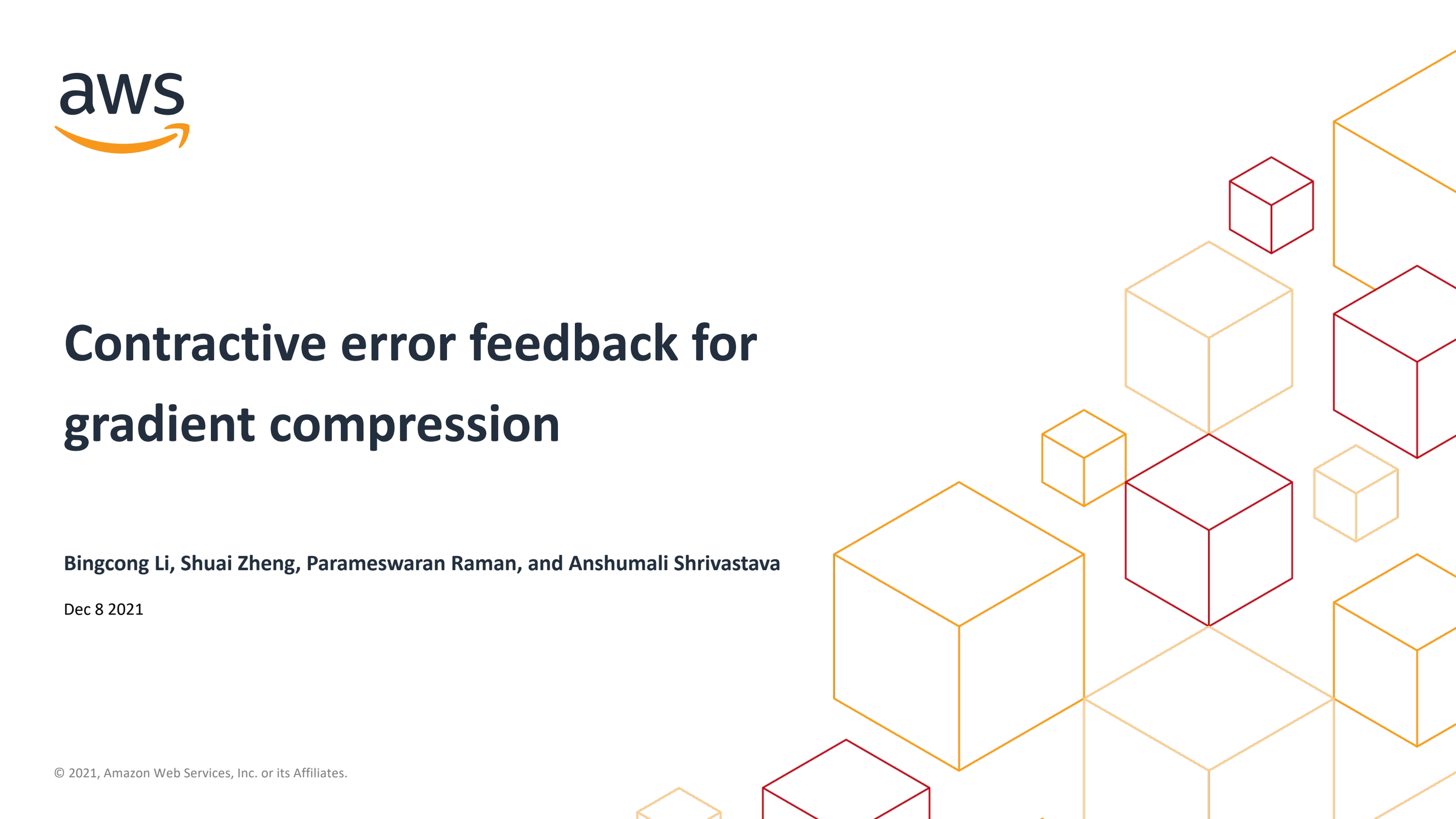

Contractive error feedback for gradient compression

Bingcong Li, Shuai Zheng, Parameswaran Raman, and Anshumali Shrivastava

Dec 8 2021

Roadmap

- ❑ **Motivation and project overview**
- ❑ Algorithm design
- ❑ Numerical experiments
- ❑ Distributed training for large models redux

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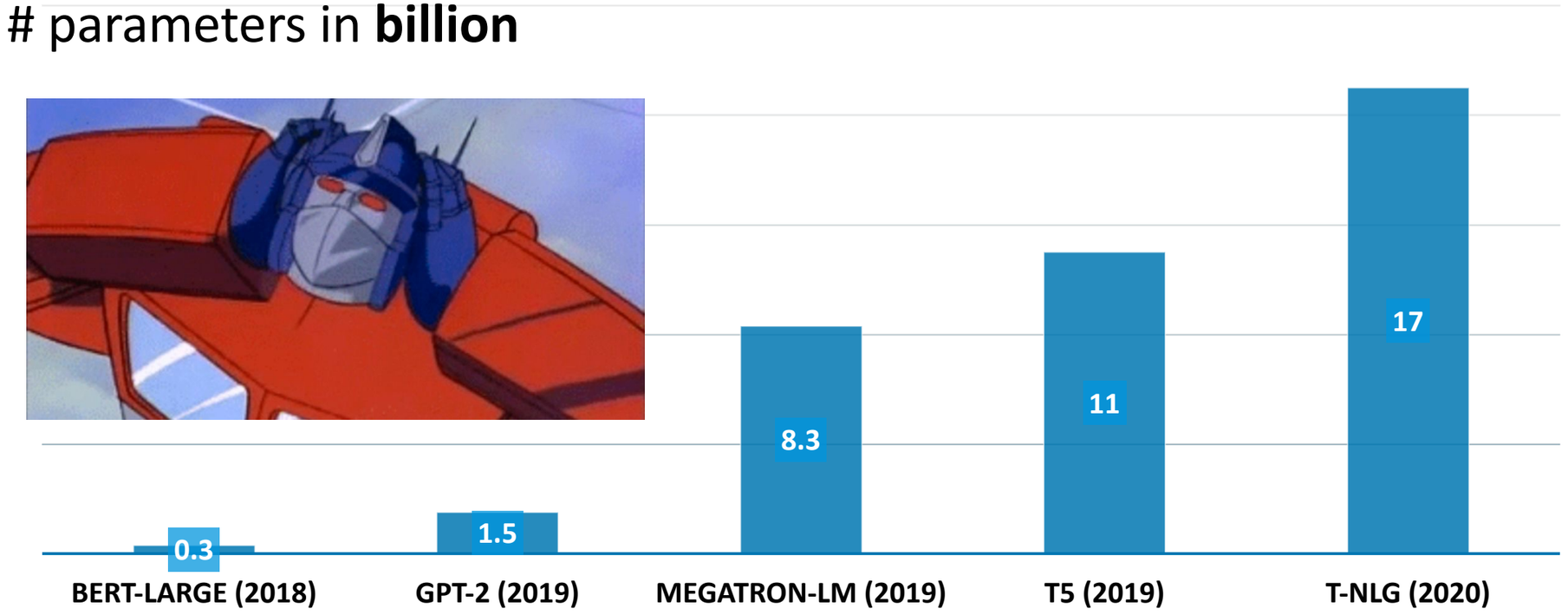
After transformers, neural networks are getting out of control



