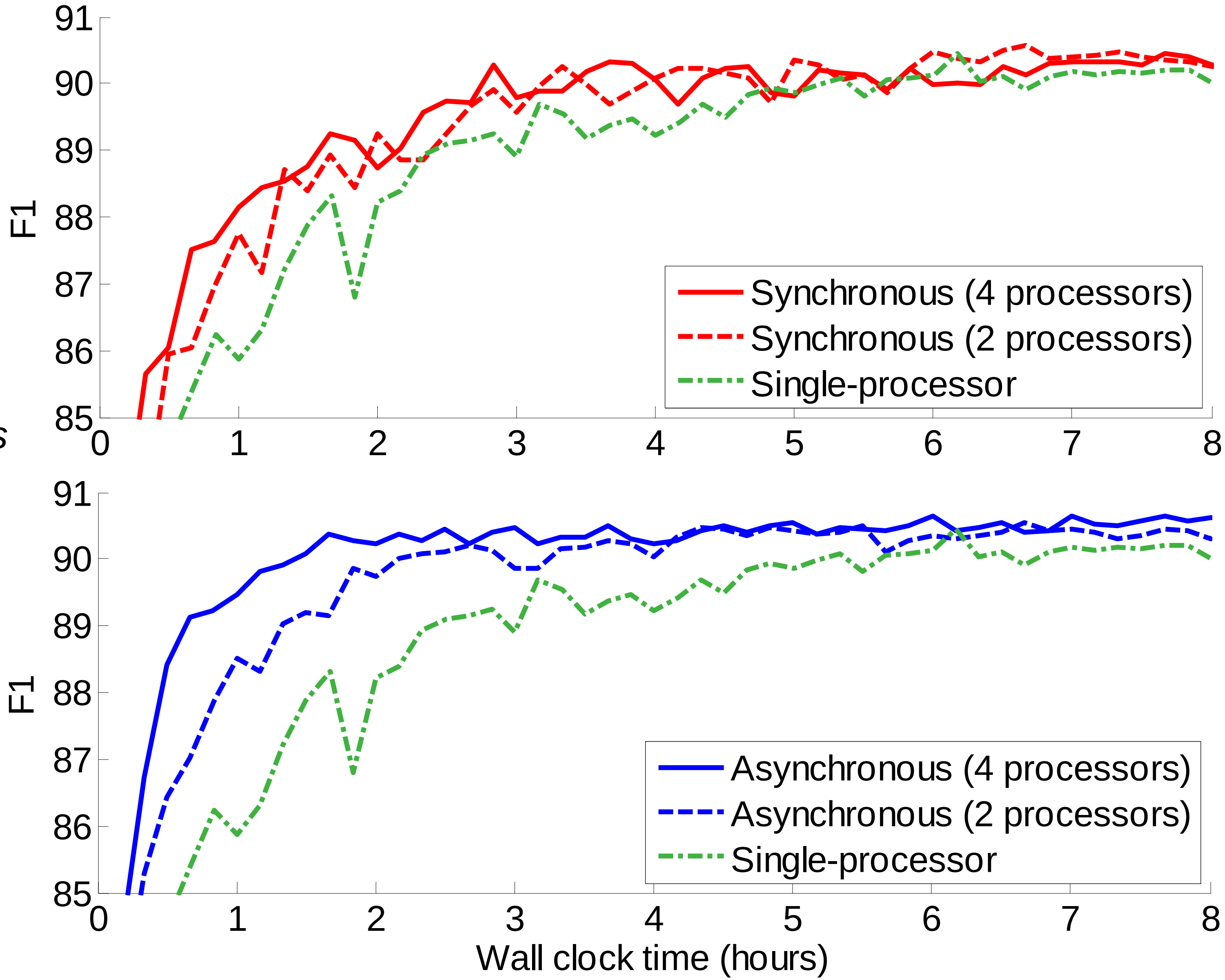
Comparison with Ideal Speed-up



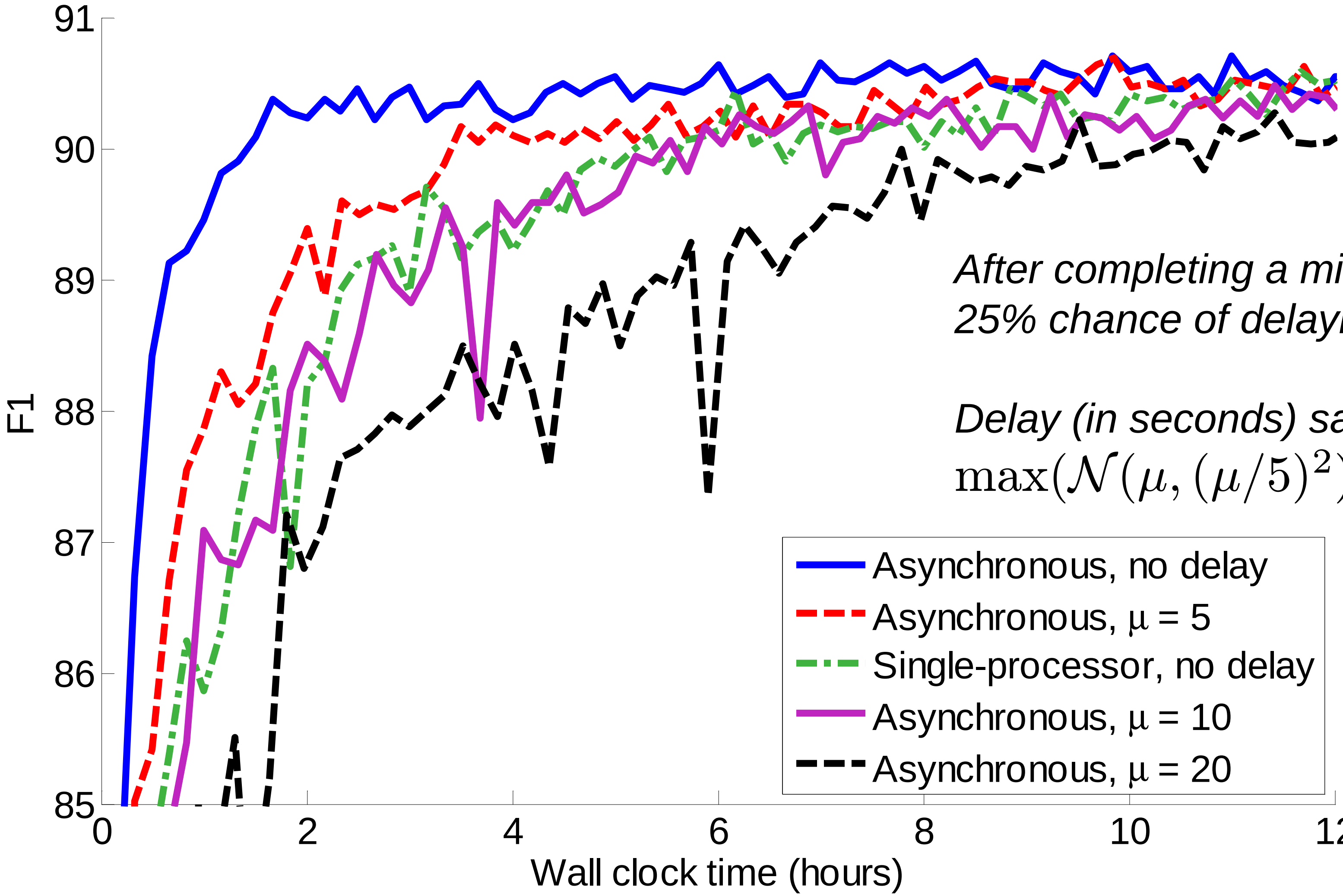
Why Does Asynchronous Converge Faster?

