

# Effective Model Calibration for Terascale Analytics

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## Motivation & Goal

- ▶ We present our gradient descent solution in **GLADE** with **three distinct features** from other data analytics infrastructures:
- ▶ **I/O-bound** execution with **linear** speed-up
- ▶ **Data-model-mixed** parallelism
- ▶ **On-the-fly concurrent** hyper-parameter testing and convergence detection by utilizing **online aggregation (OLA)**

## (Incremental) Gradient Descent

- ▶ Problem definition:

$$\min_{\vec{w} \in \mathbb{R}^d} \Lambda(\vec{w}) \stackrel{\text{def}}{=} \sum_{i=1}^N f(\vec{w}, \vec{x}_i; y_i) + \mu R(\vec{w}) \quad (1)$$

$\vec{w}$  is the parameter to be learned,  $\vec{x}_i$  is feature vector,  $y_i$  is label

- ▶ Batch Gradient Descent (BGD)

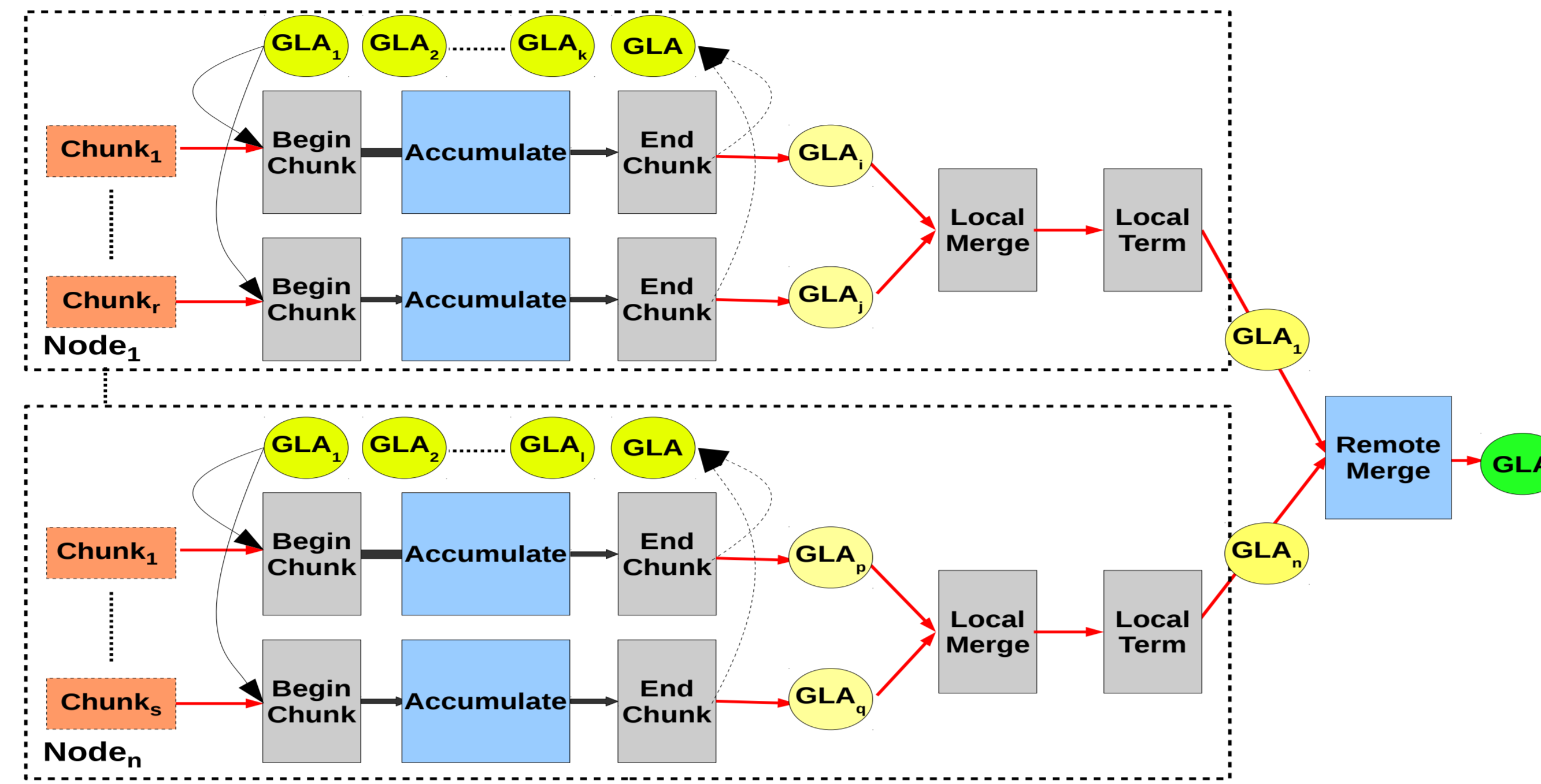
$$\vec{w}^{(k+1)} = \vec{w}^{(k)} - \alpha^{(k)} \nabla \Lambda(\vec{w}^{(k)})$$

