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Training large-scale language models with limited GPU memory: a survey

Key words: Training techniques; Memory optimization; Model parameters; Model states; Model activations

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GPU memory wall

- Further advancement of large-scale models is substantially hindered by the limited GPU memory.

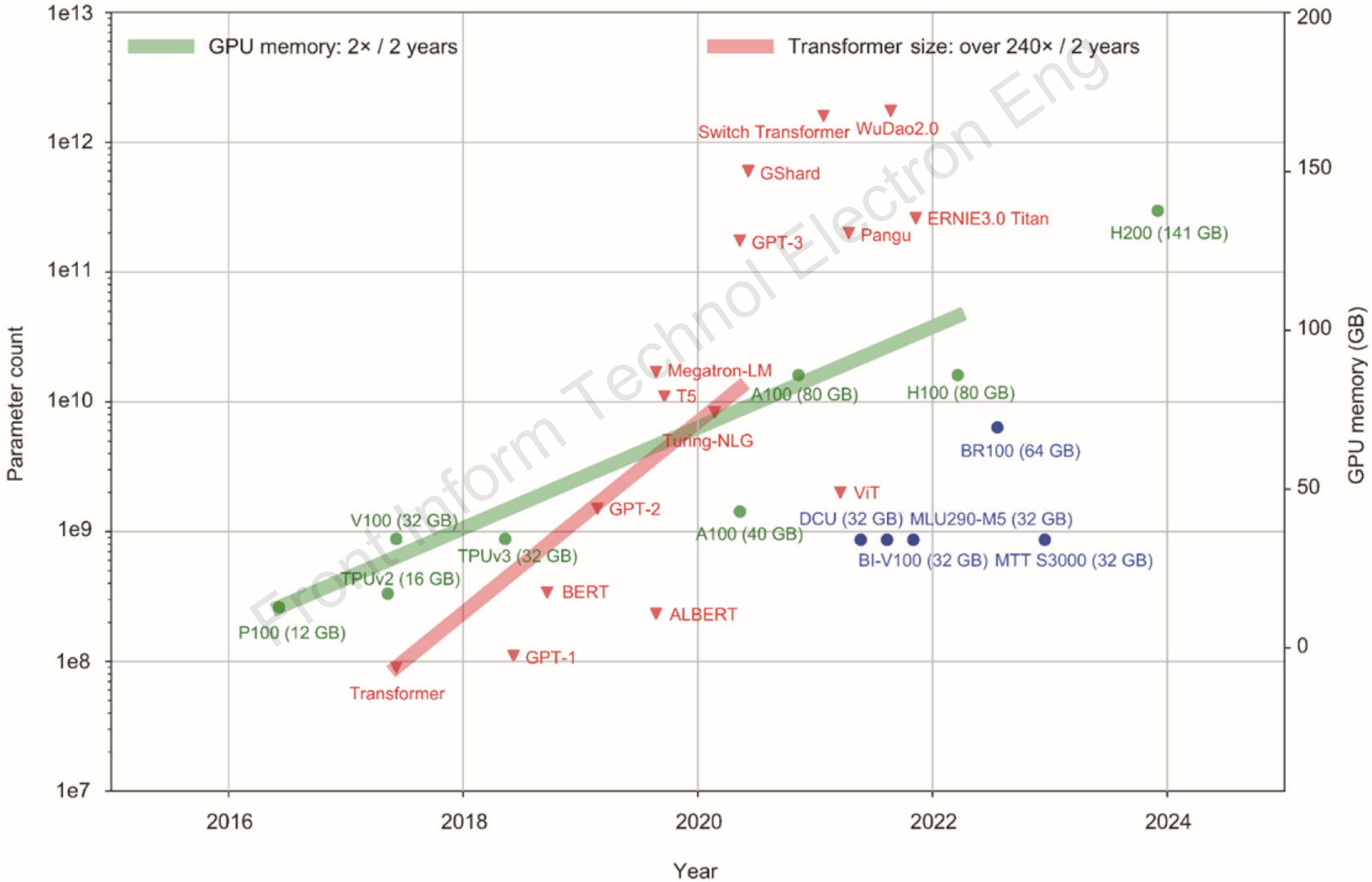
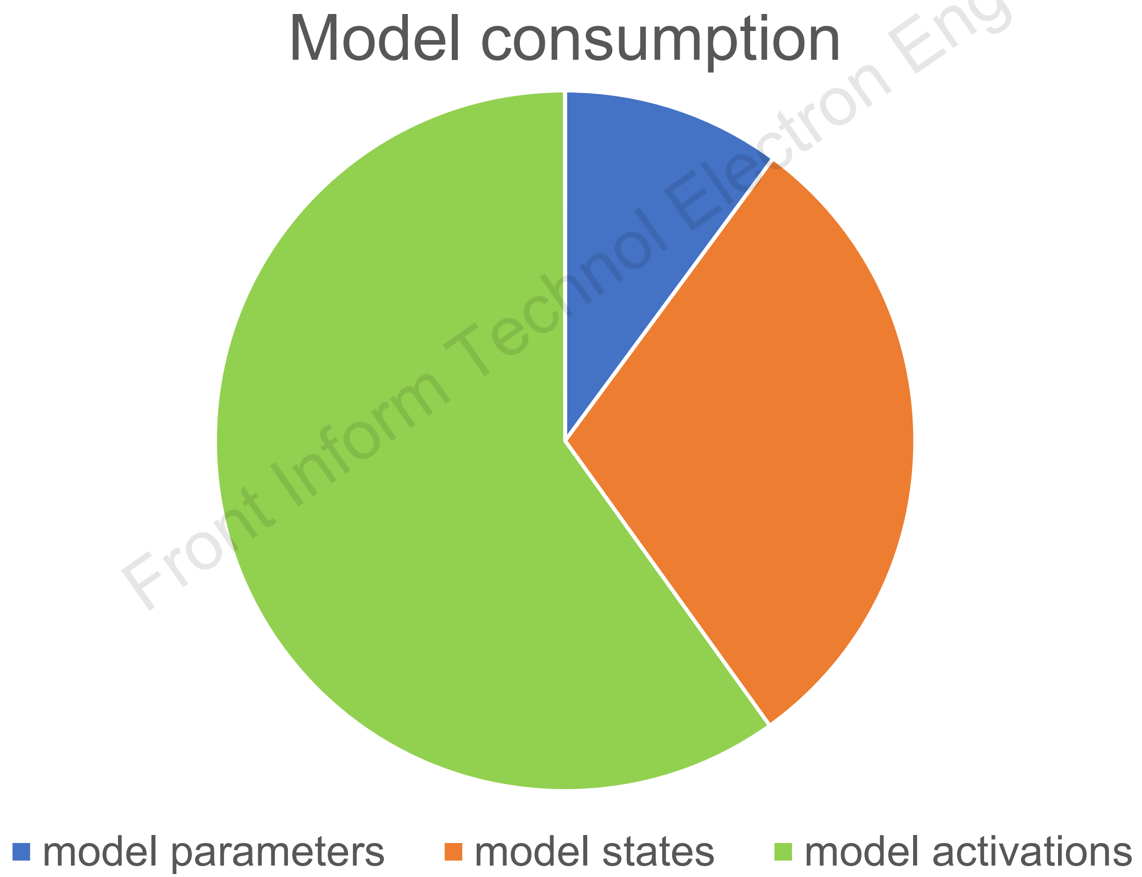