- Memory issues: model does not fit into a GPU such as V100 (16 or 32 GB memory)
- Runtime issues: training requires a few days if not weeks
- Memory is a dimension that is **largely ignored** in communication efficient methods

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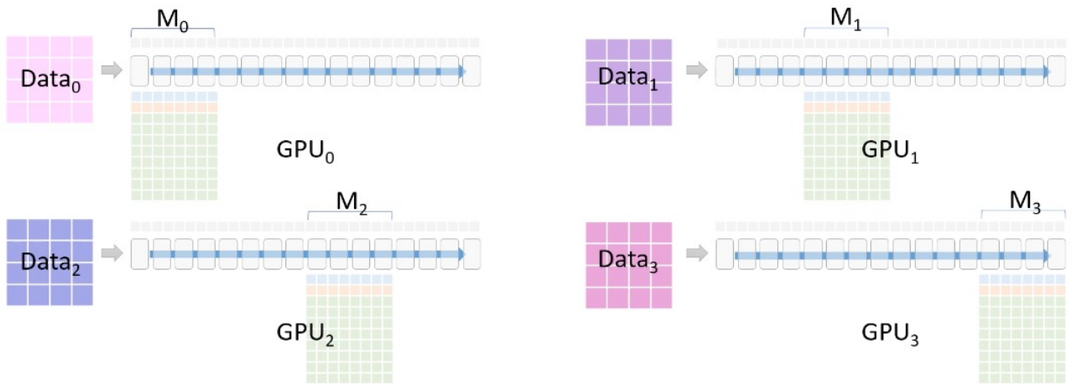
ZeRO3 increases communication overhead

- Memory: ZeRO3 partitions parameters / gradients / optimizer states

Each cell represents GPU memory used by its corresponding transformer layer



Each GPU is responsible for 1 piece of the end model
ZeRO P_{os+g+p} and Gradient accumulation are used with the 4-way data parallelism

- Communication: ZeRO3 increases communication overhead by 50% to save memory

- **Goal:** understanding the memory and communication tradeoff

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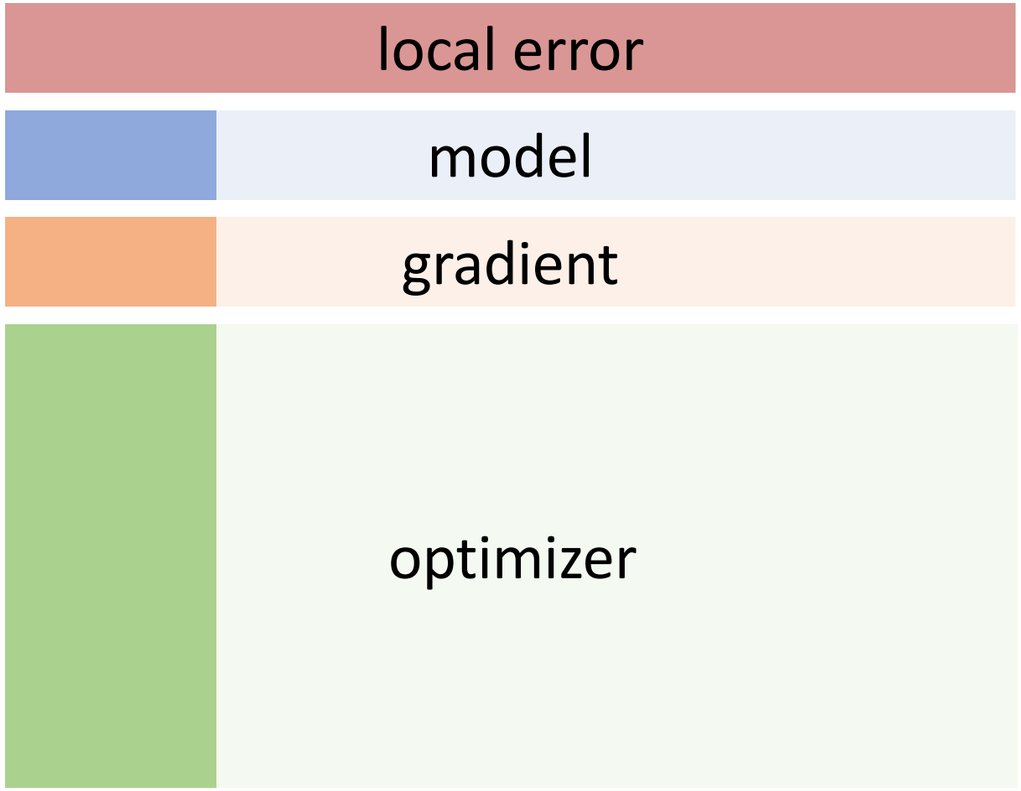
How to reduce the communication overhead for ZeRO3



EFSGD

Initialize: $\mathbf{x}_0 \in \mathbb{R}^d, \mathbf{e}_0 = \mathbf{0} \in \mathbb{R}^d, \eta$
for $t = 0, 1, \ldots, T-1$ **do**
  assert $\mathbf{x}_t = \mathbf{x}_t^i$ for every worker i
  for worker i in parallel **do**
    $\mathbf{p}_t^i = \eta \mathbf{g}_t^i + \mathbf{e}_t^i$
    $\mathbf{\Delta}_t^i = \mathcal{Q}(\mathbf{p}_t^i)$
    $\mathbf{\Delta}_t = \text{Aggregate}(\mathbf{\Delta}_t^i, \forall i)$
    $\mathbf{x}_{t+1} = \mathbf{x}_t - \mathbf{\Delta}_t$
    $\mathbf{e}_{t+1}^i = \mathbf{p}_t^i - \mathbf{\Delta}_t^i$
  end for
end for

