machine learning conference

signSGD: adaptive gradient meets gradient compression for distributed deep learning

Yu-Xiang Wang @yuxiangw
Applied Scientist | AWS Deep Engine-Science

Based on joint work with:
Jeremy Bernstein, Kamyar Azizzadenesheli, Anima Anandkumar, Rahul Huilgol



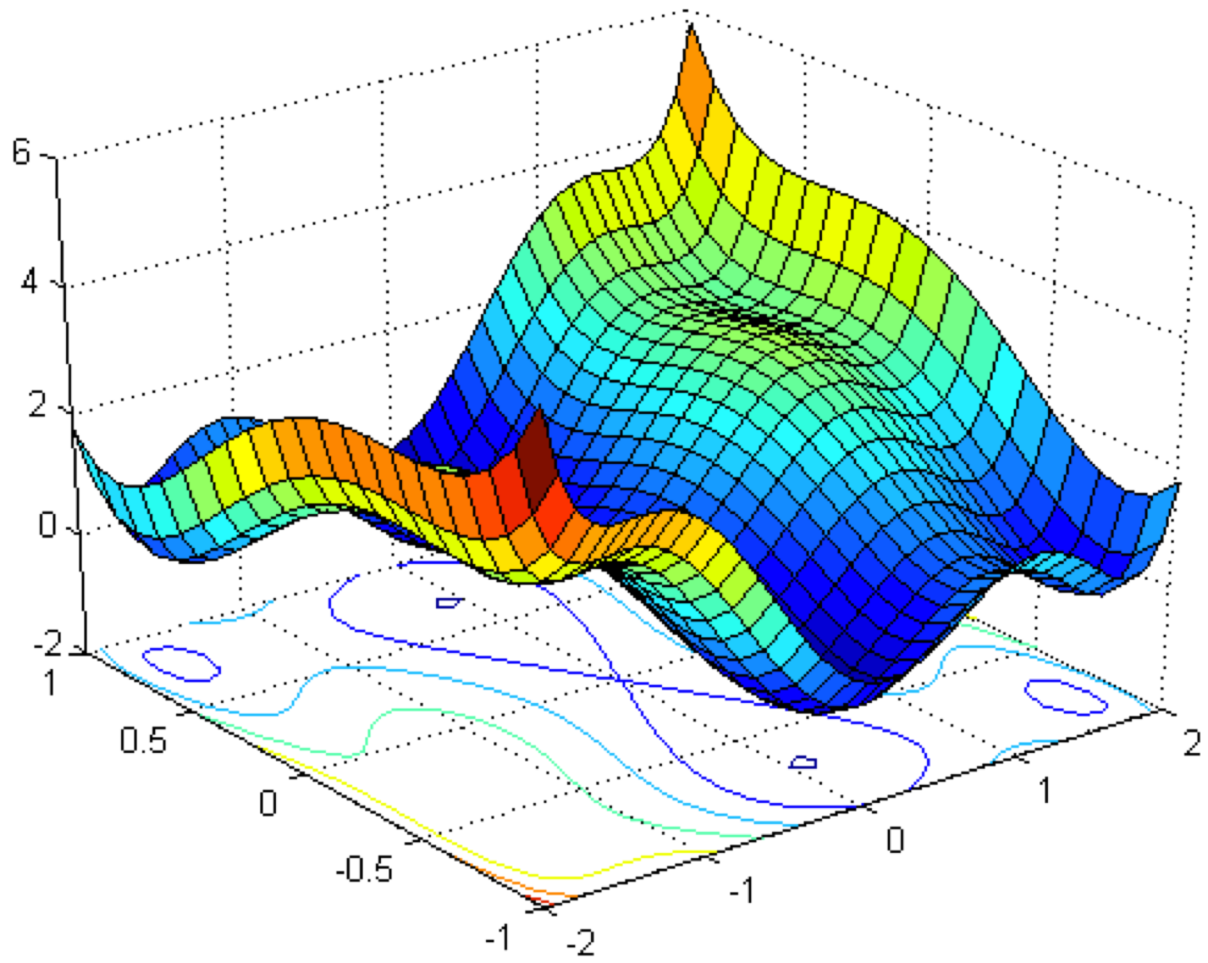

Outline:

1. From Adam to Signum in practical deep learning

2. The convergence rate of signSGD / Signum

3. 1-bit compression and communication-efficient distributed training with signSGD / Signum

Deep learning is a nonconvex optimization problem



Zoos of algorithms: for nonconvex optimization **theory**

- Nonconvex SVRG [Reddi et. al., 2015, Allen-Zhu & Hazan, 2015]
- Noisy GD / SGD [Ge et. al.2015, Jin et. al. 2017]
- Trust-region method [Sun et. al., 2015]
- Natasha 1/2 [Allen-Zhu, 2017]

Detailed computational theory on convergence rate to **stationary points** and to **local minima**!