Fig. 1 Development of large-scale models' sizes and GPU memory capacity in recent years. It is obvious that the sizes of these models are increasing more and more rapidly and far beyond the capacity of GPU. References to color refer to the online version of this figure

GPU memory consumption analysis

- In training large-scale models, most memory consumption comes from model parameters, model states, and model activations.



Reducing memory of model parameters

- Multi-GPU training: Model Parallel, Pipeline Parallel, Mixed Parallel
- Mixed-precision training
- Specific model design: ReZero

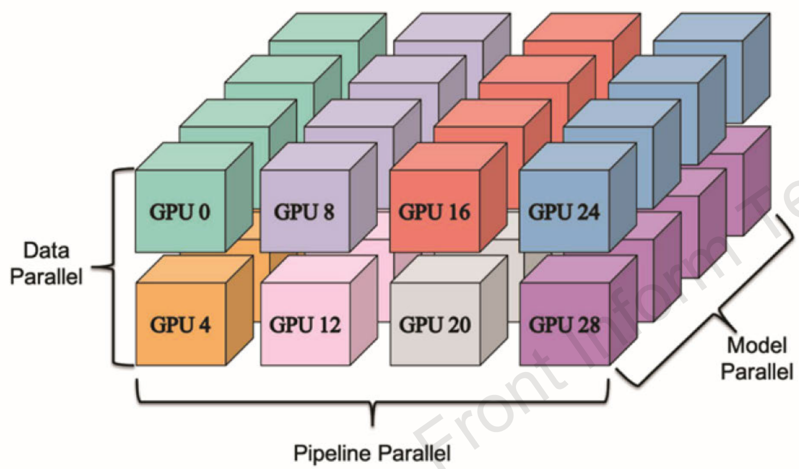


Fig. 5 Overview of 3D Parallel, which consists of Data Parallel, MP, and Pipeline Parallel. These parallel dimensions shard GPUs as their degrees in the training system