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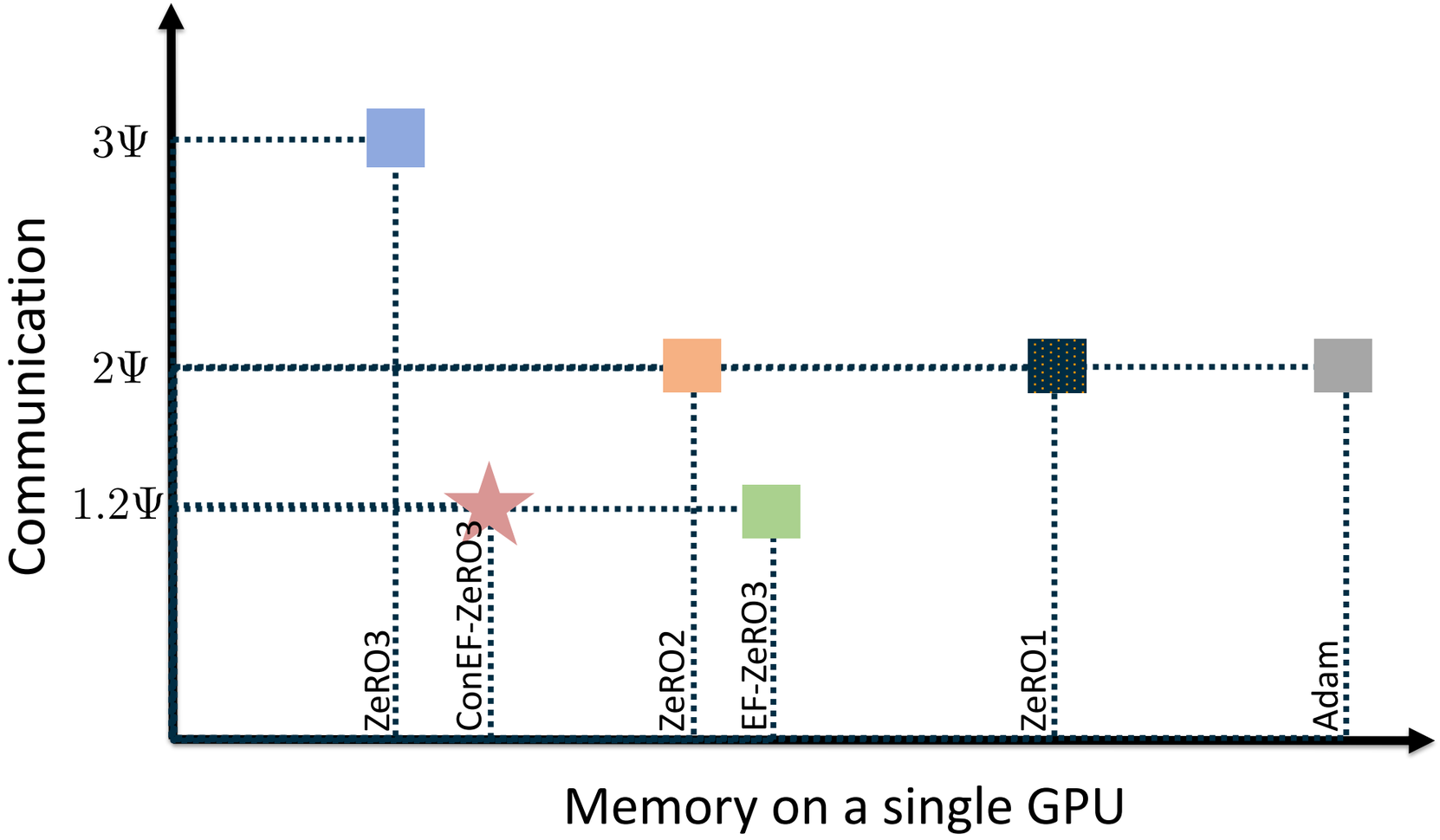
Memory - communication tradeoff in ZeRO



How to get to ★

- Step 1: algorithm design
- Step 2: test with adam
- Step 3: integrate to ZeRO3

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Roadmap

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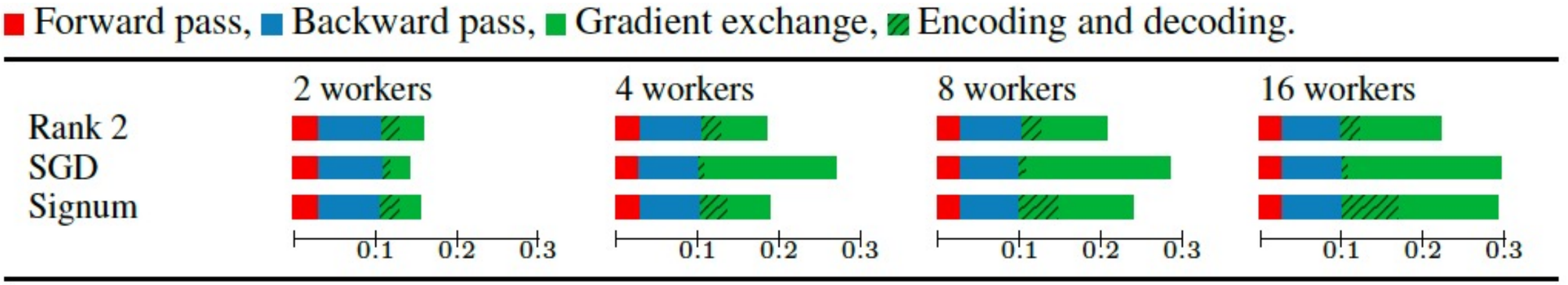
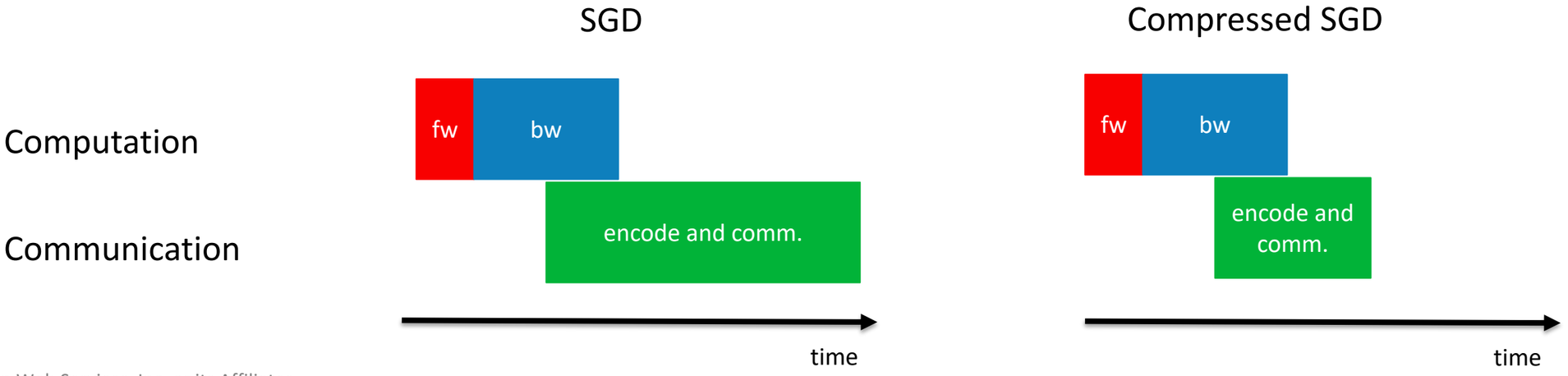
Communication bottleneck

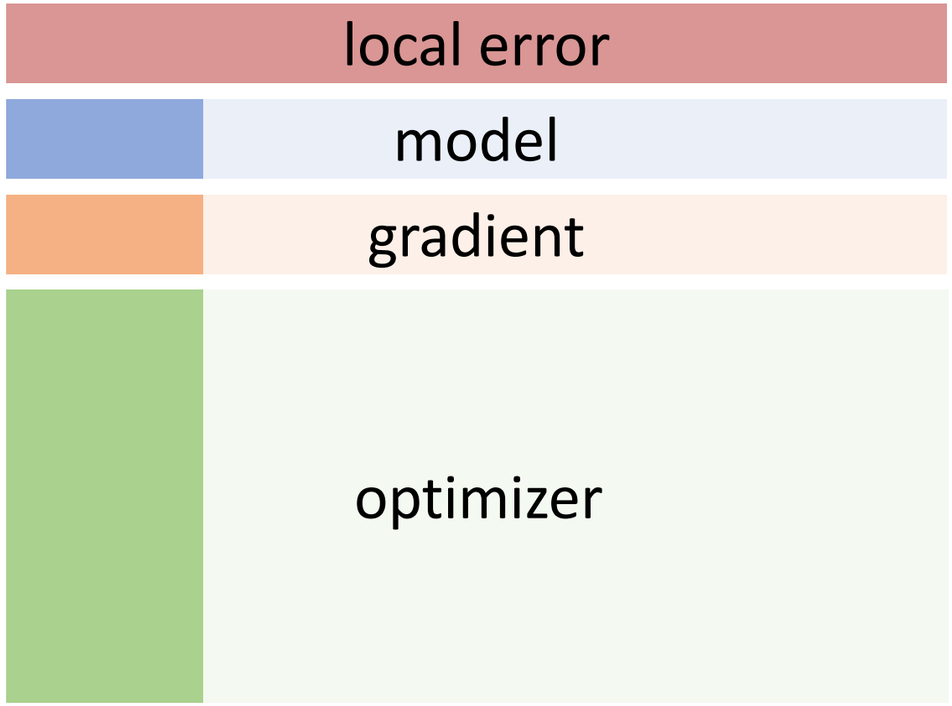
- Communication time increases with workers [VKM' 19]



