



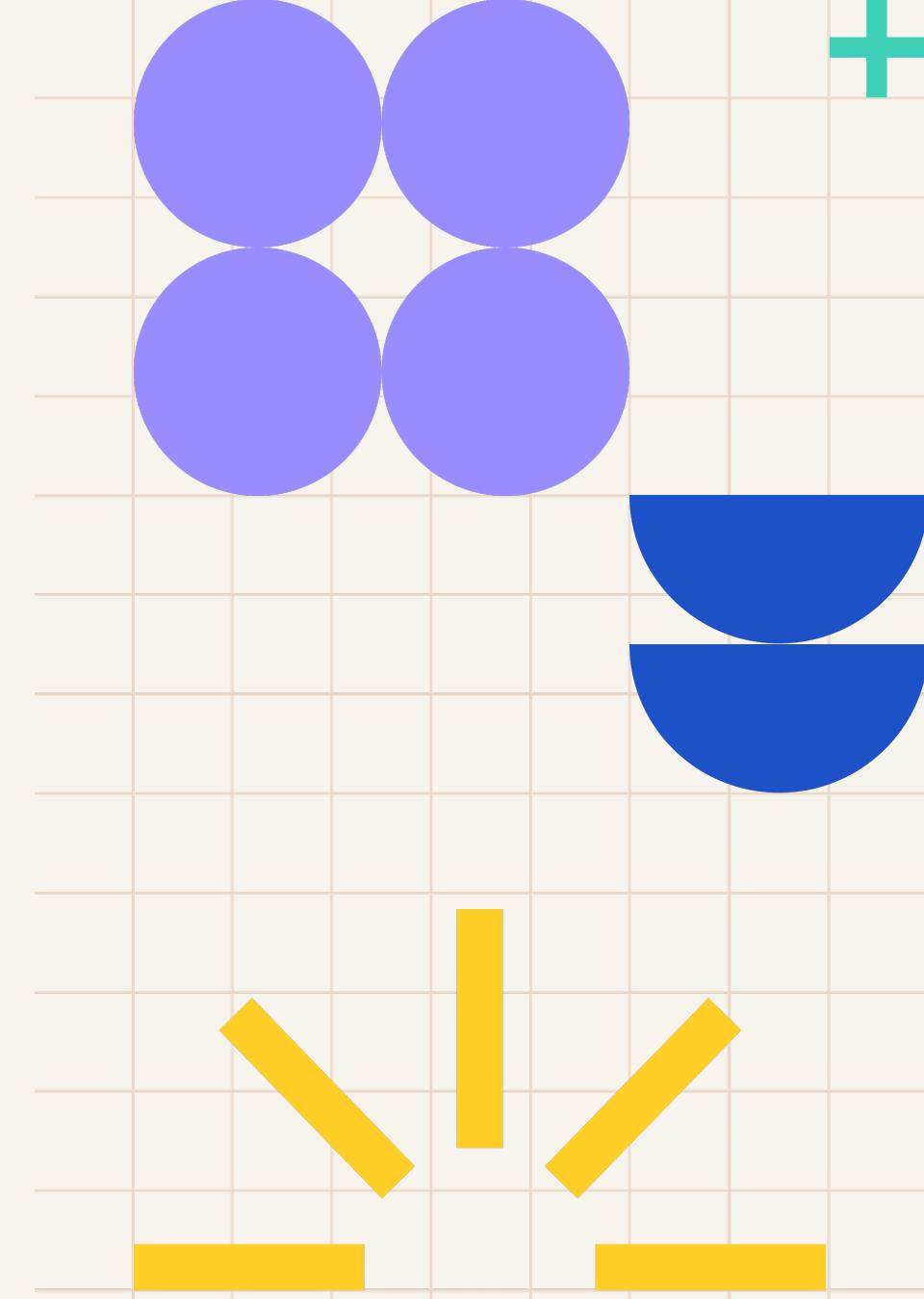
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Optimisation methods for training large models

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Plan

- 01 Problem statement
- 02 Basic optimisers
- 03 What is changed with large models?
- 04 Main approaches
- 05 Summary

Problem statement

What problem we are going to solve?