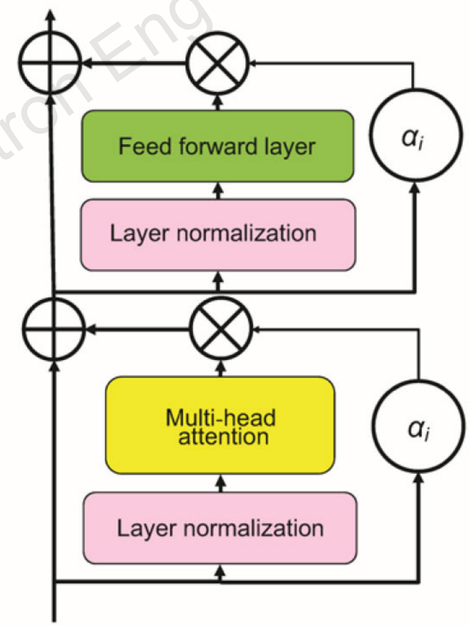
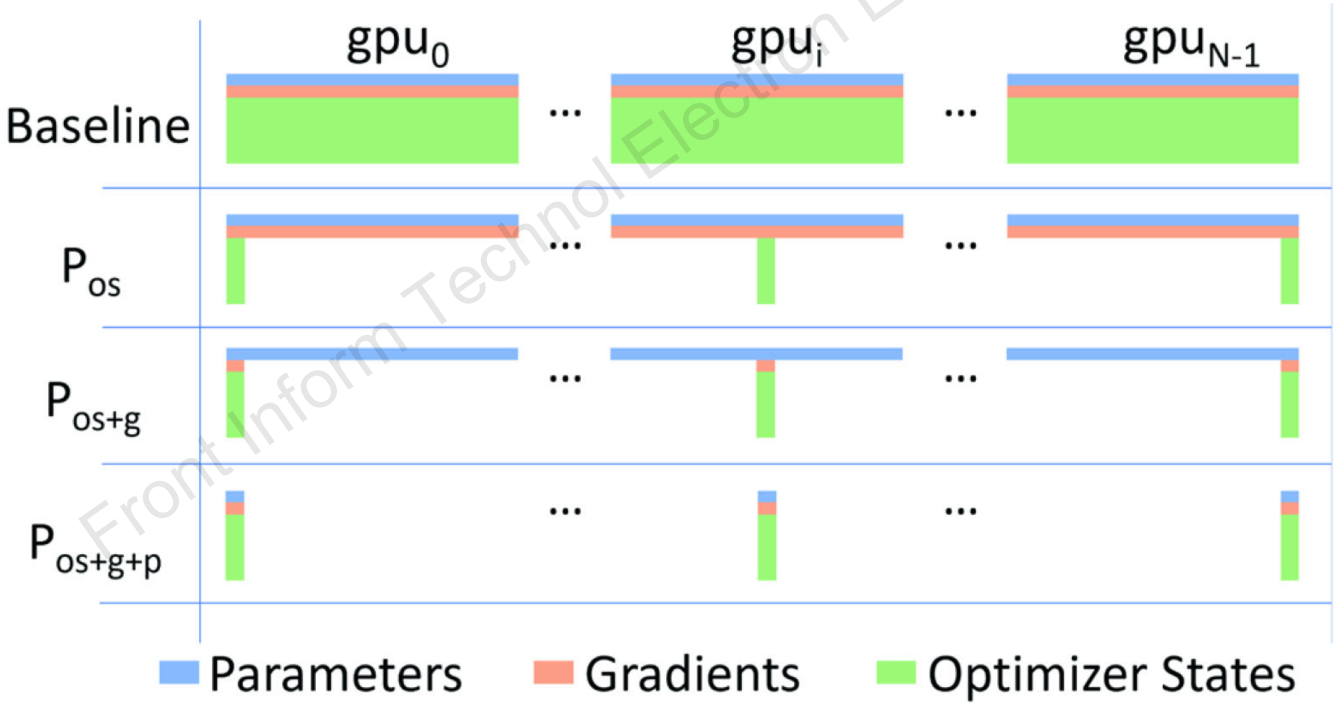