- Processors are kept in near-constant use
- Synchronous SGD leads to idle processors → need for load-balancing

Clearer improvement for asynchronous algorithms when increasing number of processors



Artificial Delays



After completing a mini-batch, 25% chance of delaying

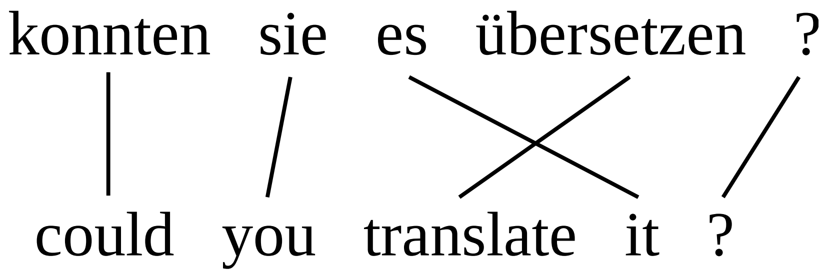
Delay (in seconds) sampled from
$$\max(\mathcal{N}(\mu, (\mu/5)^2), 0)$$

Avg. time per mini-batch = 0.62 s

Experiments

Task	Model	Method	Convex?	$\|\mathcal{D}\|$	$\|\theta\|$	$\boldsymbol{m}$
Word Alignment	IBM Model 1	Stepwise EM	Y	300k	14.2M	10k

- Given parallel sentences, draw links between words:



- We show convergence in log-likelihood (convergence in AER is similar)

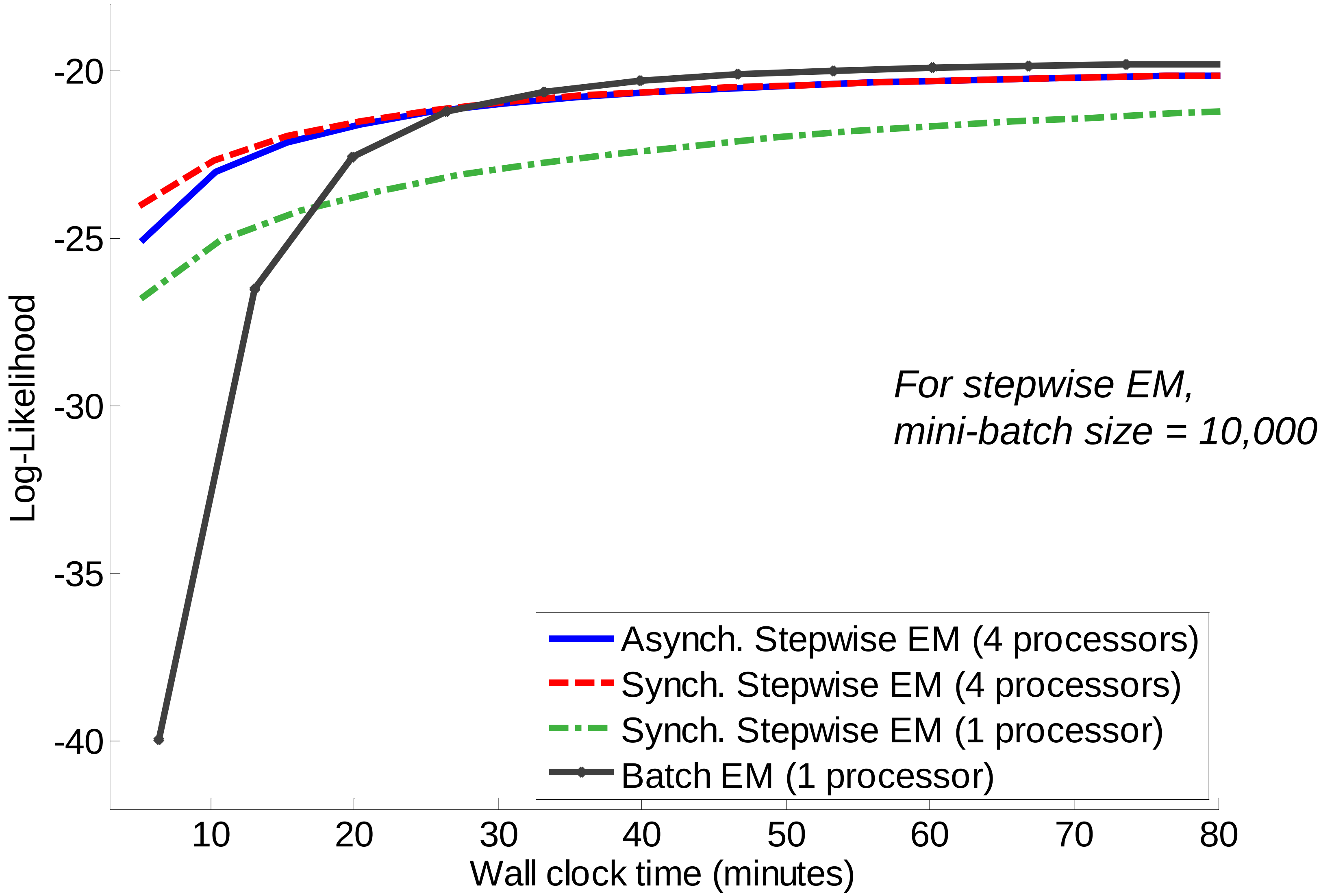
Stepwise EM

(Sato and Ishii, 2000; Cappe and Moulines, 2009)

- Similar to stochastic gradient descent in the space of sufficient statistics, with a particular scaling of the update
- More efficient than incremental EM

  (Neal and Hinton, 1998)
- Found to converge much faster than batch EM (Liang and Klein, 2009)