Zoos of algorithms: for deep learning practice

- SGD [Robbins and Monro, 1951]
- Momentum [Polyak, 1964; Nesterov, 1983]
- Adagrad [Duchi et. al., 2011] / Adam [Kingma & Ba, 2014]
- Rprop [Riedmiller&Braun, 1993] / RMSprop [Tieleman&Hinton, 2012]

Not well understood theoretically (perhaps except SGD).

Hammers and tricks

- Variance reduction
- Active noise adding
- Hessian-vector product
- Cubic regularization

v.s.

- Momentum
- Gradient clipping
- Adaptive gradient
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Why don’t we try to analyze the tricks?

The Adam algorithm

Adam: A method for stochastic optimization

D **Kingma**, J Ba - arXiv preprint arXiv:1412.6980, 2014 - arxiv.org

Abstract: We introduce Adam, an algorithm for first-order gradient-based optimization of stochastic objective functions, based on adaptive estimates of lower-order moments. The method is straightforward to implement, is computationally efficient, has little memory

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[PDF] A stochastic approximation method

H **Robbins**, S **Monro** - The annals of mathematical statistics, 1951 - JSTOR

Let M (x) denote the expected value at level x of the response to a certain experiment. M (x) is assumed to be a monotone function of x but is unknown to the experimenter, and it is desired to find the solution x= θ of the equation M (x)= α, where α is a given constant. We

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The Adam algorithm

- Adam update:

$$m_t = \beta m_{t-1} + (1-\beta) g_t$$ momentum

$$v_t = \gamma v_{t-1} + (1-\gamma) g_t^2$$ variance

$$x_t = x_{t-1} + \eta \frac{m_t}{\sqrt{v_t}}$$ variance adjusted momentum update

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$$x_t = x_{t-1} + \eta \frac{m_t}{\sqrt{v_t}}$$ variance adjusted momentum update

Key idea: dividing the gradient (coordinate wise) by its magnitude!

From Adam to SignSGD to Signum

- SignSGD update: (Related to Rprop [Riedmiller&Braun, 1993])

$$x_t = x_{t-1} + \eta \frac{g_t}{|g_t|}$$

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- Signum (SIGN momentUM):

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From Adam to SignSGD to Signum

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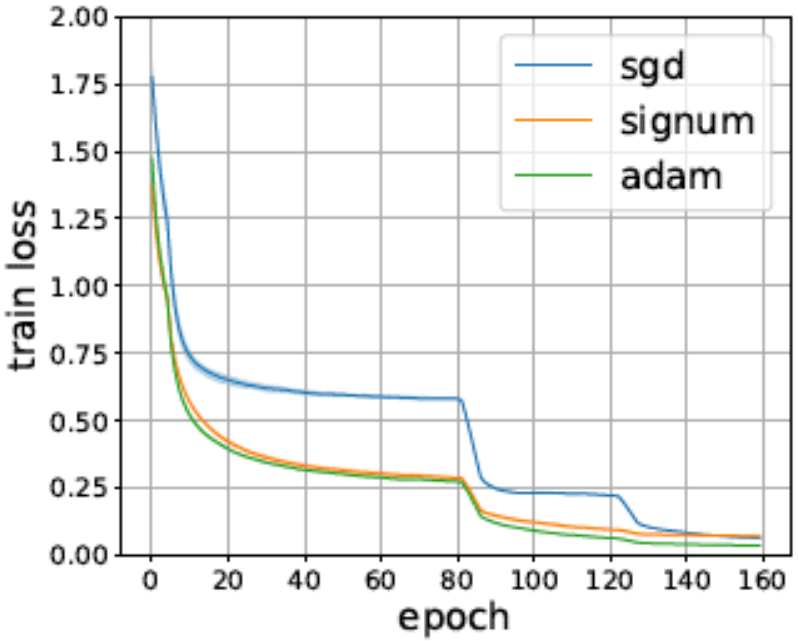
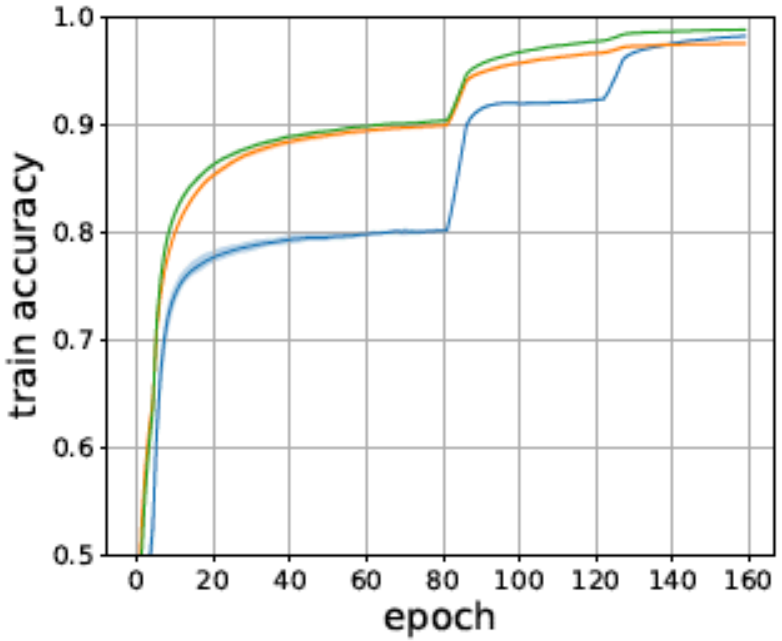
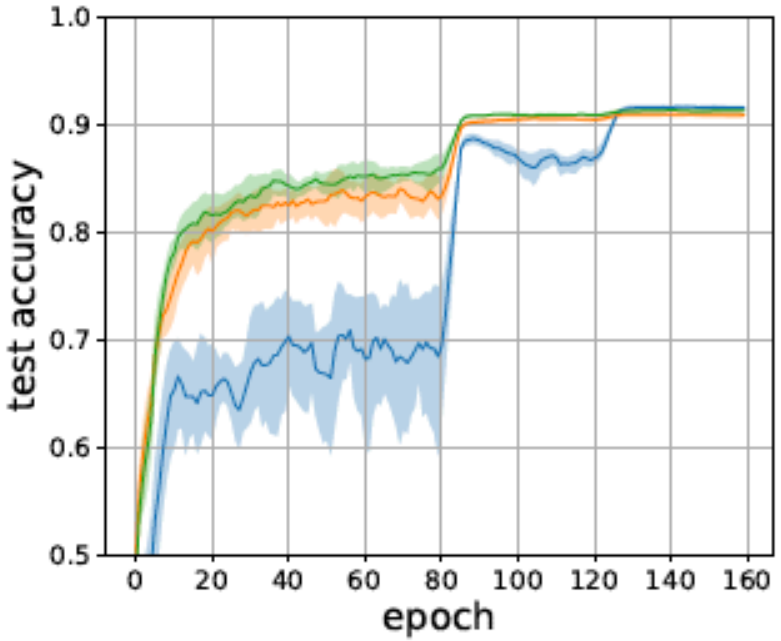
Experiment on CIFAR10 suggests Signum and Adam are very similar