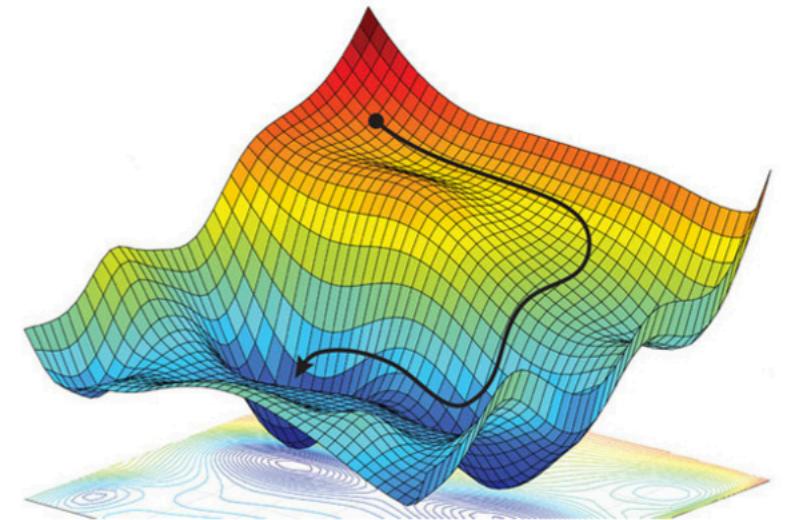
- Given dataset $X = \{x_i\}_{i=1}^N$
- According to the target task we have the corresponding loss function

$$L(w | X) = \frac{1}{N} \sum_{i=1}^N L(w | x_i), \quad L_i(w) \equiv L(w | x_i)$$

and the model $f(w, x_i)$ which is simulated by DNN

- The main problem is

$$w^* = \arg \min_w L(w | X)$$



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Main features of the problem

- Non-convexity: multiple local minima of different quality
- Overfitting is a problem although DNNs are typically overparametrized
- Generalisation is important property of the final model
- Adversarial attacks are also a challenge in model training
- DNNs require massive parallel computations to treat the sufficient amount of data

Features of the problem statement:

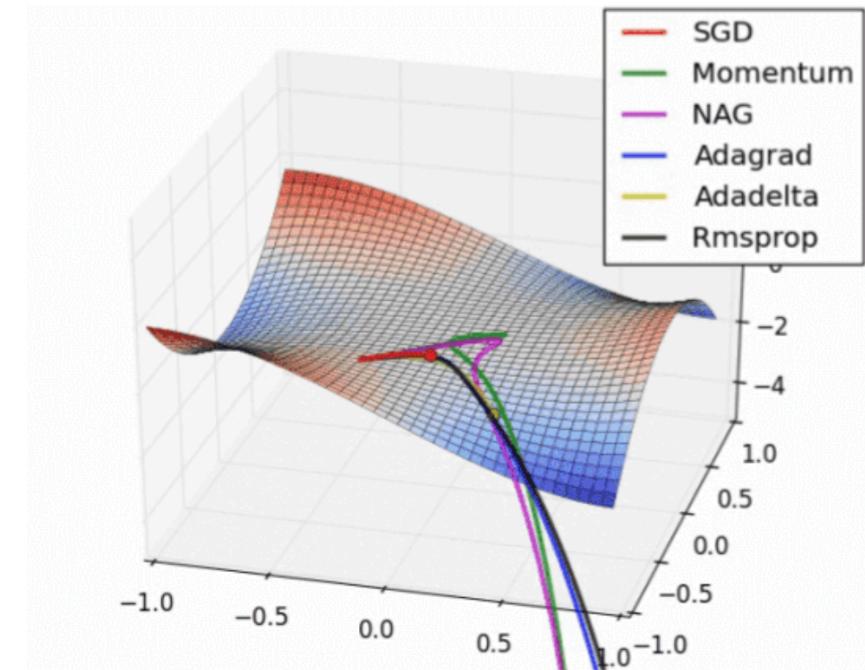
- Non-convexity
- Non-smoothness
- Generalisation
- Robustness w.r.t. adversarial attacks
- Limited of the computational and storage resources

02

Basic optimisation methods

What do we want from optimisers?