- Efficient communication reduces idle time



Why EF is necessary



- Local SGD [Stich' 19]
  - Communicate every a few iterations
  - Infeasible for ZeRO3 since optimizer states are partitioned

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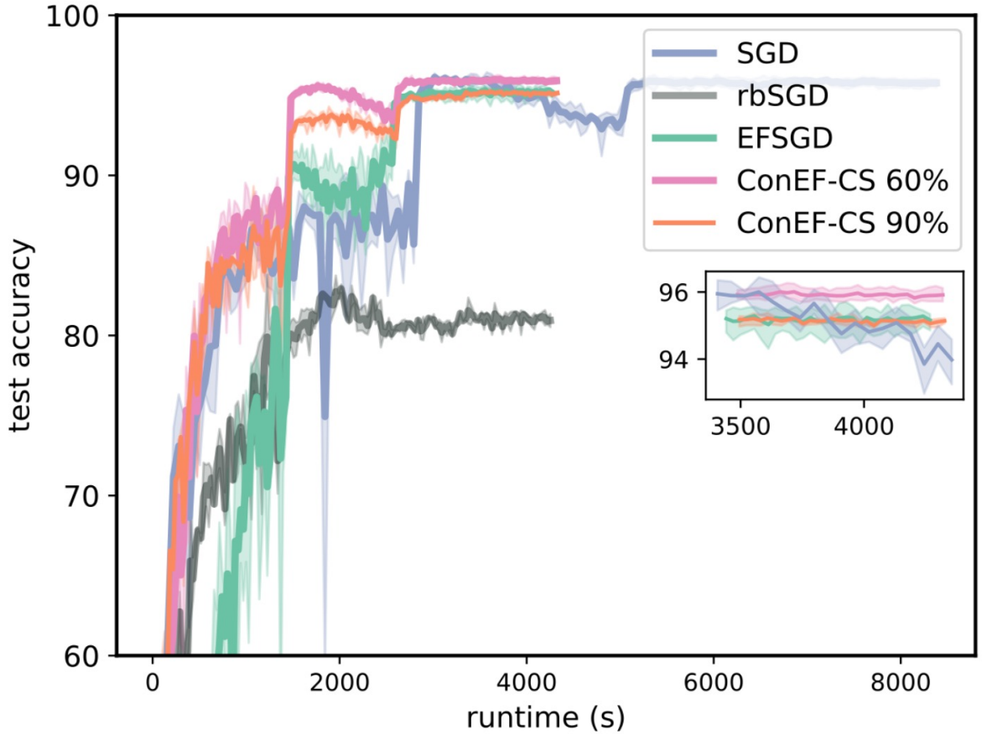
Why EF is necessary



- Unbiased gradient compressors [ADGLTV' 17]
  - Enlarged gradient variance hurts performance (e.g., accuracy)

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Contractive error feedback (ConEF)

ConEF

Initialize: $\mathbf{x}_0 \in \mathbb{R}^d, \mathbf{e}_0^i = \mathbf{0} \in \mathbb{R}^d, \forall i, \eta$
for $t = 0, 1, \ldots, T-1$ **do**
  assert $\mathbf{x}_t = \mathbf{x}_t^i$ for every worker i
  for worker $i = 1, \ldots, N$ in parallel **do**
    $\mathbf{p}_t^i = \eta \mathbf{g}_t^i + \mathbf{e}_t^i$
    $\boldsymbol{\Delta}_t^i = \mathcal{Q}(\mathbf{p}_t^i)$
    $\boldsymbol{\Delta}_t = \text{Aggregate}(\boldsymbol{\Delta}_t^i, \forall i)$
    $\mathbf{x}_{t+1} = \mathbf{x}_t - \boldsymbol{\Delta}_t$
    $\mathbf{e}_{t+1}^i = \mathcal{C}(\mathbf{p}_t^i - \boldsymbol{\Delta}_t^i)$
  end for
end for

EFSGD

Initialize: $\mathbf{x}_0 \in \mathbb{R}^d, \mathbf{e}_0^i = \mathbf{0} \in \mathbb{R}^d, \forall i, \eta$
for $t = 0, 1, \ldots, T-1$ **do**
  assert $\mathbf{x}_t = \mathbf{x}_t^i$ for every worker i
  for worker $i = 1, \ldots, N$ in parallel **do**
    $\mathbf{p}_t^i = \eta \mathbf{g}_t^i + \mathbf{e}_t^i$
    $\boldsymbol{\Delta}_t^i = \mathcal{Q}(\mathbf{p}_t^i)$
    $\boldsymbol{\Delta}_t = \text{Aggregate}(\boldsymbol{\Delta}_t^i, \forall i)$
    $\mathbf{x}_{t+1} = \mathbf{x}_t - \boldsymbol{\Delta}_t$
    $\mathbf{e}_{t+1}^i = \mathbf{p}_t^i - \boldsymbol{\Delta}_t^i$
  end for
end for

- **Key idea:** compressors can be used on local error as well
- Simple operation saves more runtime
- **Convergence:** ConEF finds the sweet spot of QSGD and EFSGD
- **Practicality:** depending on which error compressor to use