- ▶ Incremental Gradient Descent (IGD)

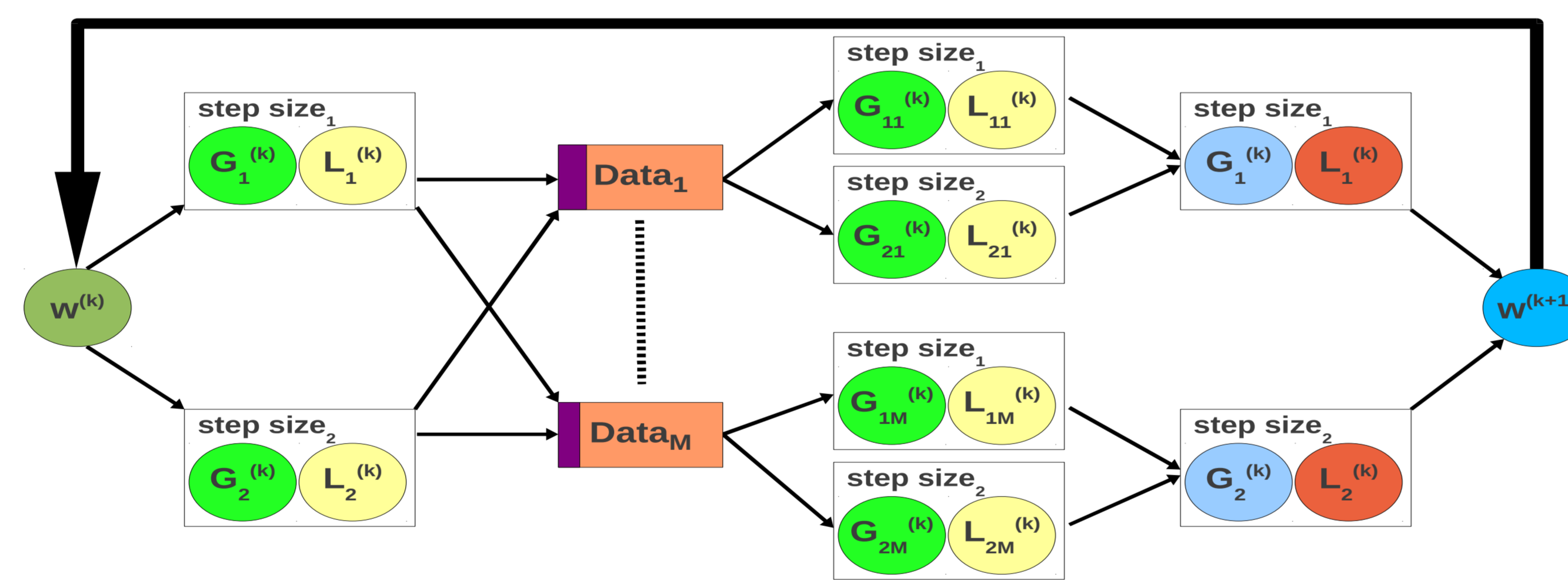
$$\vec{w}^{(k+1)} = \vec{w}^{(k)} - \alpha^{(k)} \nabla f_i(\vec{w}^{(k)})$$

- ▶ The hyper-parameter step-size  $\alpha$  is critical to convergence rate. In all the systems  $\alpha$  has to be hand-tuned by the user for different training tasks and datasets combinations.