- Train loss minimisation
- High generalisation, i.e. test loss minimisation simultaneously
- Fast convergence
- No special tuning of hyperparameters
- Adversarial robustness to attacks of the resulting model
- Low consumption of the additional memory



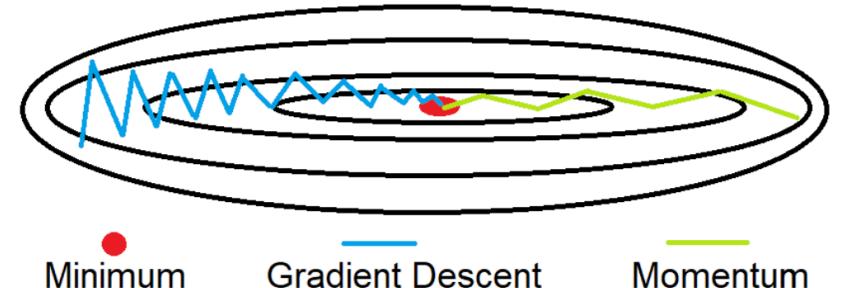
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Stochastic gradient descent

- Gradient estimation from batch B_k

$$L'_k(w) = \frac{1}{|B_k|} \sum_{i \in B_k} L'_i(w)$$

- SGD: $w_{k+1} = w_k - \alpha L'_k(w), \alpha > 0$
- SGD + Momentum: $w_{k+1} = w_k - \alpha L'_k(w) + \beta(w_k - w_{k-1})$
- Adaptive learning rate: $\alpha = \text{const} \rightarrow \alpha_k = s(\cdot)$



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What we can already observe?

- Batch size $|B_k|$ affects the noise in gradient estimate
- Momentum methods require storage additional vectors
- Learning rate tuning can help

Some theory about such methods

Theorem

Let f be convex, L -smooth function. Then if SGD generates directions \mathbf{h}_k such that $\text{Var}(\mathbf{h}_k) \leq \sigma^2$ and $\alpha_k \leq \frac{1}{L}$ then

$$\mathbb{E}[f(\bar{\mathbf{x}}_k)] - f^* \leq \frac{\|\mathbf{x}_0 - \mathbf{x}^*\|_2^2}{\alpha_k k} + \frac{\alpha_k \sigma^2}{2}.$$

In particular, after $k = \frac{(\sigma^2 + L\|\mathbf{x}^* - \mathbf{x}_0\|_2^2)^2}{\varepsilon^2}$ iterations if $\alpha_k = \frac{1}{\sqrt{k}}$ we get the solution with accuracy 2ε .

- No convergence due to noise term
- Averaging of gradients leads to convergent method - SAG [Schmidt, et al, 2013] - impractical due to memory limitations
- Only for convex case the theory is well-developed