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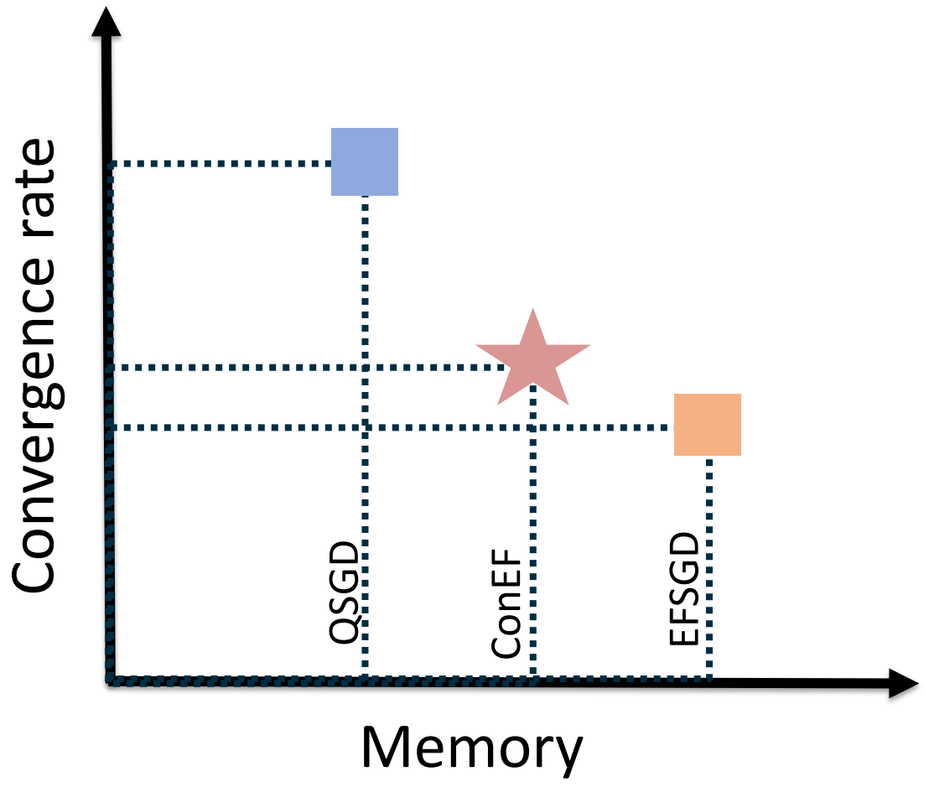
Convergence of ConEF



ConEF

Initialize: $\mathbf{x}_0 \in \mathbb{R}^d, \mathbf{e}_0^i = \mathbf{0} \in \mathbb{R}^d, \forall i, \eta$
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    $\mathbf{x}_{t+1} = \mathbf{x}_t - \boldsymbol{\Delta}_t$
    $\mathbf{e}_{t+1}^i = \mathcal{C}(\mathbf{p}_t^i - \boldsymbol{\Delta}_t^i)$
  end for
end for

- Assumption on error compressor $\mathbb{E}[\mathcal{C}(\mathbf{x})] = \mathbf{x}$ and $\mathbb{E}[\|\mathcal{C}(\mathbf{x}) - \mathbf{x}\|^2] \leq \theta \mathbb{E}[\|\mathbf{x}\|^2]$
- Assumption on gradient compressor $\exists \delta \in (0, 1),$ s.t. $\mathbb{E}[\|\mathcal{Q}(\mathbf{x}) - \mathbf{x}\|^2] \leq \delta \mathbb{E}[\|\mathbf{x}\|^2]$

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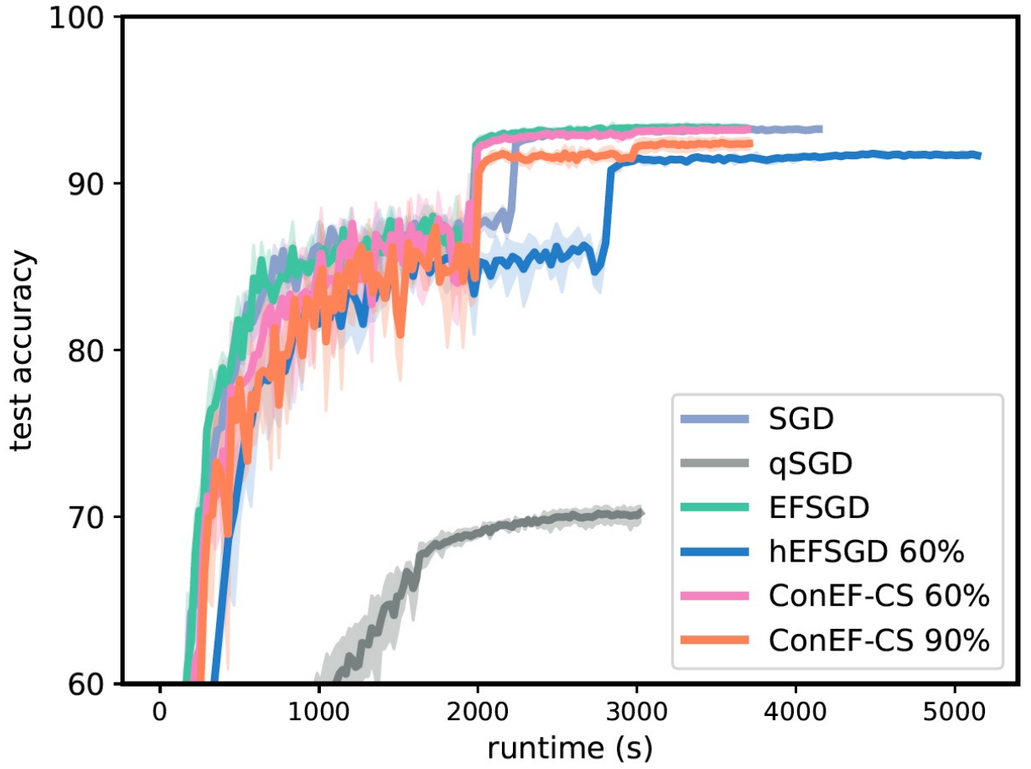
Deeper dive into error compressors *C*

- Assumption on error compressor $\mathbb{E}[\mathcal{C}(\mathbf{x})] = \mathbf{x}$ and $\mathbb{E}[\|\mathcal{C}(\mathbf{x}) - \mathbf{x}\|^2] \leq \theta \mathbb{E}[\|\mathbf{x}\|^2]$