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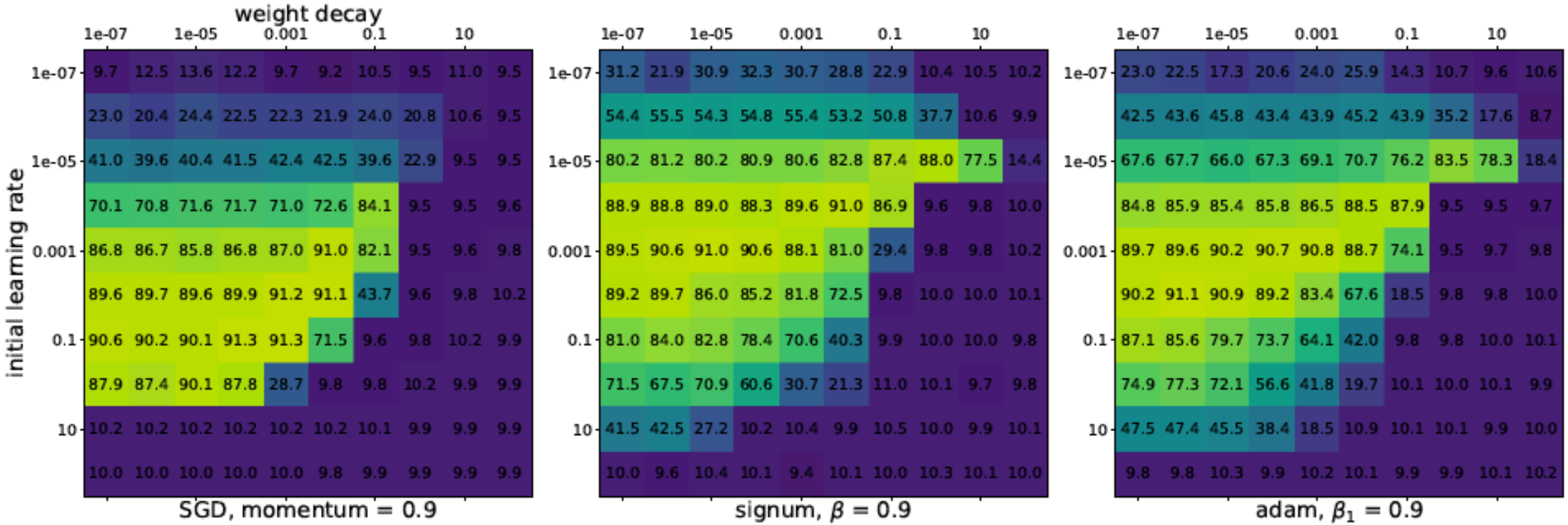