Adaptive learning rate methods

- Adam [Kingma, et al, 2014] is the most representative method

$$w_{k+1} = w_k - \alpha \frac{\hat{m}_k}{\sqrt{\hat{v}_k} + \epsilon}$$

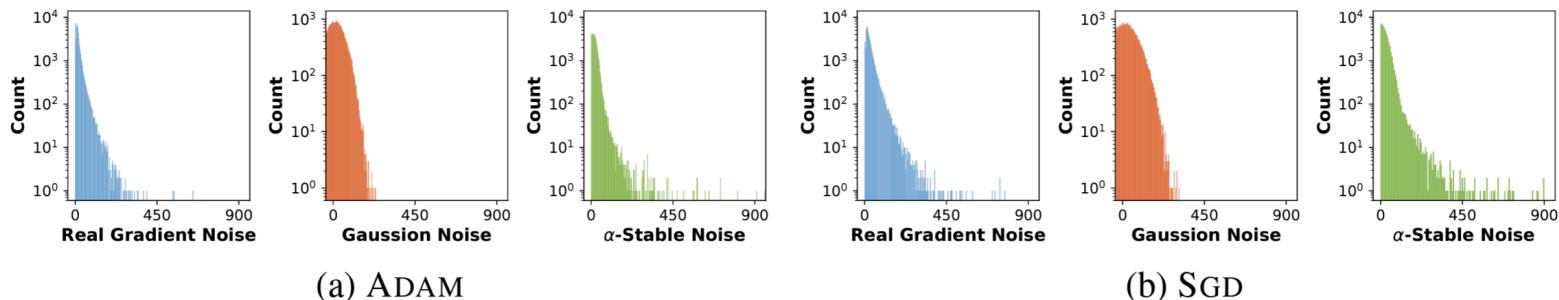
- $\hat{m}_k = \frac{m_k}{1 - \beta_1^k}, \quad m_k = \beta_1 m_{k-1} + (1 - \beta_1) L'_k$
- $\hat{v}_k = \frac{v_k}{1 - \beta_2^k}, \quad v_k = \beta_2 v_{k-1} + (1 - \beta_2) (L'_k \cdot L'_k)$
- All operations are elementwise

SGD vs Adam

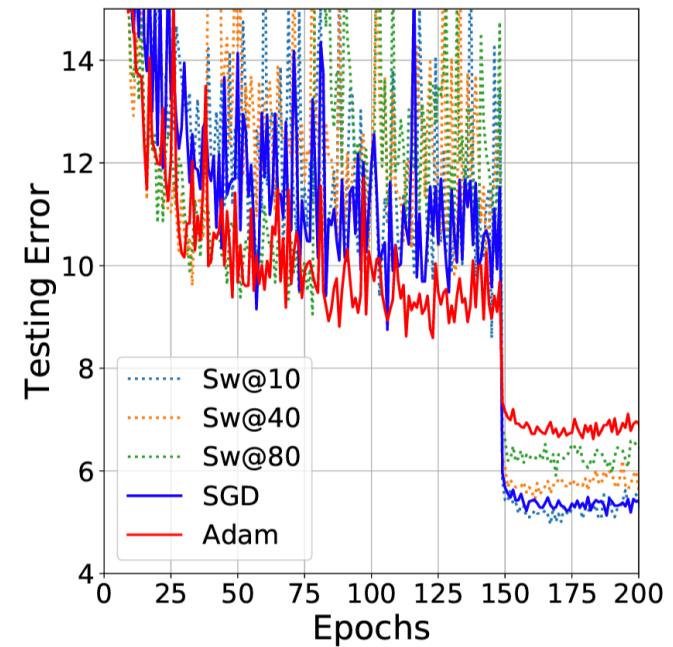
- Adam stores two vectors of the size of #parameters
- More computations per step
- Learning rate in Adam differs from SGD

Adam can generalise worse

- It was observed that though Adam converges faster, it gives less generalisable model
- Possible explanations
 - SGD faster escapes from the local minima
 - Adam average leads to lighter gradient noise tails
 - Formal proofs are based on SDE interpretation of SGD:
$$dw_t = -L'(w_t)dt + \varepsilon\Sigma_t dL_t^{(s)}$$
, where L_t is Levi process



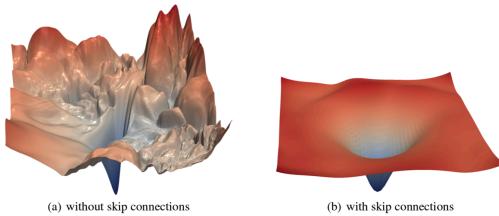
Source is "[Towards Theoretically Understanding Why SGD Generalizes Better Than ADAM in Deep Learning](#)", P. Zhou et al., NeurIPS 2020



Source is "[Improving Generalization Performance by Switching from Adam to SGD](#)", N.S.Keskar et al., 2017