Word Alignment Results



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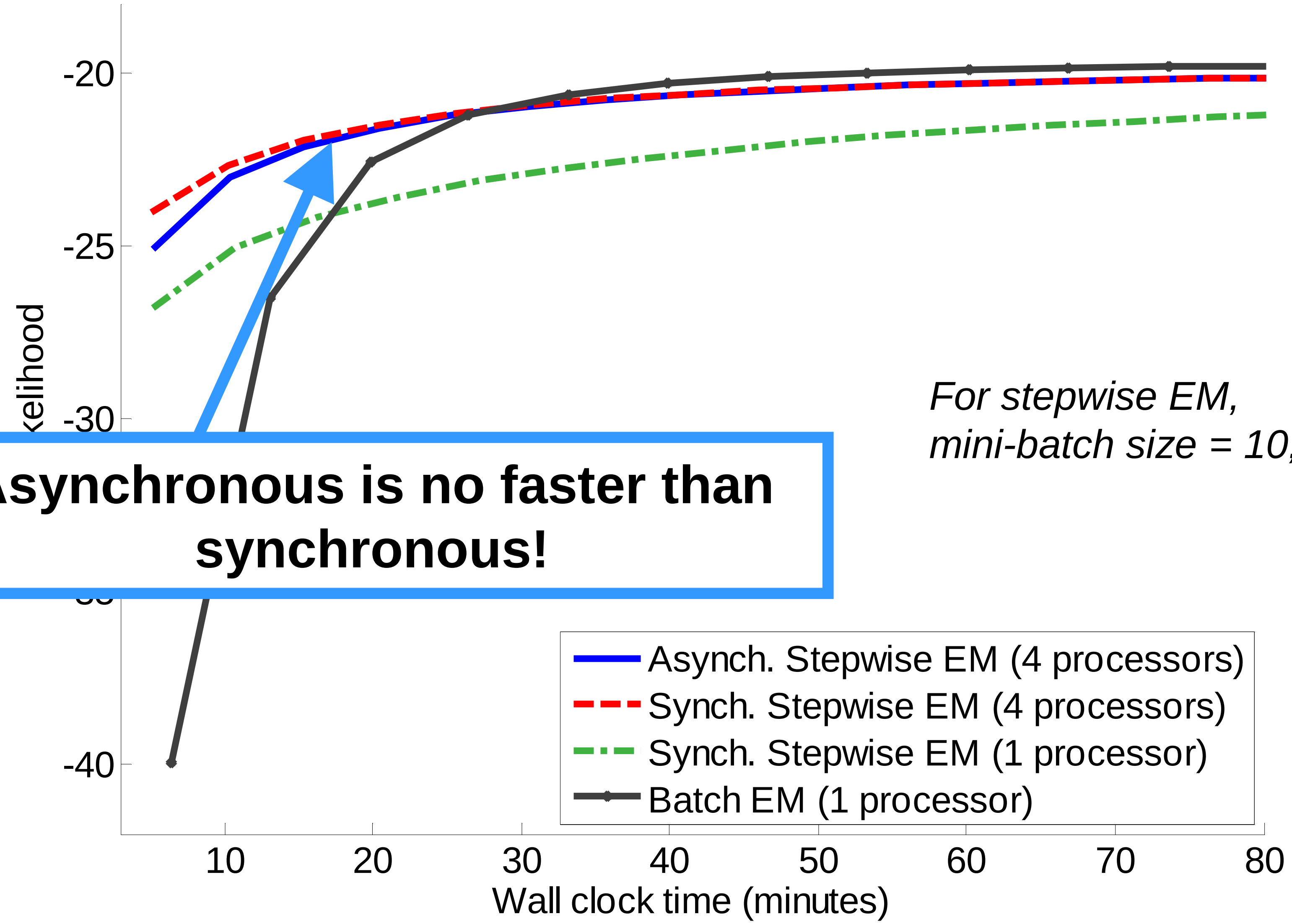
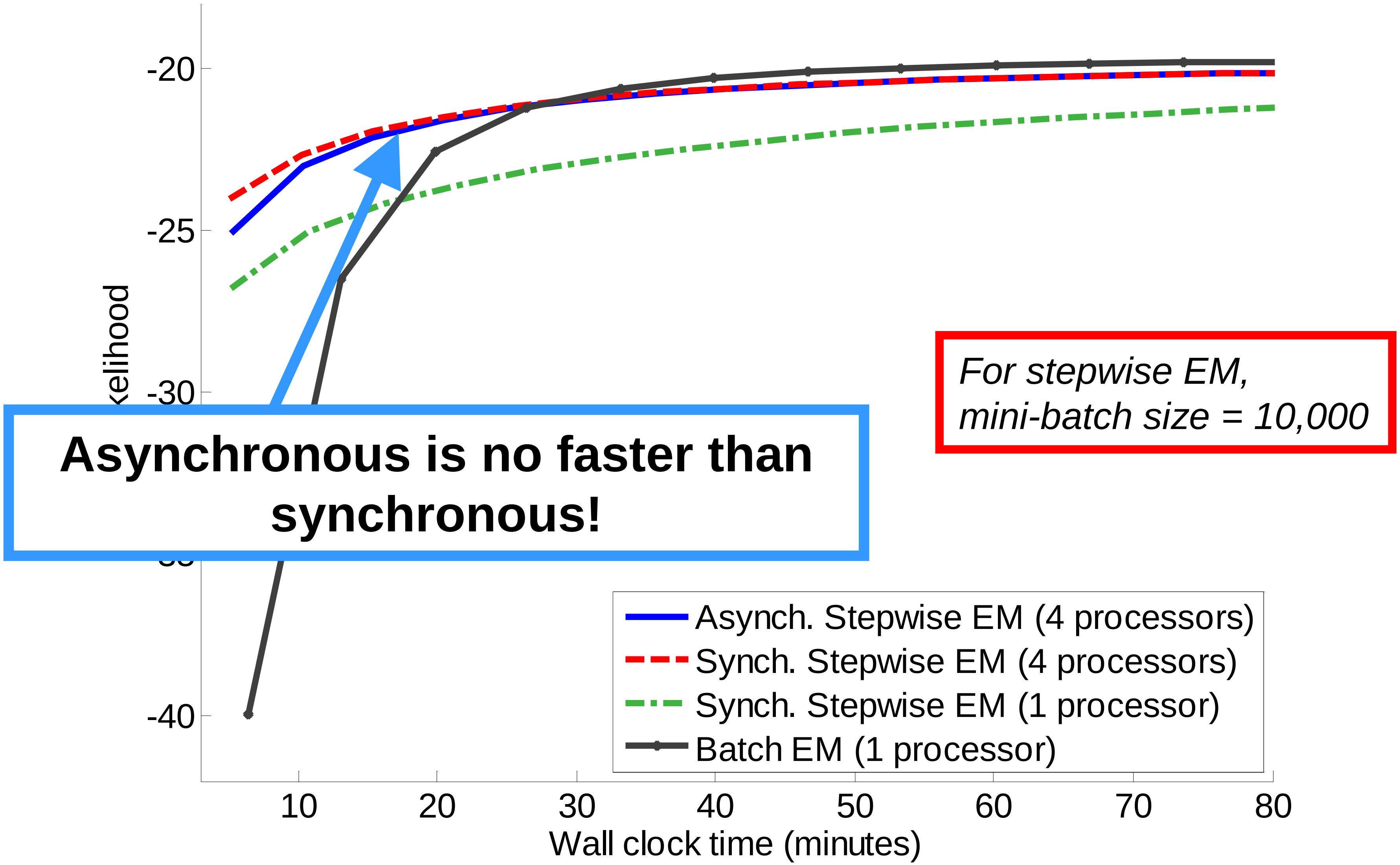