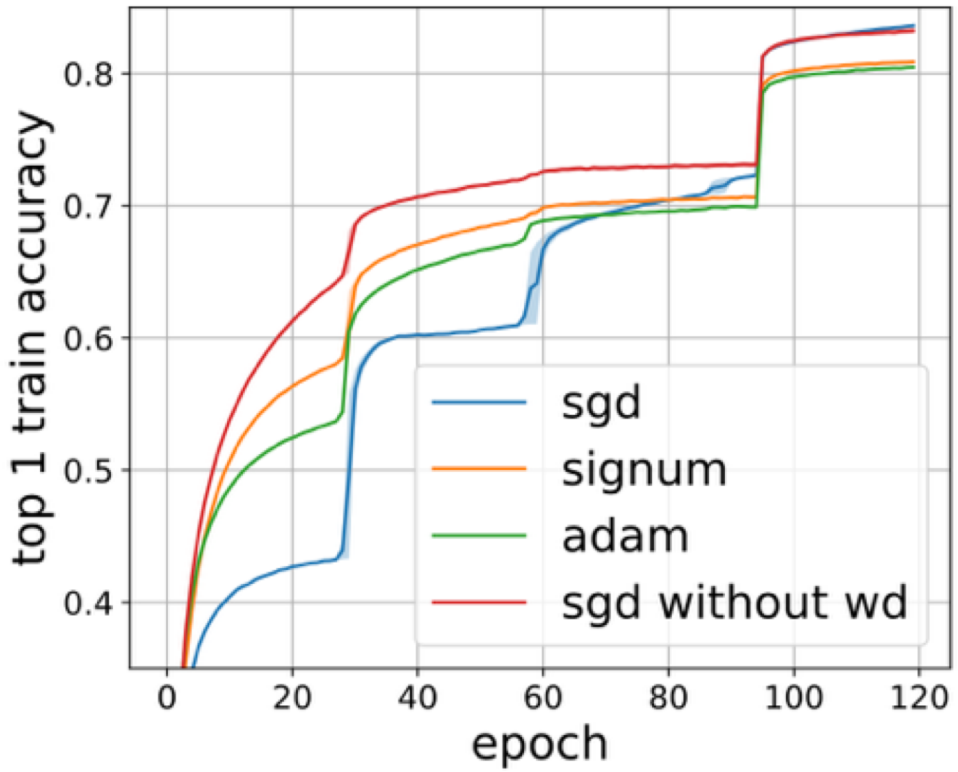
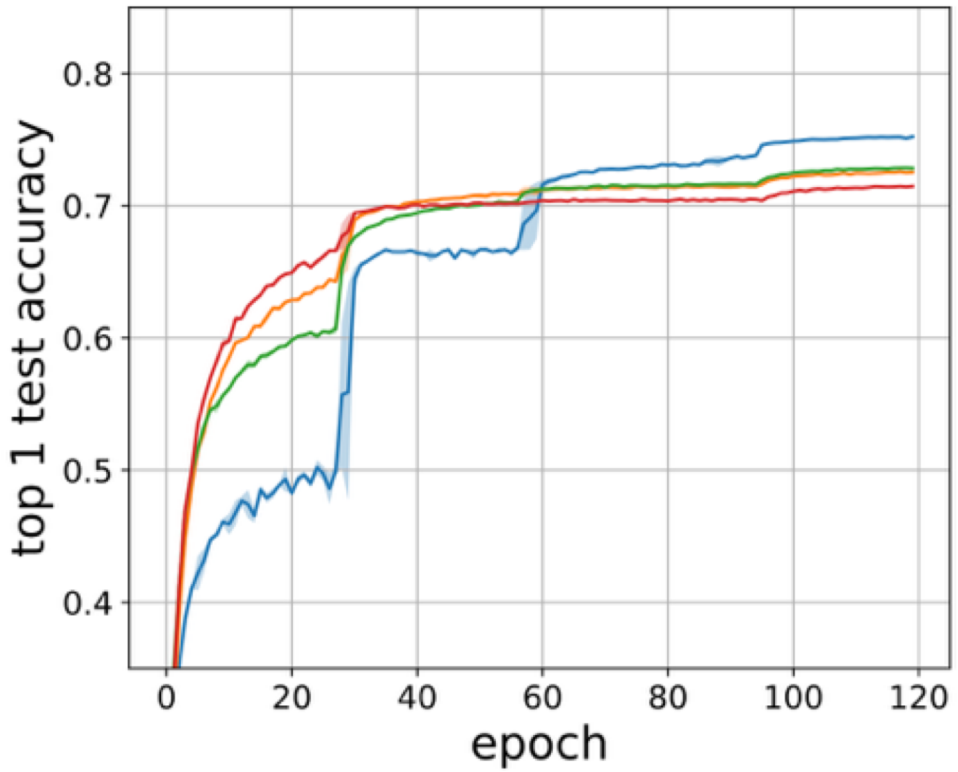