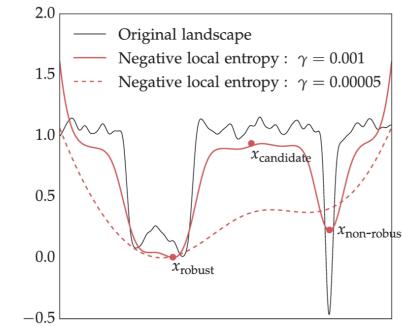
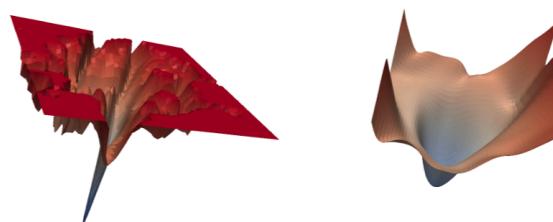
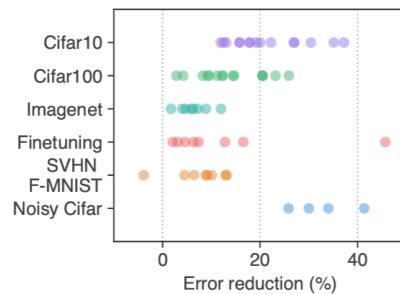
Flat vs sharp local minima

- Generalisation is also affected by the geometry of loss landscape
- Compare different architectures

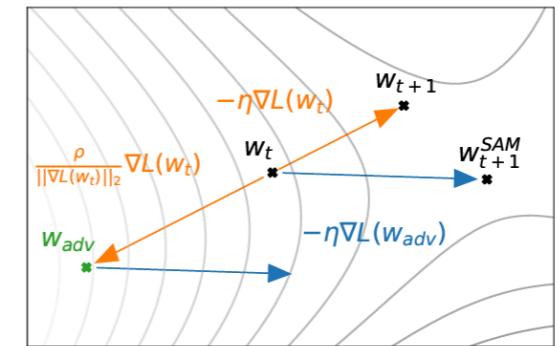


ResNet-56 architecture. Source is
["Visualizing the Loss Landscape of Neural Nets"](#), H. Li et al, NeurIPS 2018

- Sharpness aware minimisation (SAM) method suggests computing adversarial direction and updates parameters to avoid



Source is "Entropy-SGD: biasing gradient descent into wide valleys", Pratik Chaudhari et al J. Stat. Mech. (2019)



Source is ["Sharpness-aware minimization for efficiently improving generalization"](#), P. Foret, ICLR 2020

Statistics from <https://paperswithcode.com/>

Method	Year	Papers
 Adam Adam: A Method for Stochastic Optimization	2014	8544
 SGD	1951	1286
 RMSProp	2013	316
 Adafactor Adafactor: Adaptive Learning Rates with Sublinear Memory Cost	2018	220
 LAMB Large Batch Optimization for Deep Learning: Training BERT in 76 minutes	2019	138
 SGD with Momentum	1999	133
 AdaGrad	2011	112

Main features of basic optimisers

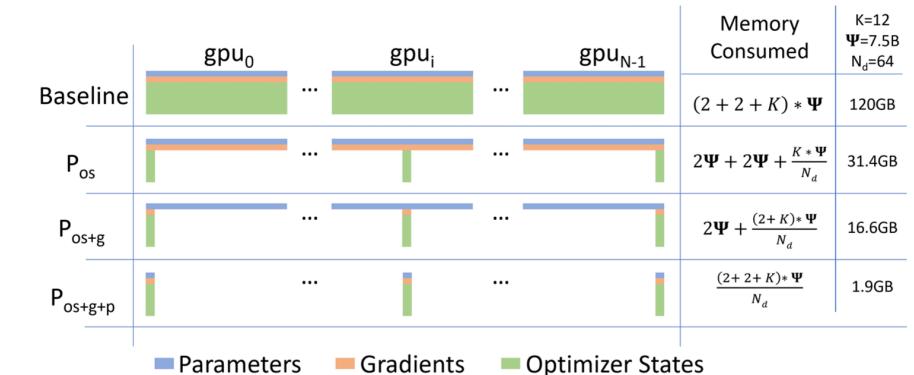
- Adaptive learning rate
- Smoothing of gradient statistics

03

What is changed with large models?