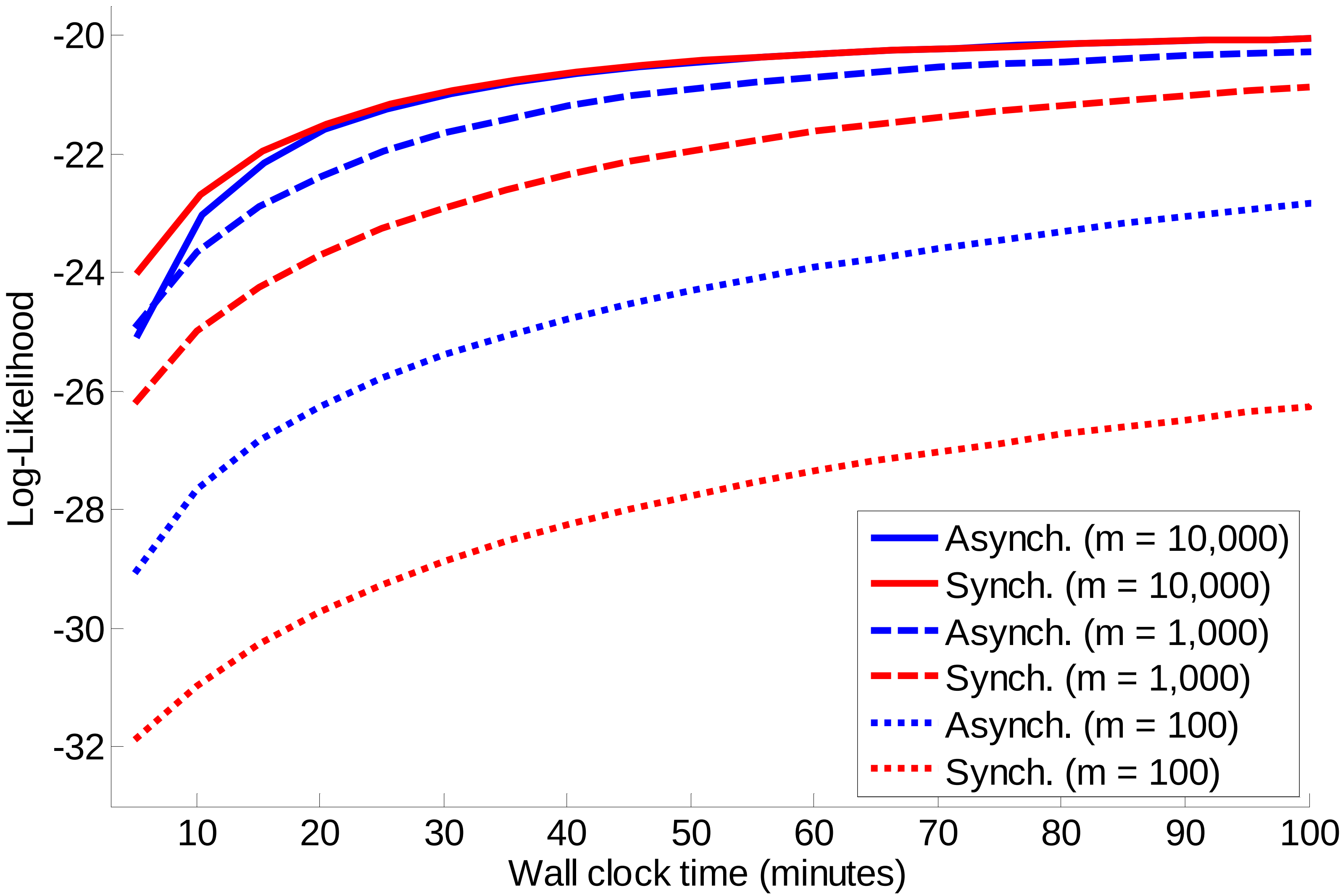
For stepwise EM,
mini-batch size = 10,000

Asynchronous is no faster than synchronous!

Word Alignment Results



Comparing Mini-Batch Sizes



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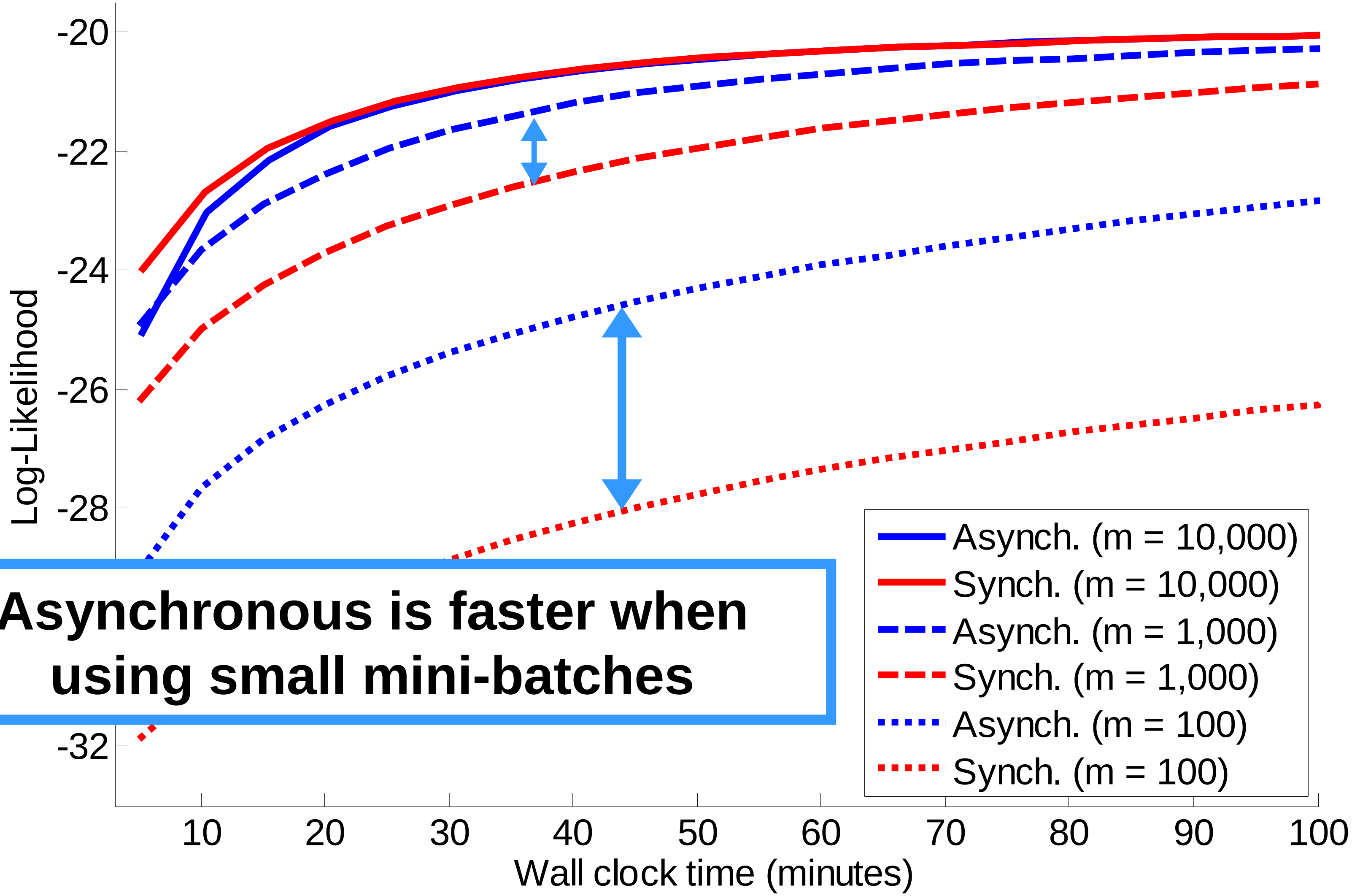
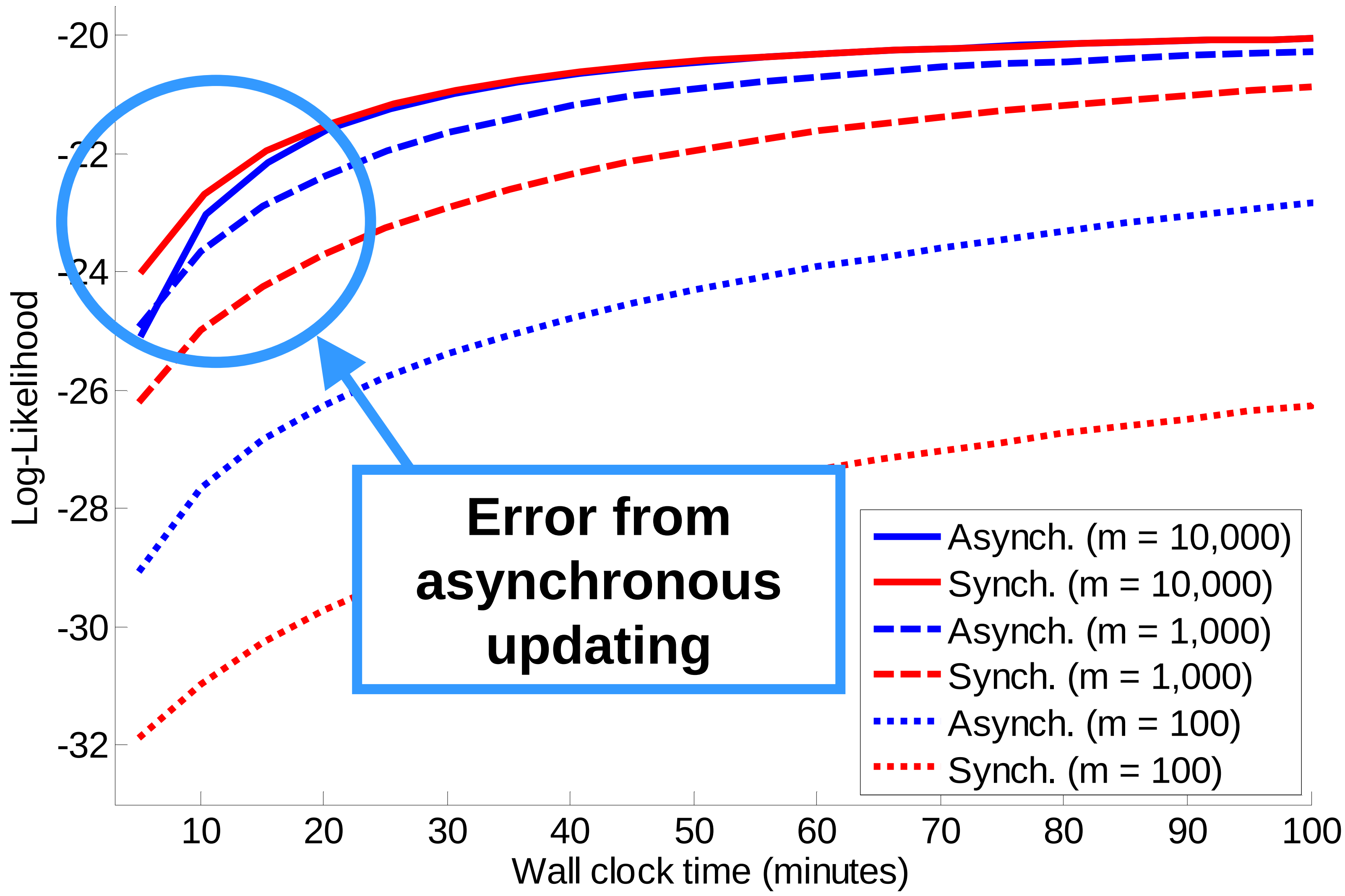