- Unbiased *C* has some generalization merits



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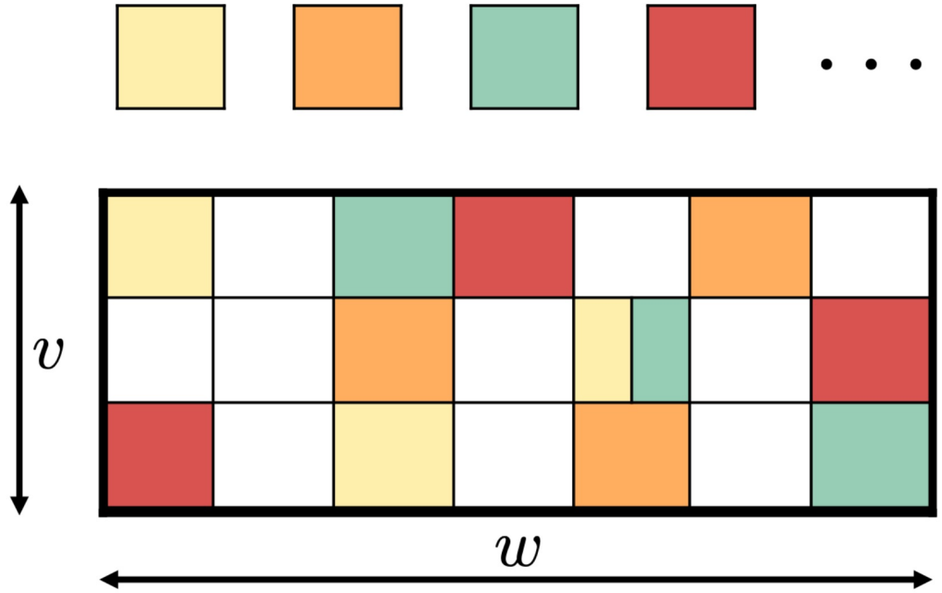
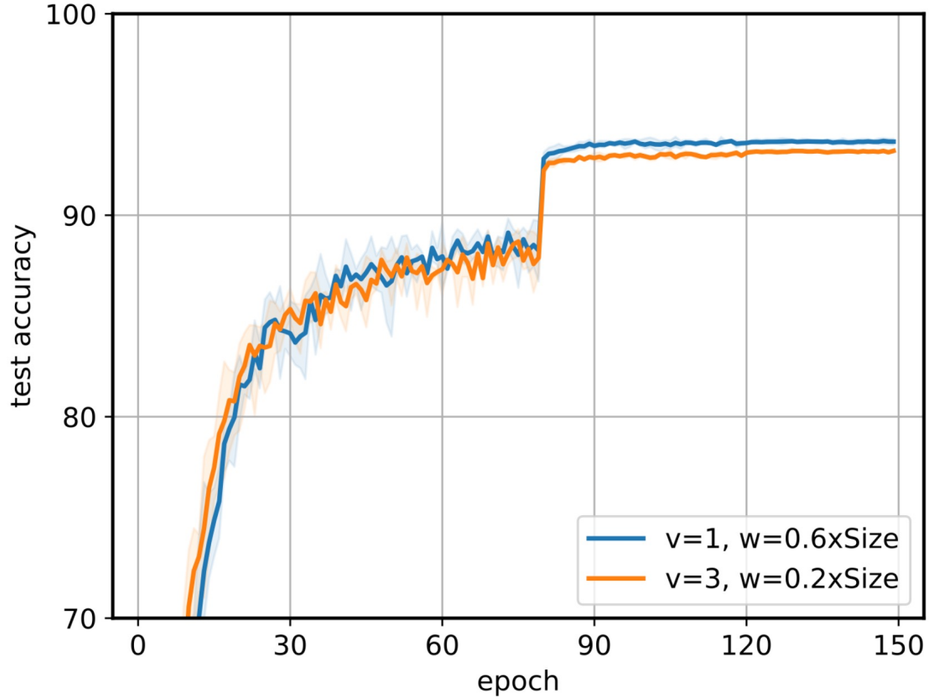
Deeper dive into error compressors *C*

- Rule of thumb: **count sketch** [CCF ‘02]





- One can also use e.g., stochastic quantization [ADGLTM’ 17] and its variants

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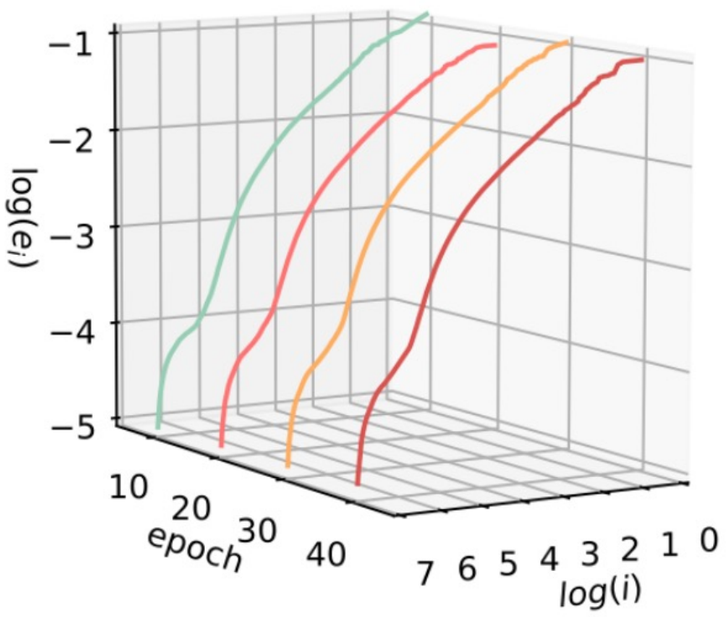
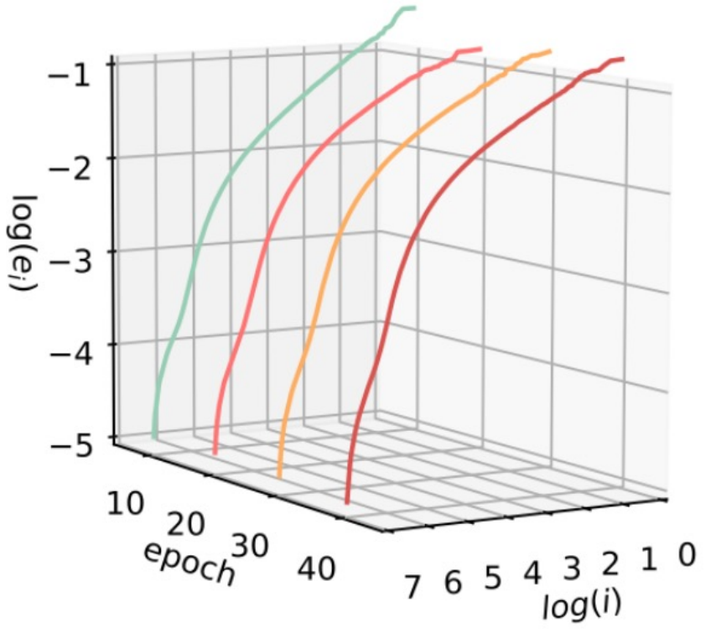
Deeper dive into error compressors *C*



EFSGD



(partial)-EFSGD [AF' 20]

Initialize: $\mathbf{x}_0 \in \mathbb{R}^d, \mathbf{e}_0 = \mathbf{0} \in \mathbb{R}^d, \eta$
for $t = 0, 1, \ldots, T-1$ **do**
  assert $\mathbf{x}_t = \mathbf{x}_t^i$ for every worker i
  for worker i in parallel **do**
    $\mathbf{p}_t^i = \eta \mathbf{g}_t^i + (1-\beta)\mathbf{e}_t^i$
    $\mathbf{\Delta}_t^i = \mathcal{Q}(\mathbf{p}_t^i)$
    $\mathbf{\Delta}_t = \text{Aggregate}(\mathbf{\Delta}_t^i, \forall i)$
    $\mathbf{x}_{t+1} = \mathbf{x}_t - \mathbf{\Delta}_t$
    $\mathbf{e}_{t+1}^i = \mathcal{C}(\beta \mathbf{e}_t + \mathbf{p}_t^i - \mathbf{\Delta}_t^i)$
  end for
end for

Table 1: β vs. sketch size for convergence

β	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
smallest sketch size	0.9	0.8	0.7	0.6	0.4	0.4	0.3	0.2	0.1