Large models from the optimisation perspective

- Huge #parameters affects the storage of optimiser state
- Parameters of the model can be stored in distributed manner. Remember about ZeRO framework
- The communication between GPUs appears - new factor in our scheme
- Large batch size increases GPU utilisation but affects the scheduler of other hyperparameters



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New factors

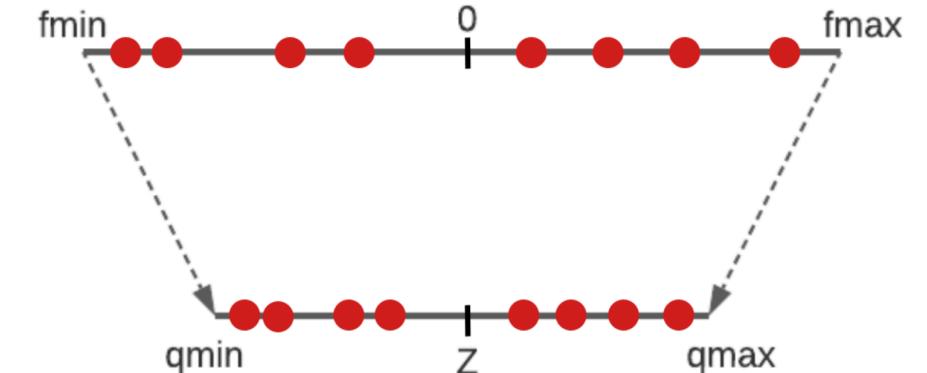
- We need more memory: CPU vs GPU
- Communications between nodes
- Distributed storage of model and optimiser state

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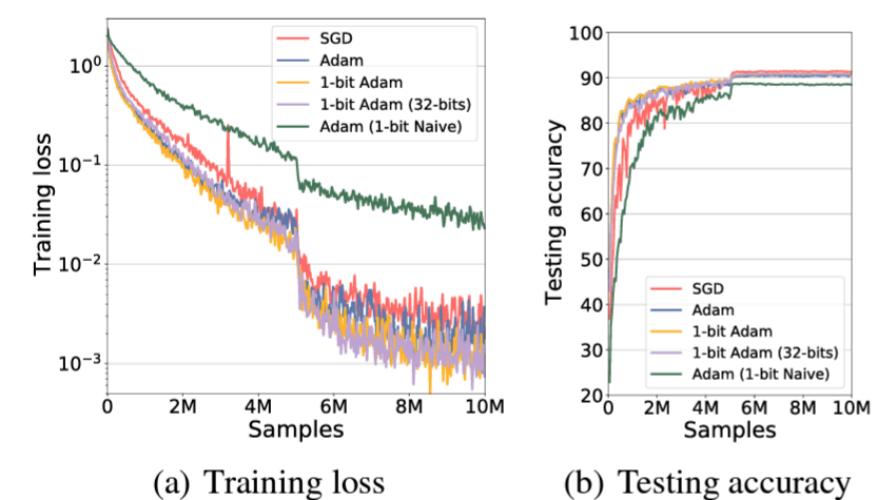
Main approaches

Quantisation

- The easy way to reduce memory footprint - decrease the accuracy of numbers representation
- It affects the property of optimisers
- FP32 is standard format
- [FP16](#), [bfloating-point](#) and [TensorFloat](#) alternatives
- Even just integers can be used [S. Kim et al, 2021]
- Quantisation is for optimiser state or for parameters
- Extreme case: 1-bit SGD and 1-bit Adam for efficient communications



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(a) Training loss

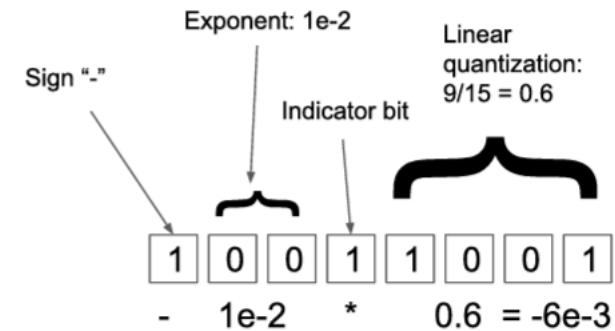
(b) Testing accuracy

Adaptive quantisation, 8-bit Adam

- Blockwise quantisation improves optimisers
- Example is [here](#) for momentum and Adam
- Idea: adaptively choose the range of values that should be covered by the quantised numbers