Signum is competitive on ImageNet





Advantages of SignSGD/Signum over Adam

- Theoretical guarantee on convergence
  - For nonconvex problems, with or without momentum

- Build-in 1-bit gradient compression.
  - Communication-efficient.

Stationary point convergence of signSGD & Signum

- Stochastic optimization model with “noisy gradient” access.
- How close does a budget of N such access get us to a solution?

Stationary point convergence of signSGD & Signum

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Theorem: For a fixed learning rate and minibatch size schedule

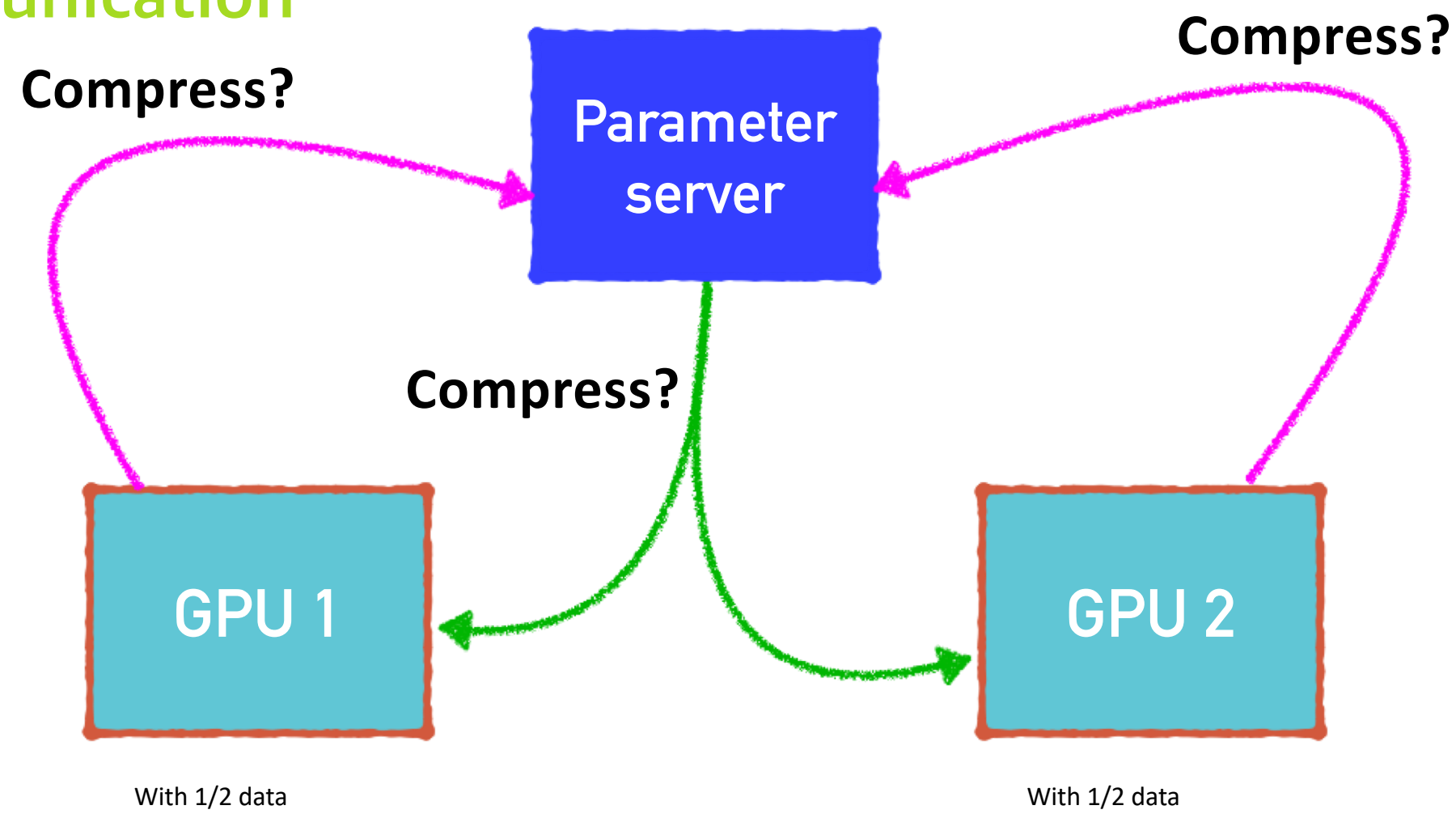
$$\min_{C \leq k \leq K-1} \mathbb{E}[\|g_k\|_1]^2 \leq \frac{1}{\sqrt{N}} \left[\sqrt{\|\vec{L}\|_1} \left(f_0 - f_* + \frac{1}{2} \right) + 2\|\vec{\sigma}\|_1 \right]^2$$

- Burn-in period: C=1 for SignSGD and O(1) for momentum.