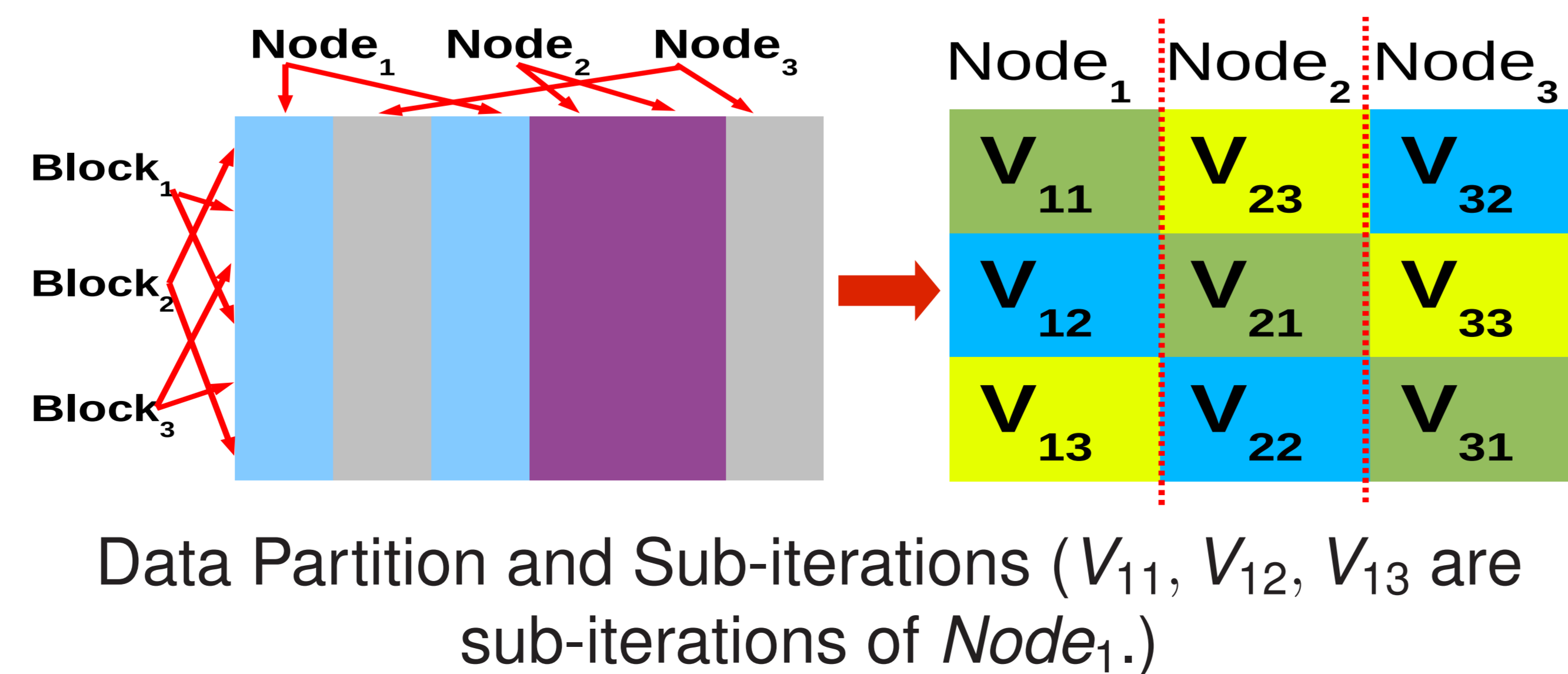
## GLADE Execution Flow



## On-the-fly Concurrent Parameter Testing



## Data-model-mixed Parallel Low-rank Matrix Factorization (LMF)



## Datasets

Dataset	Dimension	# Examples	Size
splice	13M	50M	3TB
matrix	1M × 1M	1.7B	36GB
classify	200	50M	136 GB