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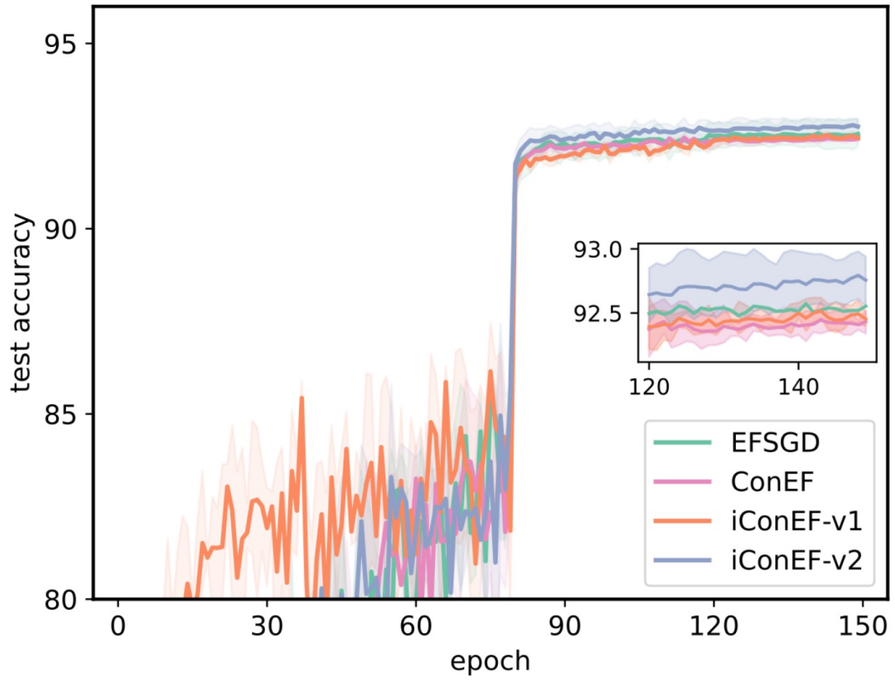
Side results on tighter bounds

- Using ConEF on top of ConEF improves the convergence rate theoretically

improved ConEF (iConEF)

Initialize: $\mathbf{x}_0, \tilde{\mathbf{e}}_0^i = \mathbf{0}, \mathbf{q}_0^i = \mathbf{0}, \eta$
for $t = 0, 1, \ldots, T-1$ **do**
  assert $\mathbf{x}_t = \mathbf{x}_t^i$ for every worker i
  for worker $i = 1, \ldots, N$ in parallel **do**
    $\mathbf{p}_t^i = \eta \mathbf{g}_t^i + \tilde{\mathbf{e}}_t^i + \mathbf{q}_t^i$
    $\boldsymbol{\Delta}_t^i = \mathcal{Q}(\mathbf{p}_t^i)$
    $\boldsymbol{\Delta}_t = \text{Aggregate}(\boldsymbol{\Delta}_t^i, \forall i)$
    $\mathbf{x}_{t+1} = \mathbf{x}_t - \boldsymbol{\Delta}_t$
    if version 1 **then**:
      $\tilde{\mathbf{e}}_{t+1}^i = \mathcal{C}(\mathbf{p}_t^i - \boldsymbol{\Delta}_t^i)$ ▷ iConEF-v1
    else:
      $\tilde{\mathbf{e}}_{t+1}^i = \mathcal{Q}(\mathbf{p}_t^i - \boldsymbol{\Delta}_t^i)$ ▷ iConEF-v2
    end if
    $\mathbf{q}_{t+1}^i = \mathcal{C}(\mathbf{p}_t^i - \boldsymbol{\Delta}_t^i - \tilde{\mathbf{e}}_{t+1}^i)$
  end for
end for



Roadmap

- ❑ Motivation and goal
- ❑ Algorithm design
- ❑ **Numerical experiments**
- ❑ Distributed training for large models redux

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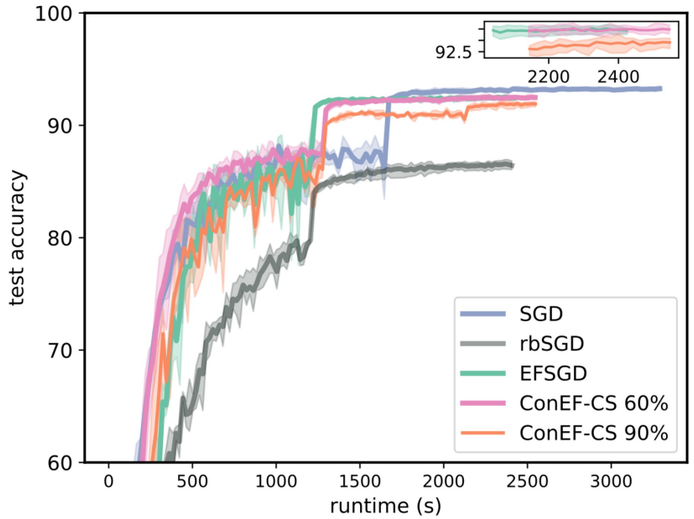
Step 1: ConEF for SGD based optimizers

- 4 Amazon p3.8xlarge instances (16 GPUs in total)
- Gradient compressor: random block k (90% reduced comm.)
- Error compressor: count sketch
- **ResNet18 on CIFAR-10**

Algorithm	test accuracy	runtime (min)	memory saving (MB)
SGD	93.20	54.83	-
rbSGD	86.58	40.12	48.2
EFSGD	92.52	40.41	0
ConEF 60%	92.53	42.45	31.5
ConEF 90%	92.02	42.45	44.1



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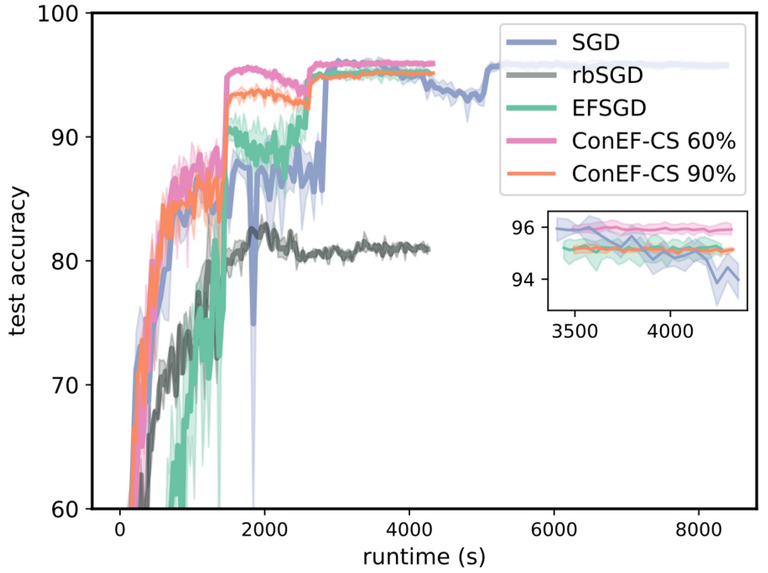
Step 1: ConEF for SGD based optimizers

- 4 Amazon p3.8xlarge instances (16 GPUs in total)
- Gradient compressor: random block k (90% reduced comm.)
- Error compressor: count sketch
- **WideResNet-28-10 on CIFAR-10**

Algorithm	test accuracy	runtime (min)	memory saving (MB)
SGD	96.12	139.70	-
rbSGD	82.92	70.88	122.1
EFSGD	95.28	71.13	0
ConEF 60%	96.00	72.11	76.2
ConEF 90%	95.23	71.98	101.5