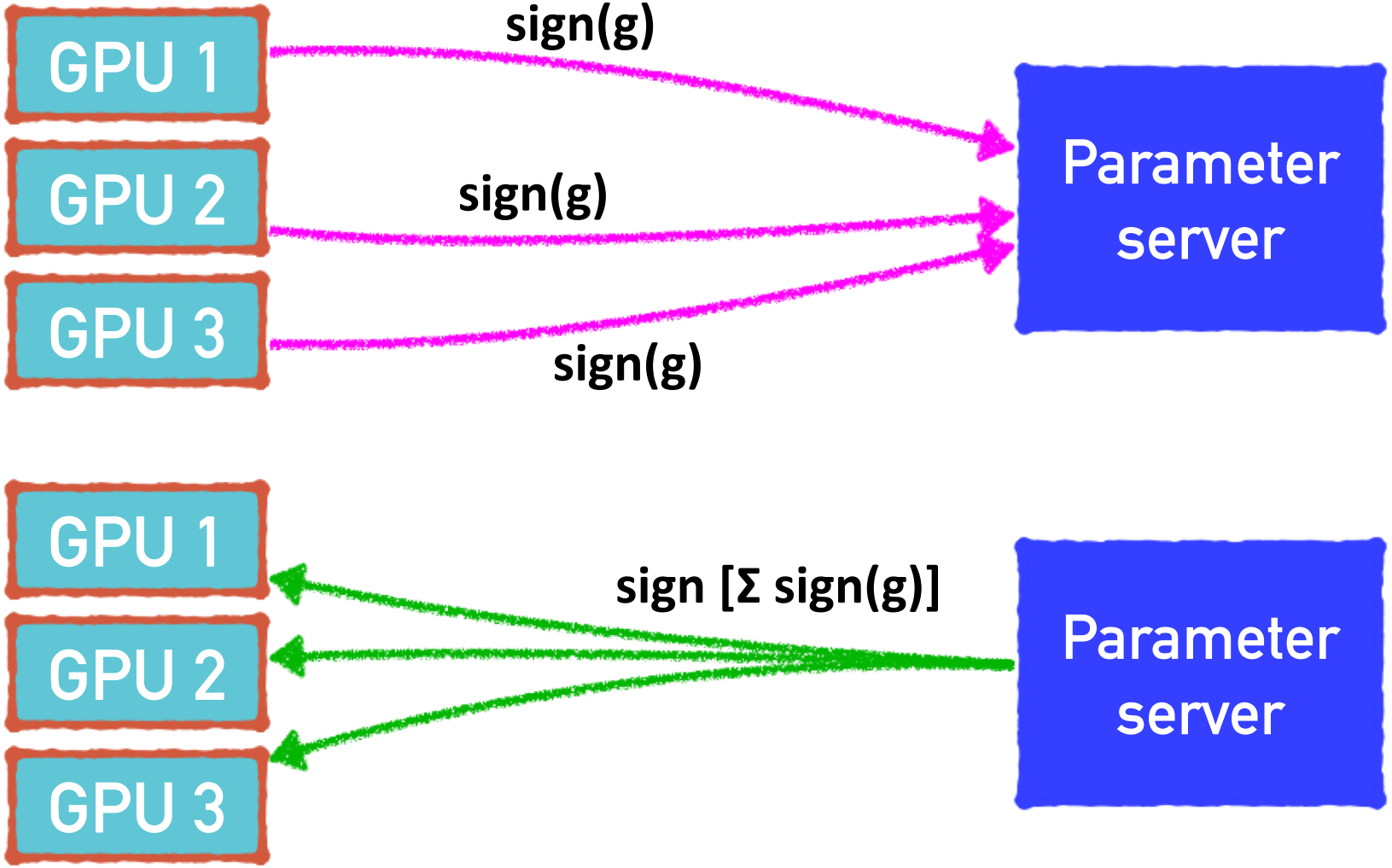
Key messages from our theory

- SignSGD is not approximating SGD.
  - Unlike Seide et. al. (2014), or Alistarh et. al. (2017).
- SignSGD can be faster than SGD in some cases (and vice versa)
- Radically low-precision training (1 bit) does **NOT** come with a price!