## Linear Speed-up Experiment

Multi-threaded execution time

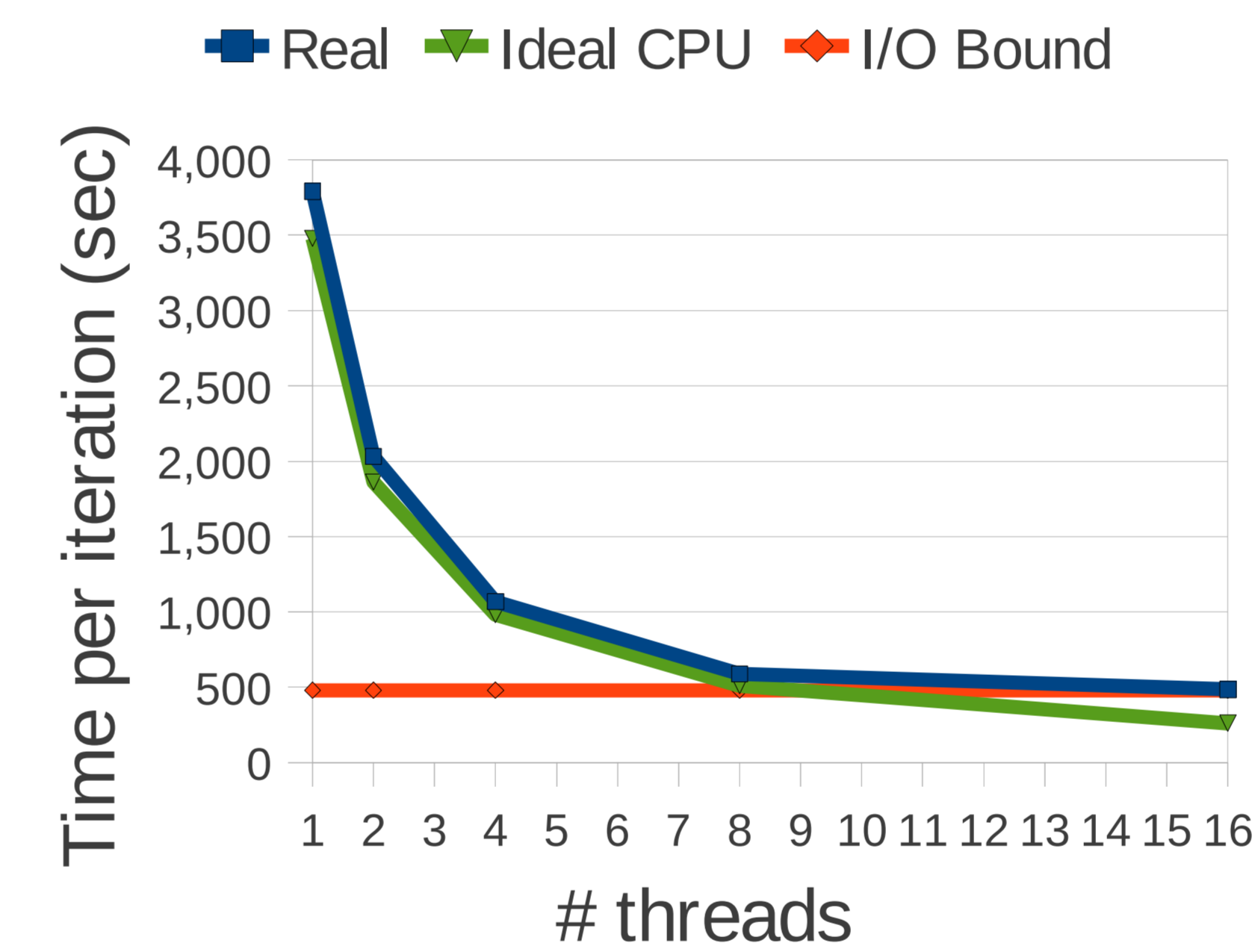