Optimizer	Task	Data	Model	Metric [†]	Time	Mem saved
32-bit AdamW	GLUE	Multiple	RoBERTa-Large	88.9	–	Reference
32-bit AdamW	GLUE	Multiple	RoBERTa-Large	88.6	17h	0.0 GB
32-bit Adafactor	GLUE	Multiple	RoBERTa-Large	88.7	24h	1.3 GB
8-bit AdamW	GLUE	Multiple	RoBERTa-Large	88.7	15h	2.0 GB
32-bit Momentum	CLS	ImageNet-1k	ResNet-50	77.1	–	Reference
32-bit Momentum	CLS	ImageNet-1k	ResNet-50	77.1	118h	0.0 GB
8-bit Momentum	CLS	ImageNet-1k	ResNet-50	77.2	116 h	0.1 GB
32-bit Adam	MT	WMT'14+16	Transformer	29.3	–	Reference
32-bit Adam	MT	WMT'14+16	Transformer	29.0	126h	0.0 GB
32-bit Adafactor	MT	WMT'14+16	Transformer	29.0	127h	0.3 GB
8-bit Adam	MT	WMT'14+16	Transformer	29.1	115h	1.1 GB
32-bit Momentum	MoCo v2	ImageNet-1k	ResNet-50	67.5	–	Reference
32-bit Momentum	MoCo v2	ImageNet-1k	ResNet-50	67.3	30 days	0.0 GB
8-bit Momentum	MoCo v2	ImageNet-1k	ResNet-50	67.4	28 days	0.1 GB
32-bit Adam	LM	Multiple	Transformer-1.5B	9.0	308 days	0.0 GB
32-bit Adafactor	LM	Multiple	Transformer-1.5B	8.9	316 days	5.6 GB
8-bit Adam	LM	Multiple	Transformer-1.5B	9.0	297 days	8.5 GB
32-bit Adam	LM	Multiple	GPT3-Medium	10.62	795 days	0.0 GB
32-bit Adafactor	LM	Multiple	GPT3-Medium	10.68	816 days	1.5 GB
8-bit Adam	LM	Multiple	GPT3-Medium	10.62	761 days	1.7 GB
32-bit Adam	Masked-LM	Multiple	RoBERTa-Base	3.49	101 days	0.0 GB
32-bit Adafactor	Masked-LM	Multiple	RoBERTa-Base	3.59	112 days	0.7 GB
8-bit Adam	Masked-LM	Multiple	RoBERTa-Base	3.48	94 days	1.1 GB

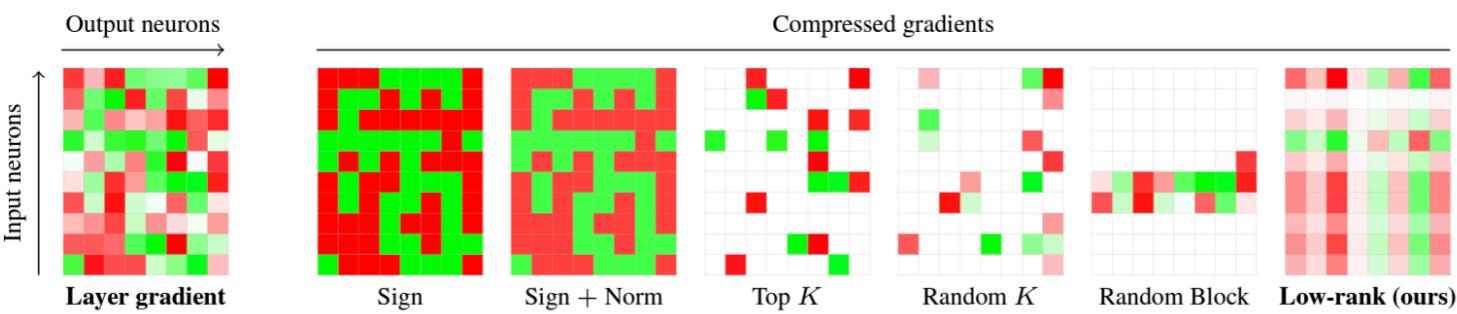
[†]Metric: GLUE=Mean Accuracy/Correlation. CLS/MoCo = Accuracy. MT=BLEU. LM=Perplexity.