Distributed training involves computation and communication

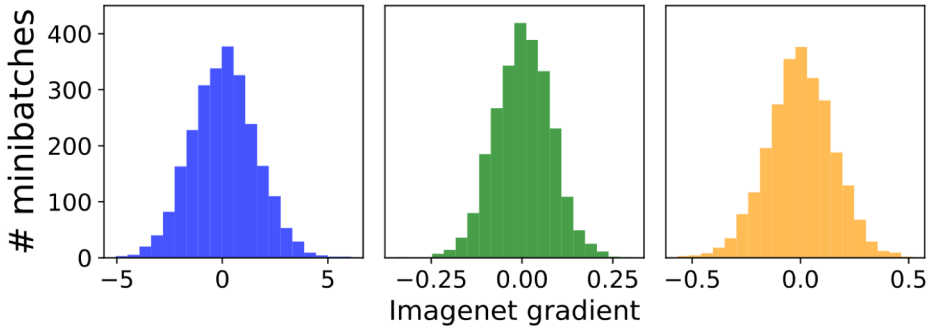


Distributed training by SignSGD with Majority Voting



Does Majority Voting work?

If gradients are unimodal
and symmetric…



…which is reasonable by the
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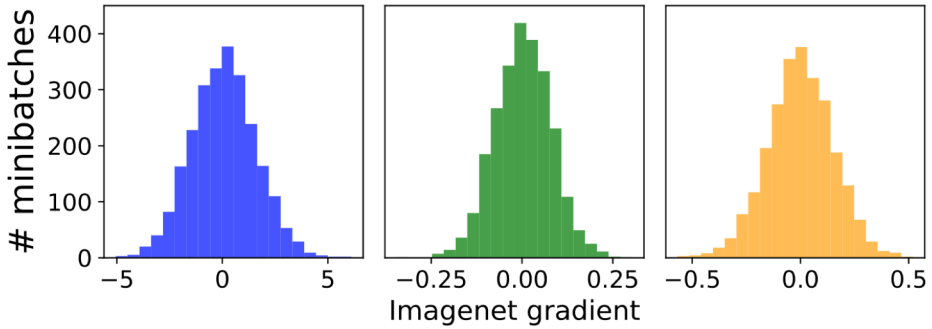


…which is reasonable by the central limit theorem…

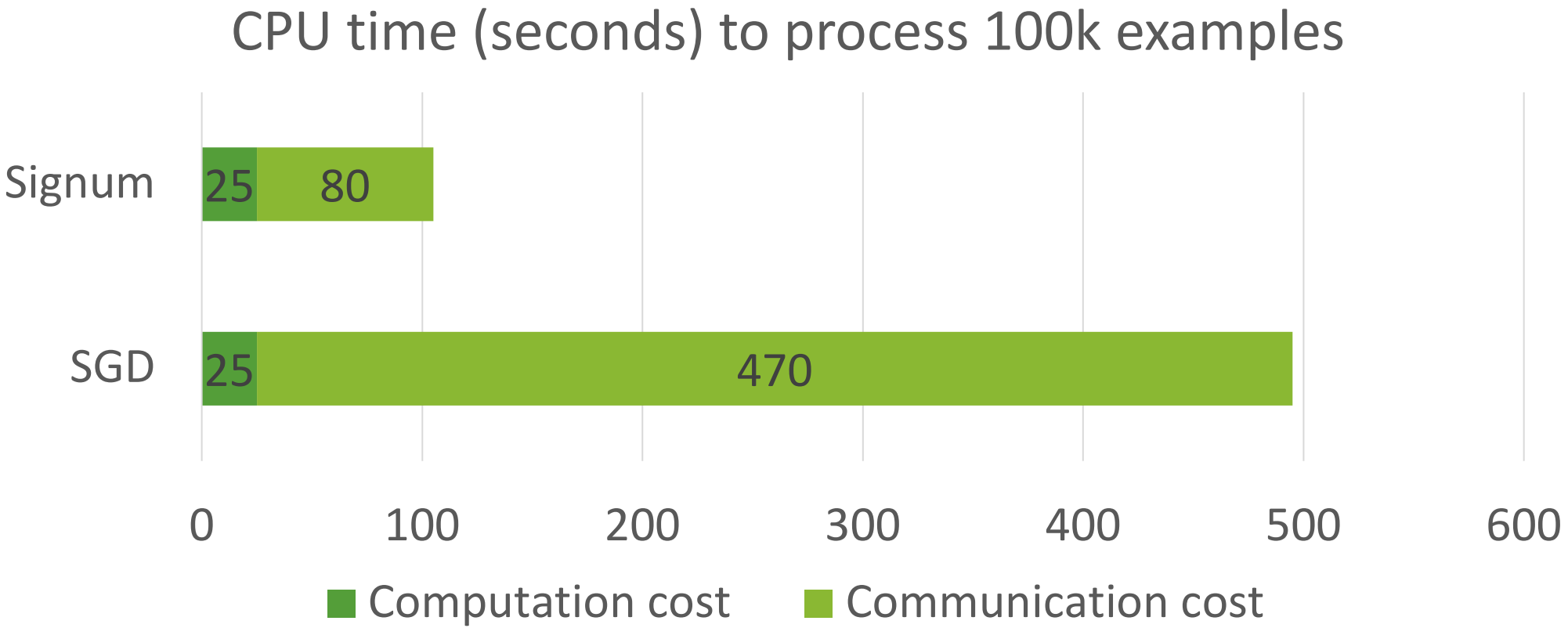
…then majority vote with M workers converges at rate:

$$\mathbb{E}\left[\min_{0\leq k\leq K-1}\|g_k\|_1\right]^2$$

$$\leq \frac{1}{\sqrt{N}}\left[\sqrt{\|\vec{L}\|_1}\left(f_0 - f_* + \frac{1}{2}\right) + \frac{2}{\sqrt{M}}\|\vec{\sigma}\|_1\right]^2$$

Distributed training of VGG-19 on ImageNet

Setup: 10 machine cluster of p3.8x machines in the same placement group. 10k data each.



Rahul Huilgol

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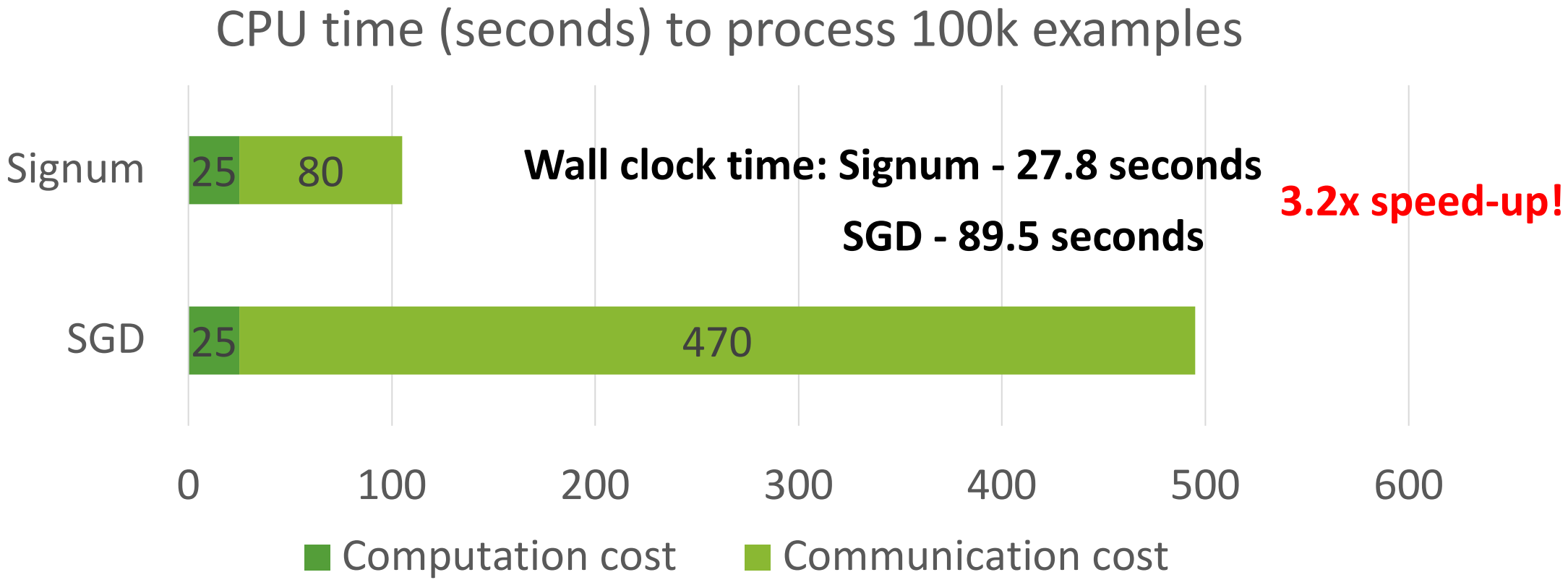

Wall clock time: Signum - 27.8 seconds

SGD - 89.5 seconds

3.2x speed-up!

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Conclusion: **Just follow the signs!**

- SignSGD and Signum optimizers ≈ Adam
- They come with theoretical guarantees with a rate of convergence
- Majority voting: 1-bit compression in both ways for distributed training!

Signum implementation available in mxnet:

1. Uncompressed version

```
trainer = gluon.Trainer( net.collect_params(),
                                                    'sgd',
                                                   {'learning_rate': opt.lr,
                                                    'momentum': opt.momentum})

trainer = gluon.Trainer( net.collect_params(),
                                                    'signum',
                                                   {'learning_rate': opt.lr/10,
                                                    'momentum': opt.momentum})
```

2. Compressed version——————Majority vote

Coming soon!!

Thanks for your attention!

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