Figure: Multi-threaded LMF on matrix

## Data-model-mixed Parallel LMF

Execution time per epoch

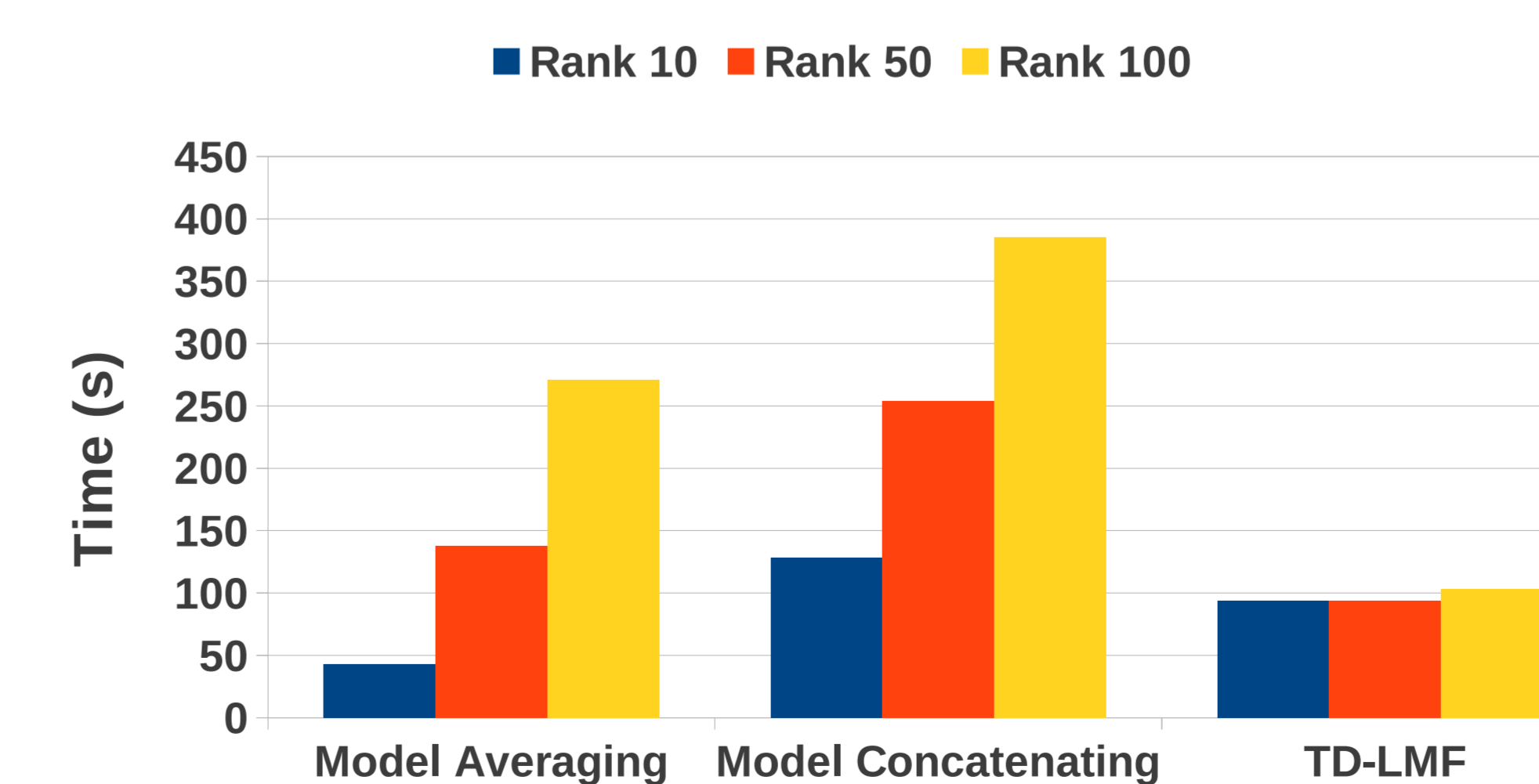