Asynchronous is faster when using small mini-batches

Comparing Mini-Batch Sizes



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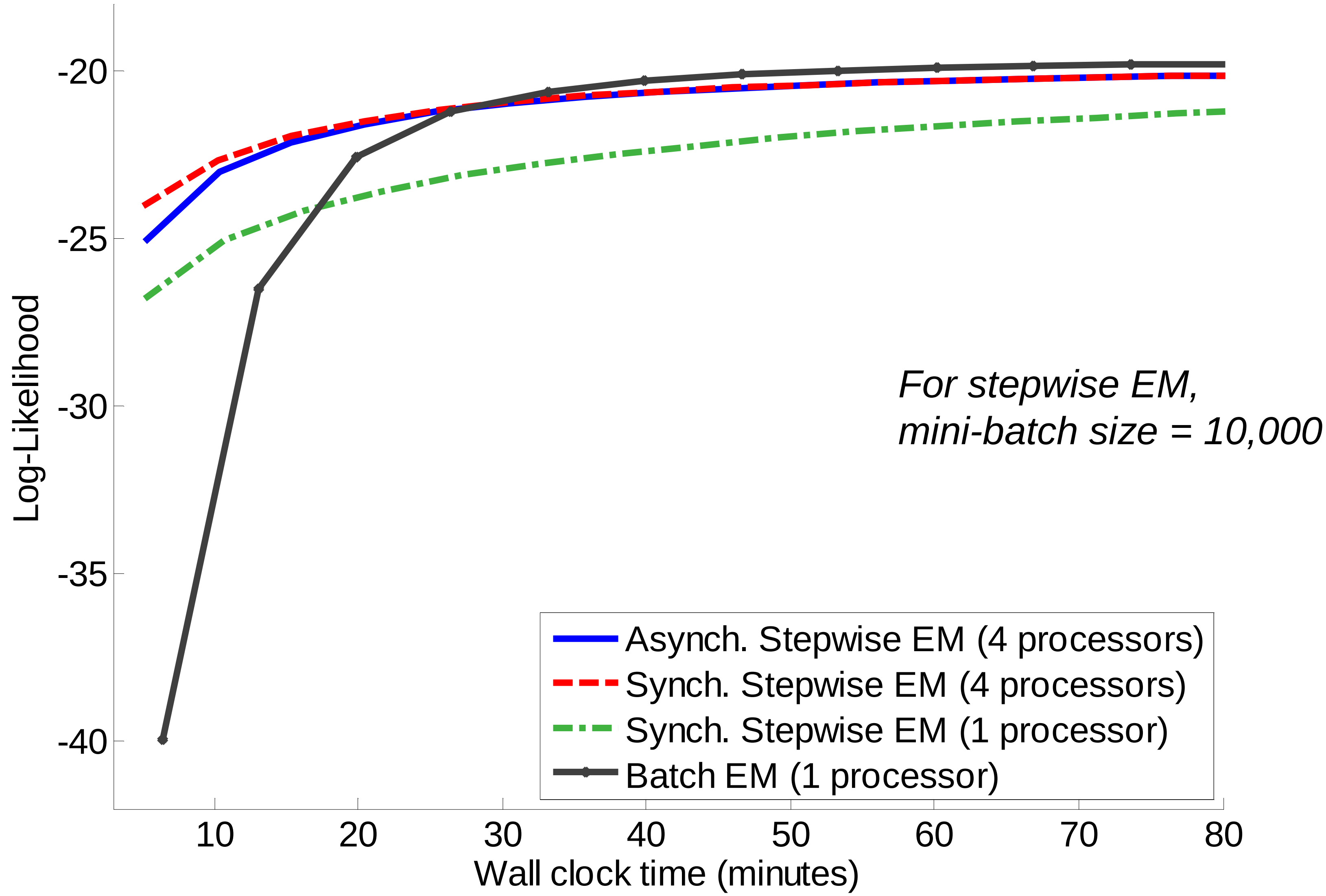