- ConEF is more suitable for larger models

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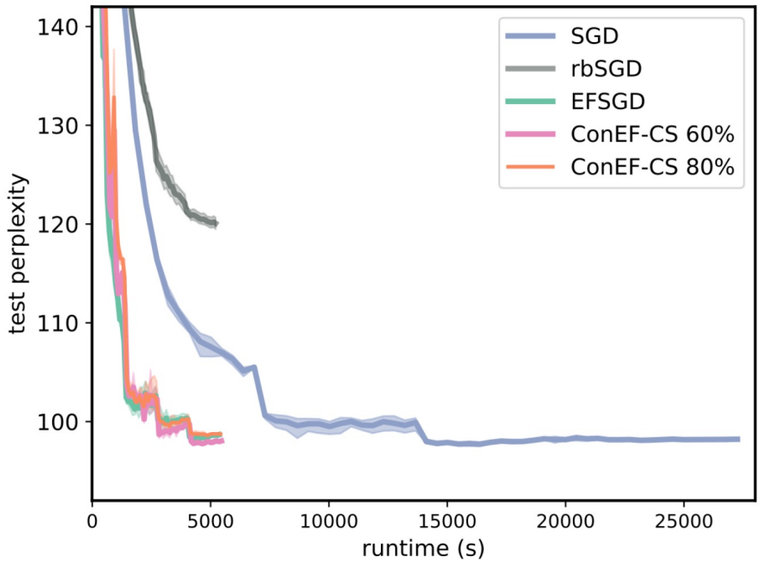
Step 1: ConEF for SGD based optimizers

- 4 Amazon p3.8xlarge instances (16 GPUs in total)
- Gradient compressor: random block k (90% reduced comm.)
- Error compressor: count sketch
- **2-layer LSTM on WikiText-2**

Algorithm	perplexity	runtime (hour)	memory saving (MB)
SGD	97.72	7.57	-
rbSGD	120.07	1.45	262.5
EFSGD	98.29	1.49	0
ConEF 60%	97.76	1.51	180.3
ConEF 80%	98.59	1.50	220.2



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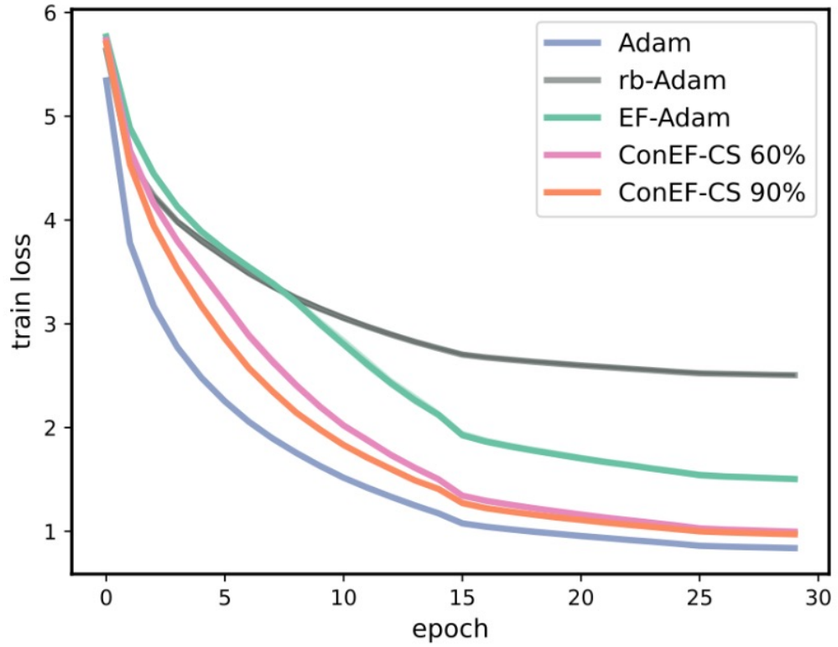
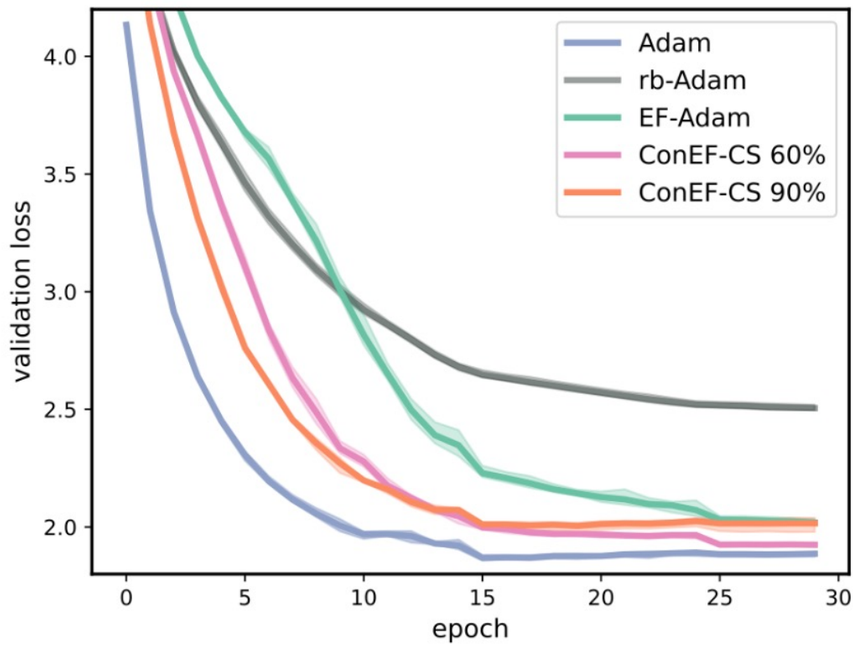
Step 2: ConEF for Adam type optimizers

- A **small transformer** for machine translation on **Multi30K**



(a) train



(b) validation

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Step 2: ConEF with Adam type optimizers

- 4 Amazon p3.16xlarge instances (32 GPUs in total)
- Gradient compressor: random block k (95% reduced comm.)
- Error compressor: count sketch

- BERT-BASE pretraining (not completed yet)

Algorithm	out of memory	Phase I loss	Phase II loss	runtime (hour)
LAMB	No	≈1.62		40.2 +
EF-LAMB	Yes	-	-	-
EF-LAMB (mix precision)	No	≈1.76		37.6 +
ConEF 80%	No	≈1.79		38.1 +

- Possible reasons for performance gap:

Step 2: ConEF with Adam type optimizers

- BERT-BASE downstream tasks (not completed yet)

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Roadmap

- ❑ Motivation and goal
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- ❑ **Distributed training for large models redux**

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Rethinking distributed training for NLP

- Current distributed training paradigm targets **consensus**
  - Communication of stochastic gradients is essential for reaching consensus
  - **Q: is consensus necessary**
  - Amazon, Google, and NVIDIA have their own pretrained BERT
  - **Q: What and how to communicate if consensus in not the ultimate goal**

Figure from https://towardsdatascience.com/how-to-train-bert-aaad00533168

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Rethinking distributed training for NLP

- In the old days (ADMM, gossip)
  - Not enough data, strongly convex problem (hence unique solution)
- In the present ... nonuniqueness seems to be necessary
  - Data explosion, highly nonconvex losses with various local minima
  - Multiple manners to translate a specific sentence
  - **Q: is a single function enough**
  - **Q: How can we take advantage of models converging to different local minima**

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Q&A

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