Figure: Time per iteration comparison on matrix

## Results For On-the-fly Parameter Testing

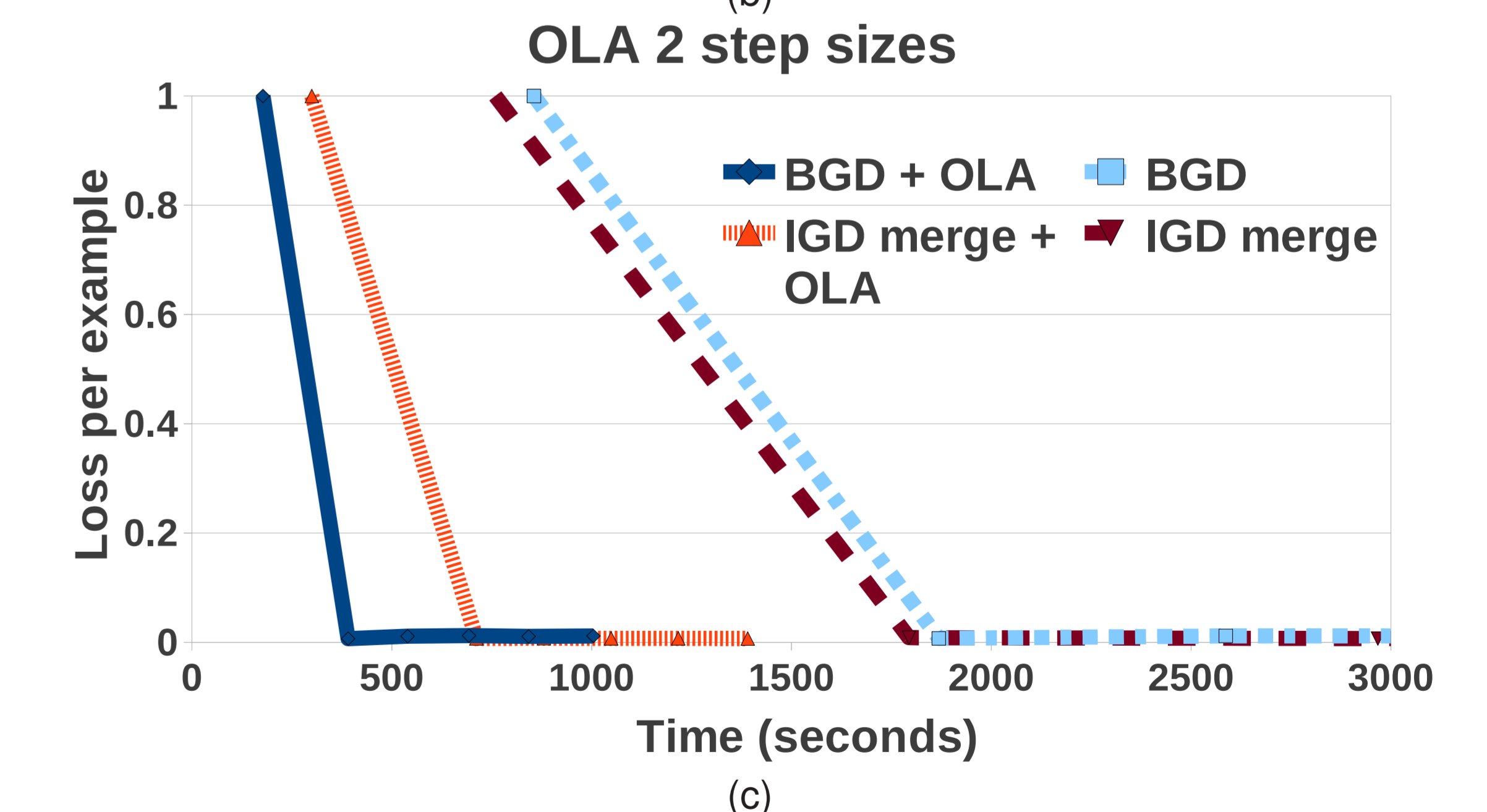
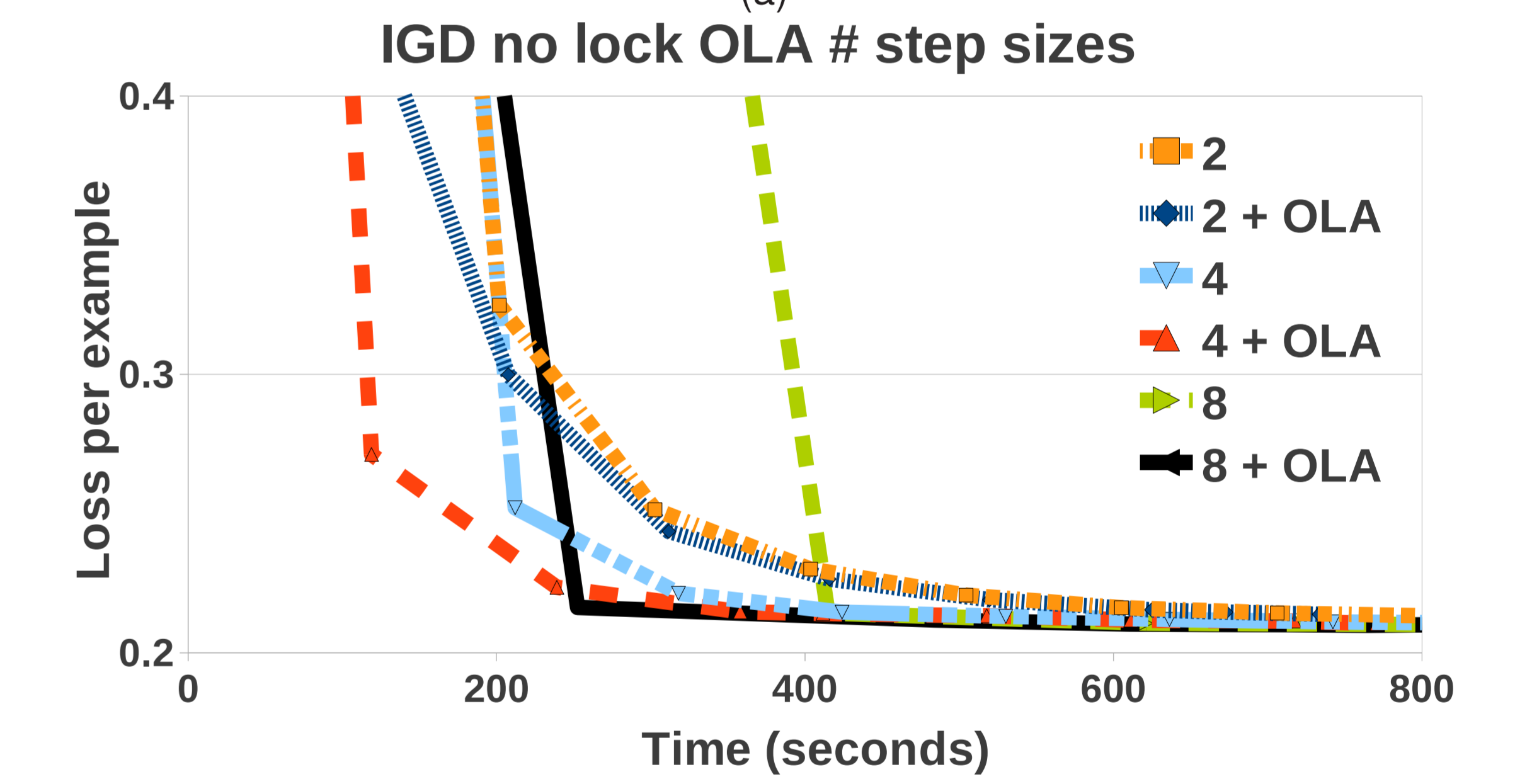
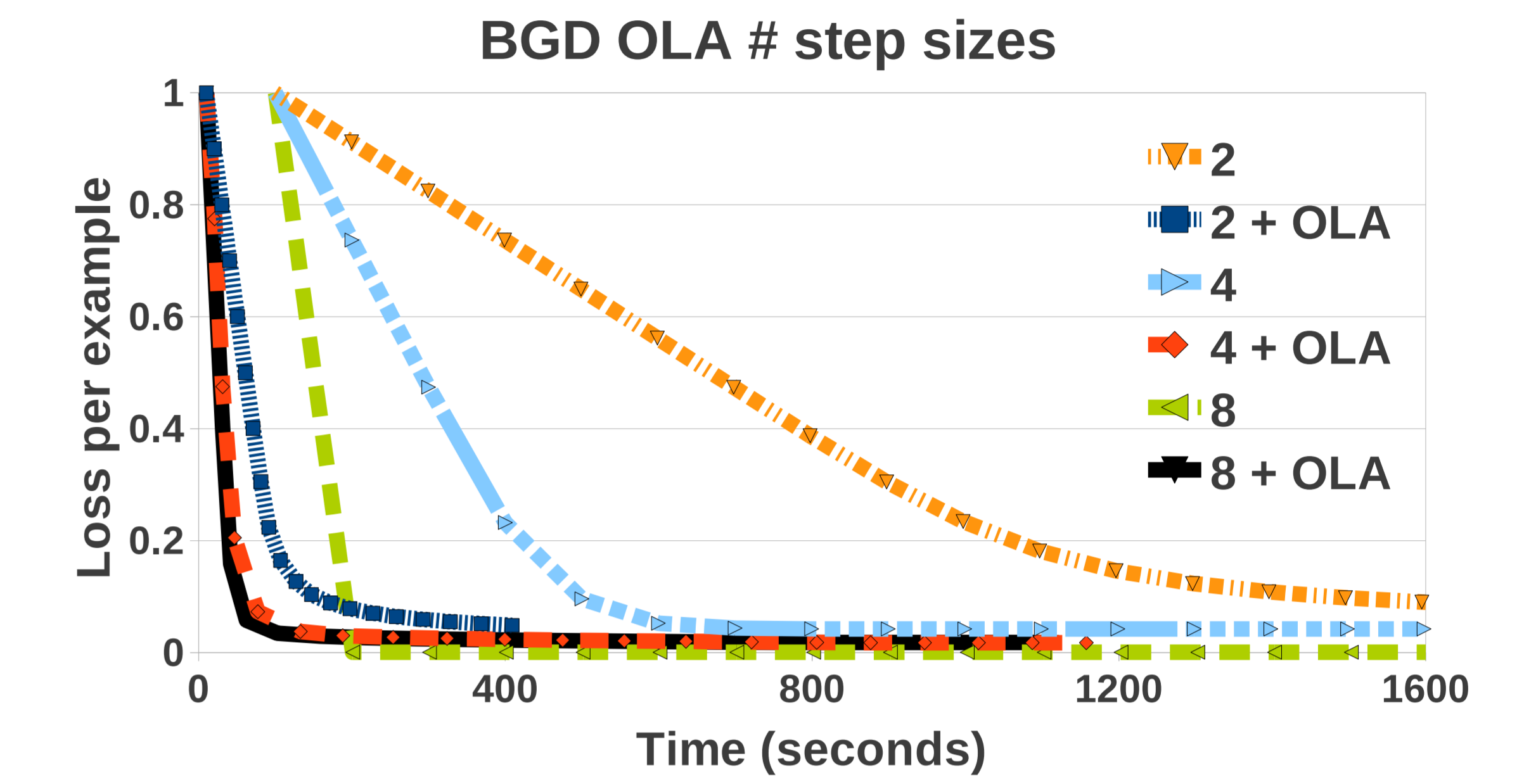


Figure: (a) Support Vector Machine (SVM) with BGD (splice). (b) Logistic Regression (LR) with IGD (classify). (c) SVM (splice).