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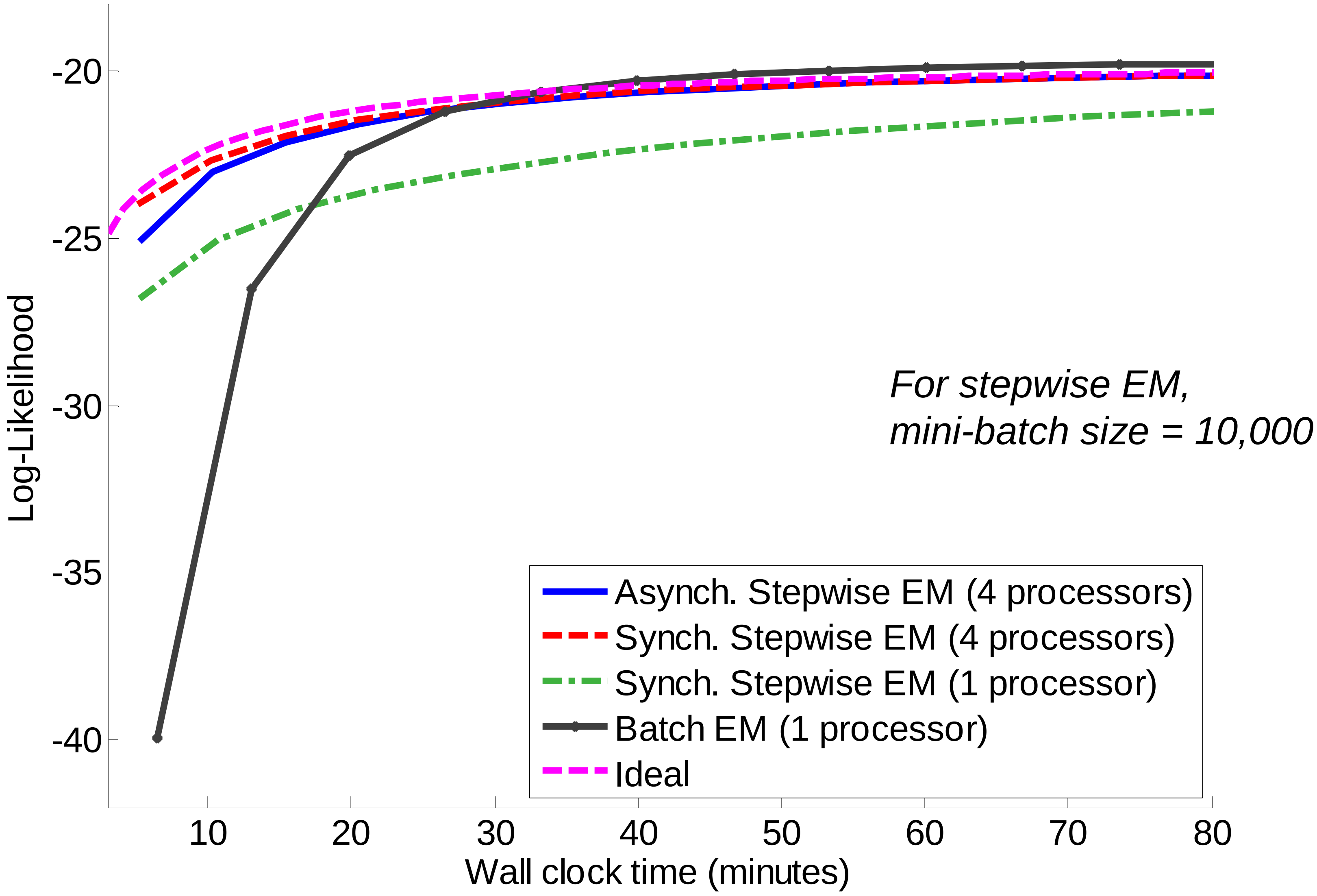
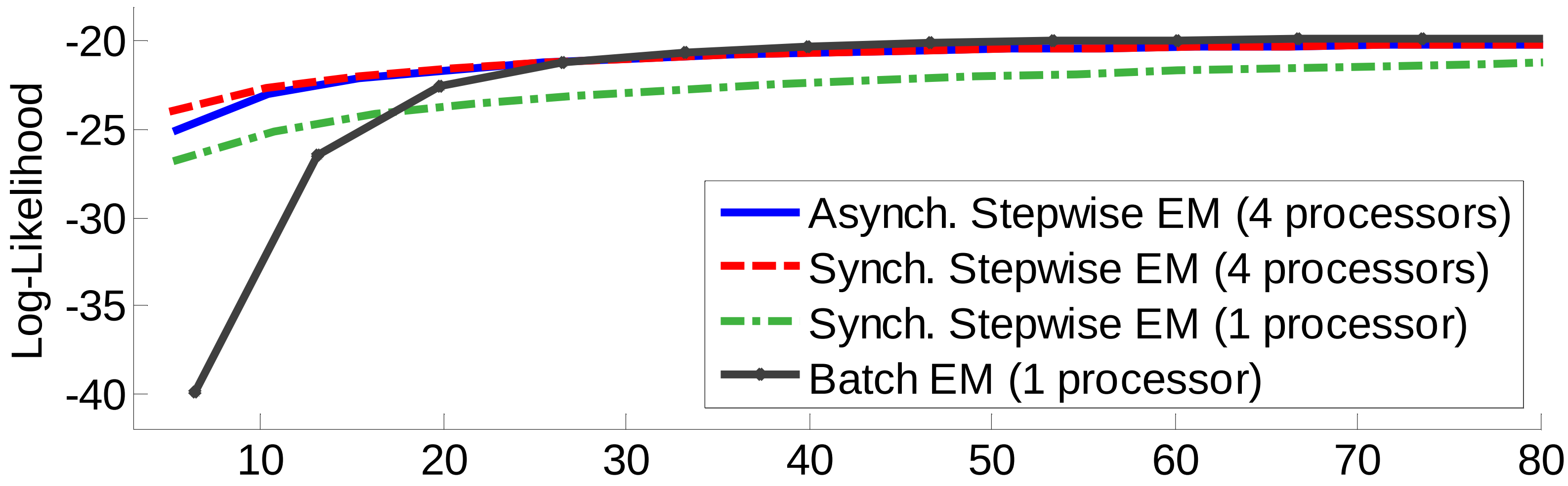


MapReduce?