GPU size in GB	Largest finetunable Model (parameters)	
	32-bit Adam	8-bit Adam
6	RoBERTa-base (110M)	RoBERTa-large (355M)
11	MT5-small (300M)	MT5-base (580M)
24	MT5-base (580M)	MT5-large (1.2B)
24	GPT-2-medium (762M)	GPT-2-large (1.5B)

Communications costs reduction

- Different methods for compression: algorithmic and network
- PowerSGD: low-rank compression from the power method
- Alternative compression methods
 - Sign
 - Sign + norm
 - Top-K
 - Random
 - Block random
- Zero-Infinity: proper memory and network usage



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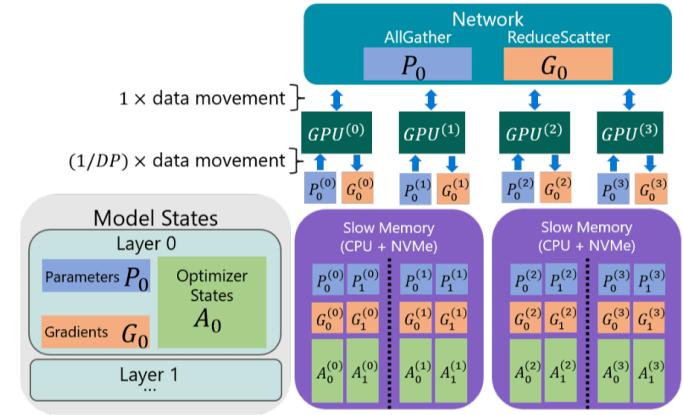


Figure 4: A snapshot of ZeRO-Infinity training a model with two layers on four data parallel (DP) ranks. Communication for the backward pass of the first layer is depicted. Partitioned parameters are moved from slow memory to GPU and then collected to form the full layer. After gradients are computed, they are aggregated, repartitioned, and then offloaded to slow memory. Layers are denoted with subscripts and DP ranks are denoted with superscripts. For example, $P_0^{(2)}$ is the portion of layer 0's parameters owned by GPU⁽²⁾.

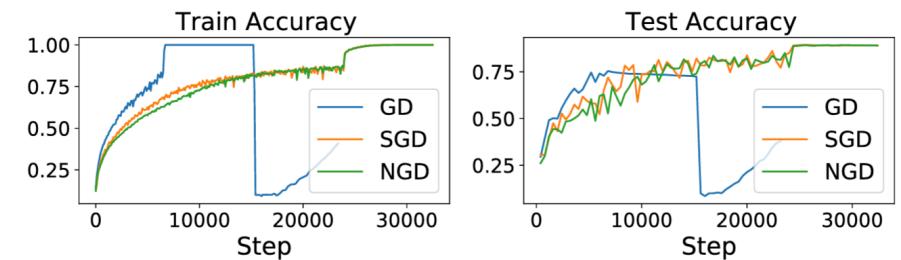
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Large batch training: idea

- Increase batch to utilise GPUs better
- This modification affects the gradient estimate noise
- As a result some modification of learning rate is needed to preserve learning curve
- Analysis of required transformation is easy with SDE approximation

$$dw_t = -L'(w_t)dt + (\alpha\Sigma(w_t))^{1/2}dW_t,$$

where W_t is Wiener process



Source is [“On the Validity of Modeling SGD with Stochastic Differential Equations \(SDEs\)”, Z. Li et al. NeurIPS 2021](#)

Main recipes

- Quantisation
- Compression
- Maximum GPUs utility

Summary

- Large models require special optimisation techniques
- Existing approaches are multi-directional
- Every direction can be further improved since no theoretical bounds are known

Questions

- What is a proper combination of described approaches?
- How test them fairly?
- Is it possible to formal prove the described heuristics?



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