Fig. 9 Architecture of the ReZero Transformer. The parameter α determines whether the layer is calculated in the process

Reducing memory of model states

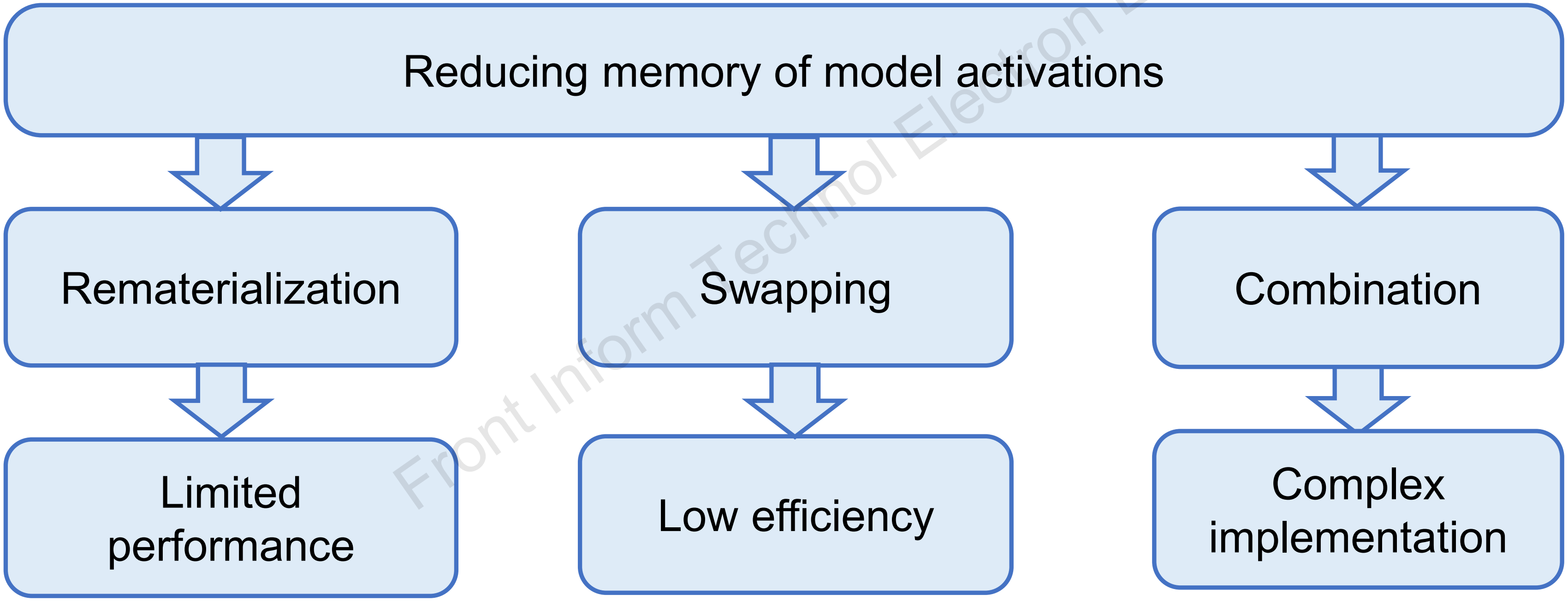
- ZeRO (Zero Redundancy Optimizer)
- PatrickStar
- Adafactor
- CAME
- DeepZeRo



Rajbhandari Samyam, et al., 2020. ZeRO: memory optimizations toward training trillion parameter models. SC20: IEEE Int Conf for High Performance Computing, Networking, Storage and Analysis.

Reducing memory of model activations

- Rematerialization: Checkpoint, DTR, and Checkmate
- Swapping: SwapAdvisor, ZeRO-Offload, and ZeRO-Infinity
- Combination: SuperNeurons, Capuchin, and DELTA



Discussion

Future research	Outlook
Supporting new parallel methods	• Expert Parallel • Sequence Parallel • FlashAttention
Ensuring the convergence of optimizers	• Theoretical analysis • Stable convergence • Less memory consumption
Improving rematerialization and swapping	• Memory fragmentation • Low throughput • Complex implementation

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