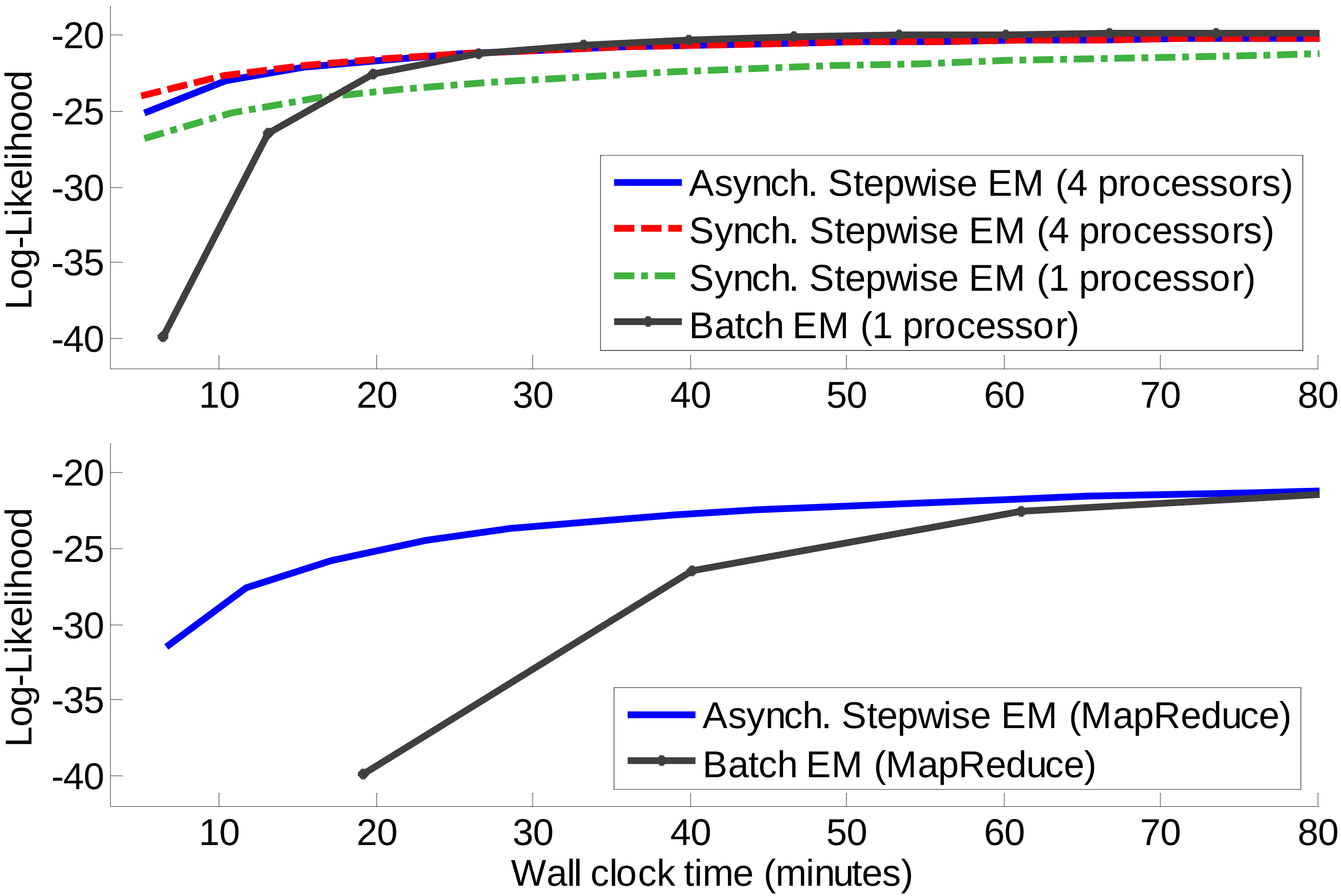
- We also ran these algorithms on a large MapReduce cluster (M45 from Yahoo!)
- Batch EM
  - Each iteration is one MapReduce job, using 24 mappers and 1 reducer
- Asynchronous Stepwise EM
  - 4 mini-batches processed simultaneously, each run as a MapReduce job
  - Each uses 6 mappers and 1 reducer

MapReduce?



Log-Likelihood
-20
-25
-30
-35
-40
10
20
30
40
50
60
70
80
Asynch. Stepwise EM (4 processors)
Synch. Stepwise EM (4 processors)
Synch. Stepwise EM (1 processor)
Batch EM (1 processor)

MapReduce?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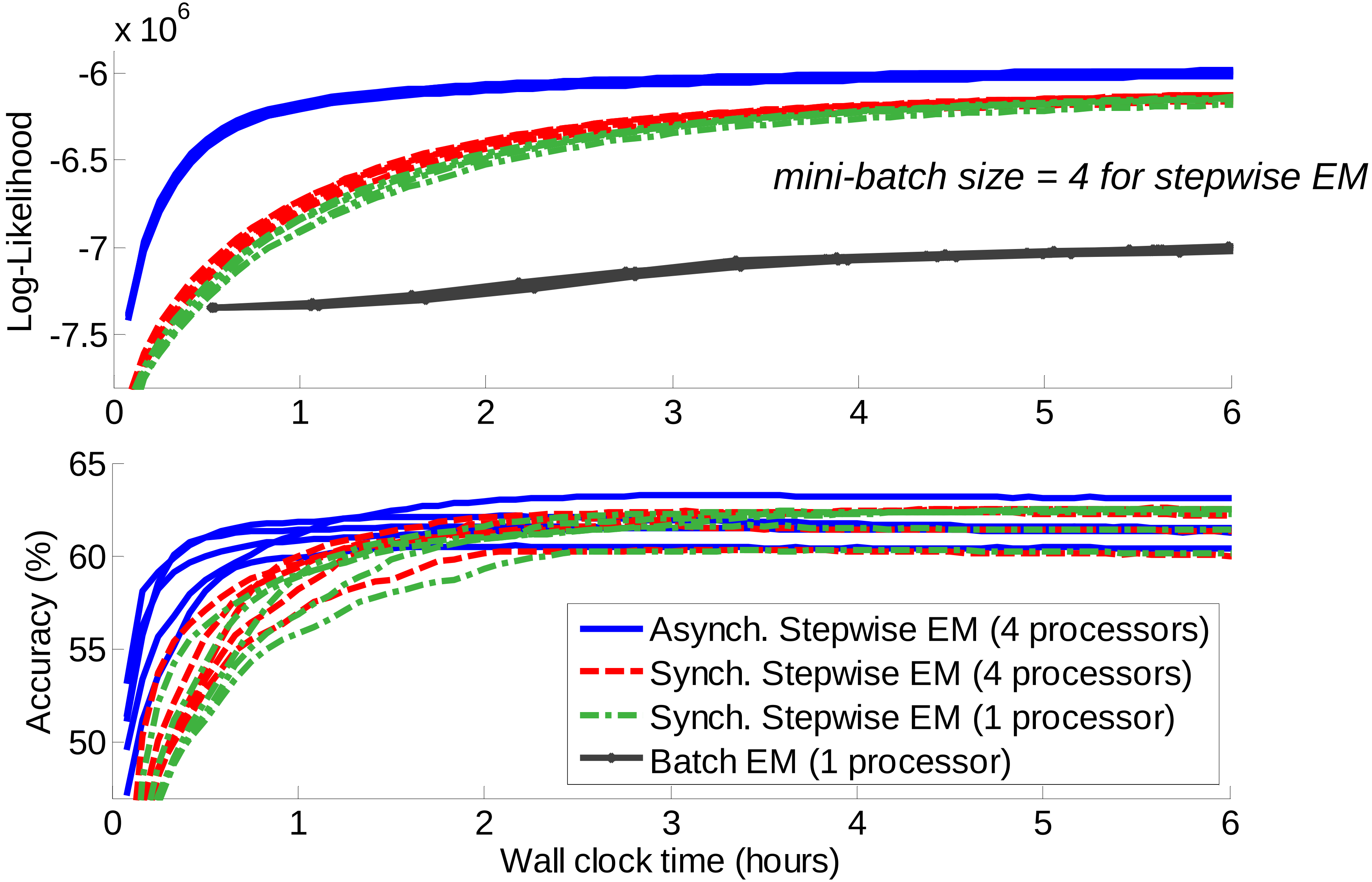
Batch EM (1 processor)
Asynch. Stepwise EM (MapReduce)
Batch EM (MapReduce)
Wall clock time (minutes)

Experiments

Task	Model	Method	Convex?	$\lvert\mathcal{D}\rvert$	$\lvert\theta\rvert$	m
Unsupervised Part-of-Speech Tagging	HMM	Stepwise EM	N	42k	2M	4

- Bigram HMM with 45 states
- We plot convergence in likelihood and many-to-1 accuracy

Part-of-Speech Tagging Results



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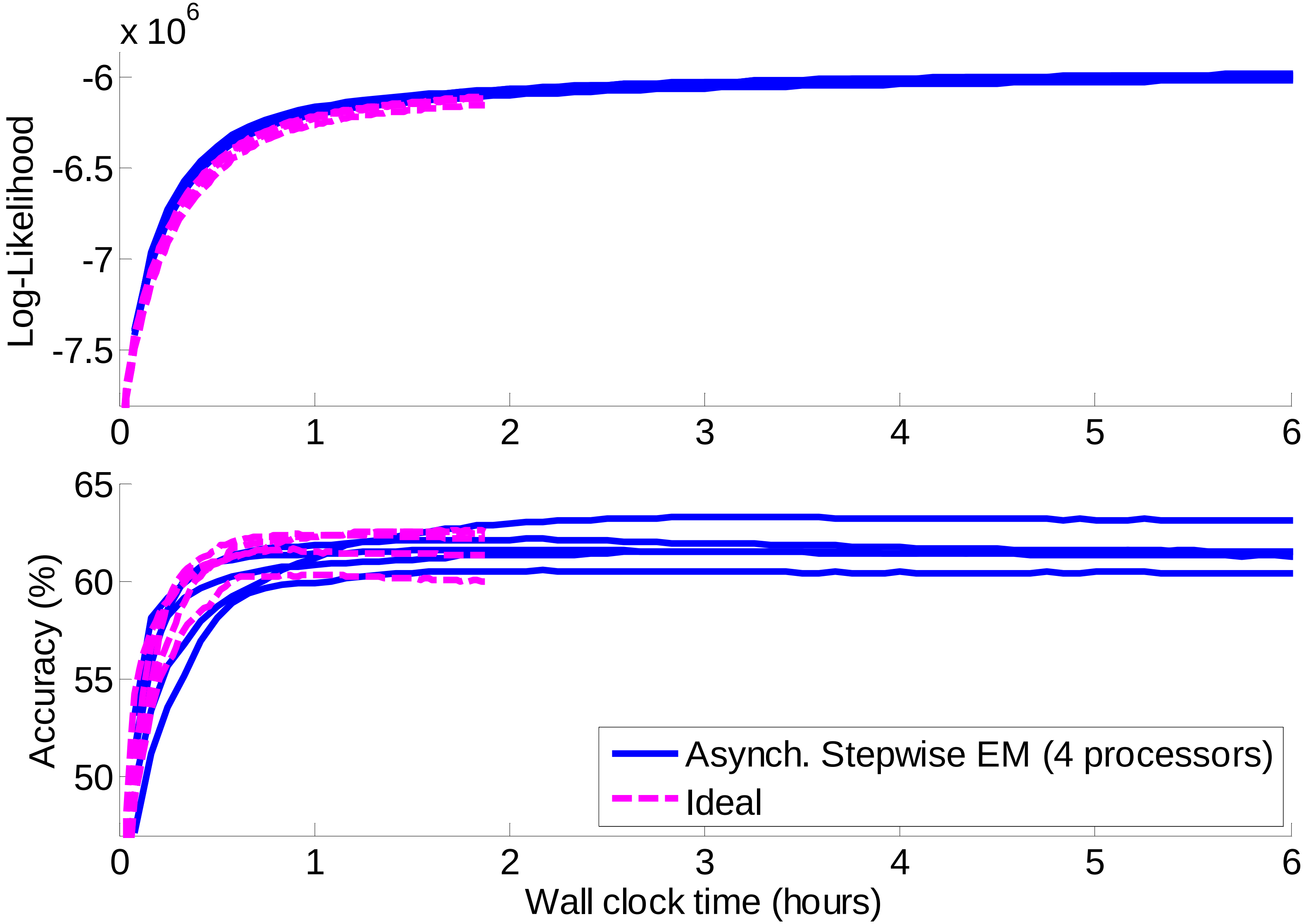
Comparison with Ideal



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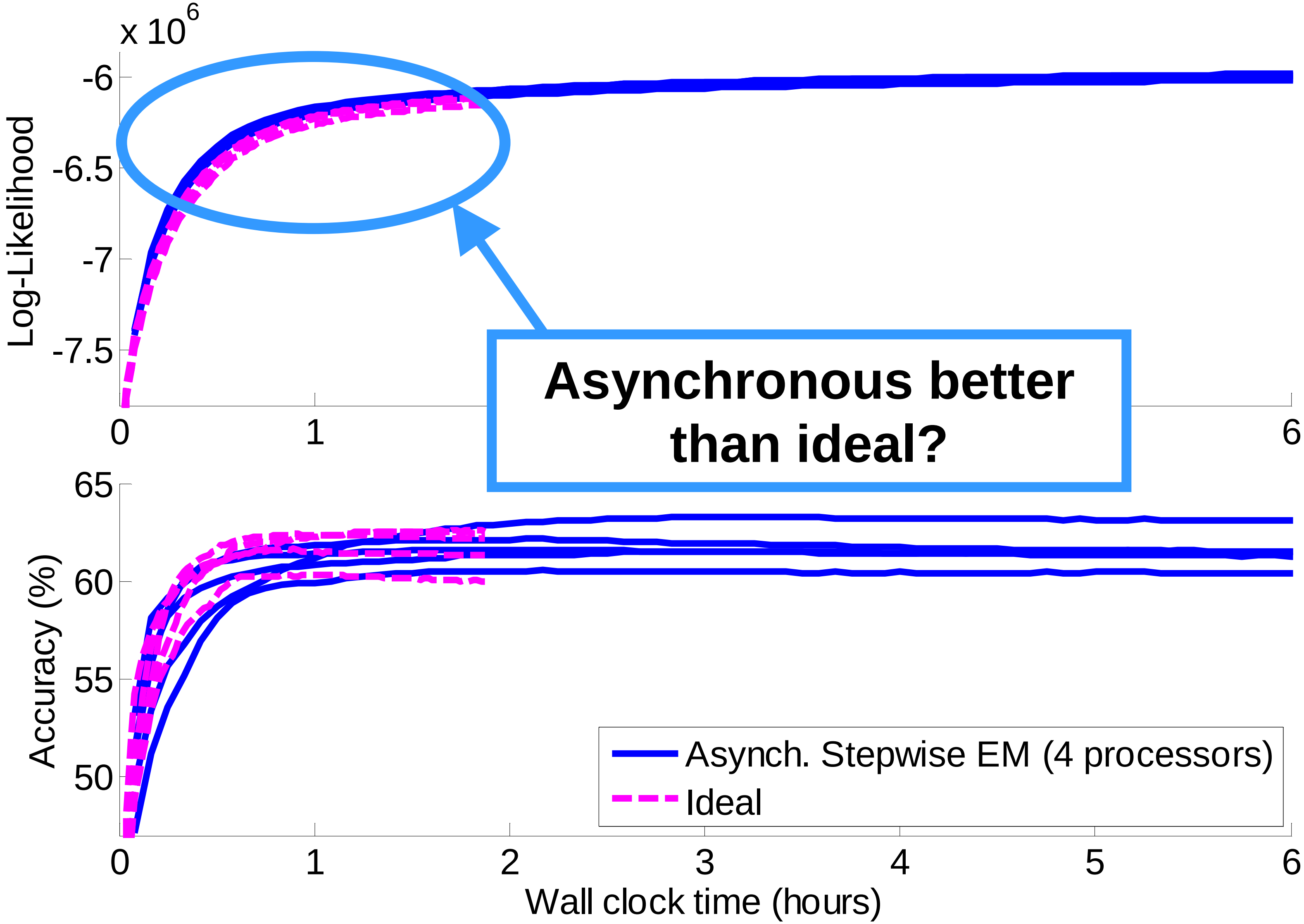

Conclusions and Future Work

- Asynchronous algorithms speed convergence and do not introduce additional error
- Effective for unsupervised learning and non-convex objectives
- If your problem works well with small mini-batches, try this!

- Future work
  - Theoretical results for non-convex case
  - Explore effects of increasing number of processors
  - New architectures (maintain multiple copies of θ)

Thanks!