



Flash-LLM: Enabling Cost-Effective and Highly-Efficient Large Generative Model Inference with Unstructured Sparsity

Haojun Xia ^{*†}
University of Sydney
hxia6845@uni.sydney.edu.au

Donglin Zhuang
University of Sydney
donglin.zhuang@sydney.edu.au

Yong Li
Alibaba Group
jiufeng.ly@alibaba-inc.com

Zhen Zheng ^{*}
Alibaba Group
james.zz@alibaba-inc.com

Zhongzhu Zhou
University of Sydney
zhongzhu.zhou@sydney.edu.au

Wei Lin
Alibaba Group
weilin.lw@alibaba-inc.com

Yuchao Li
Alibaba Group
laiyin.lyc@alibaba-inc.com

Xiafei Qiu
Alibaba Group
xiafei.qiuxf@alibaba-inc.com

Shuaiwen Leon Song
University of Sydney
shuaiwen.song@sydney.edu.au

ABSTRACT

With the fast growth of parameter size, it becomes increasingly challenging to deploy large generative models as they typically require large GPU memory consumption and massive computation. Unstructured model pruning has been a common approach to reduce both GPU memory footprint and the overall computation while retaining good model accuracy. However, the existing solutions do not provide an efficient support for handling unstructured sparsity on modern GPUs, especially on the highly-structured tensor core hardware. Therefore, we propose Flash-LLM for enabling low-cost and highly efficient large generative model inference with the sophisticated support of unstructured sparsity on high-performance but highly restrictive tensor cores. Based on our key observation that the main bottleneck of generative model inference is the several skinny matrix multiplications for which tensor cores would be significantly under-utilized due to low computational intensity, we propose a general *Load-as-Sparse and Compute-as-Dense* methodology for unstructured sparse matrix multiplication (SpMM). The basic insight is to address the significant memory bandwidth bottleneck while tolerating redundant computations that are not critical for end-to-end performance on tensor cores. Based on this, we design an effective software framework for tensor core based unstructured SpMM, leveraging on-chip resources for efficient sparse data extraction and computation/memory-access overlapping. Extensive evaluations demonstrate that (1) at SpMM kernel level, Flash-LLM significantly outperforms the state-of-the-art library, i.e., Sputnik and SparTA by an average of 2.9× and 1.5×, respectively. (2) At end-to-end framework level on OPT-30B/66B/175B models, for *tokens per GPU-second*, Flash-LLM achieves up to 3.8× and 3.6× improvement over DeepSpeed and FasterTransformer, respectively, with significantly lower inference cost.

PVLDB Reference Format:

Haojun Xia, Zhen Zheng, Yuchao Li, Donglin Zhuang, Zhongzhu Zhou, Xiafei Qiu, Yong Li, Wei Lin, and Shuaiwen Leon Song. Flash-LLM: Enabling Cost-Effective and Highly-Efficient Large Generative Model Inference with Unstructured Sparsity. PVLDB, 17(2): 211 - 224, 2023. doi:10.14778/3626292.3626303

This work is licensed under the Creative Commons BY-NC-ND 4.0 International License. Visit <https://creativecommons.org/licenses/by-nc-nd/4.0/> to view a copy of

PVLDB Artifact Availability:

The source code, data, and/or other artifacts have been made available at <https://github.com/AlibabaResearch/flash-llm>.

1 INTRODUCTION

Generative models have demonstrated their effectiveness across a wide range of language and data management tasks [3, 34, 45, 52, 53]. However, with the rapid growth of the parameter size (e.g. GPT-2 [45] 1.5 billion, GPT-3 [3] 175 billion, and Megatron-Turing NLG [50] 530 billion), it becomes increasingly challenging to efficiently deploy these models. On one hand, their weights could be too large to be placed on GPUs. For example, GPT-3 model requires 350GB memory to store only the parameters with FP16 data type, whereas the NVIDIA A100 GPU [36] only has up to 80 GB memory. On the other hand, these models also cause high inference latency due to the massive amounts of computation and memory access.

There are three basic characteristics for practical model inference: accuracy, efficiency (i.e., latency and throughput), and cost (i.e., how much hardware resource it consumes). The common approach to deploy large models by partitioning the model weights onto multiple devices [49, 63] could suffer from high cost and low efficiency. On one hand, for data-center production scenarios, using multiple GPUs for a single inference of a single model leads to a low ROI (return on investment) and can be too costly in practice. On the other hand, this conventional approach requires extra cross-device communication, further exacerbating the efficiency problem. GPU memory offloading and swapping is another approach to support large weights given limited GPU memory [1, 48]. However, the offloading and swapping approaches usually result in a long inference latency and thus can be impractical for online inference services.

this license. For any use beyond those covered by this license, obtain permission by emailing info@vldb.org. Copyright is held by the owner/author(s). Publication rights licensed to the VLDB Endowment.

Proceedings of the VLDB Endowment, Vol. 17, No. 2 ISSN 2150-8097. doi:10.14778/3626292.3626303

^{*} Haojun and Zhen contributed equally.

[†] Part of the work was done when Haojun was interned at Alibaba.

The weight pruning methods [16] (sparsification) have been demonstrated to be effective in reducing memory usage and computations for model inference while retaining good accuracy through removing a portion of less salient connections in neural networks. In practice, unstructured pruning typically retains better accuracy than more restrictive structured pruning [8, 12, 14, 16, 28, 51, 54]. However, it is difficult to support unstructured sparsity on modern GPU architectures efficiently. Thus, this design direction has been largely neglected so far since a practical speedup is tough to achieve. For example, the state-of-the-art unstructured SpMM implementations (e.g. cuSPARSE [40], Sputnik [10]) can not even outperform their dense counterpart (cuBLAS [39]) until the model sparsity is higher than 98% and 86%, respectively.

To address this critical issue that bottlenecks LLM inference performance, we propose Flash-LLM, an efficient GPU library to support unstructured sparsity on tensor cores for large generative model inference. With unstructured sparsity, Flash-LLM addresses the memory footprint problem which leads to lower costs while retaining high model accuracy. By leveraging tensor cores’ high peak performance, Flash-LLM achieves lower latency for unstructured SpMM compared to the existing sparse/dense MatMul (Matrix Multiply) solutions. The high-level design insight of Flash-LLM is the *Load-as-Sparse and Compute-as-Dense* strategy. We observe that the key MatMuls in generative model inference are very *skinny*. Furthermore, the performance of these skinny MatMuls is bound by global memory bandwidth rather than the computation capability of tensor cores. Thus, we propose to support unstructured sparsity on tensor cores by leveraging sparse memory load to reduce global memory access while effectively utilizing the dense tensor cores for high-performance computations (Section 3.2).

Given the insight above, it is still challenging to actually design and implement this high-level *Load-as-Sparse and Compute-as-Dense* approach. First, it requires a well-designed data format for efficient sparse data storage and extraction. The sparse data extraction is also non-trivial, which requires a sophisticated design to load and extract sparse data with minimal access cost in the hierarchical GPU memory given limited on-chip memory resources. It also introduces new challenges in designing the MatMul computation pipeline beyond conventional dense MatMul strategies. In Flash-LLM, we propose a new sparse format called *Tiled-CSL* to support the tile-by-tile SpMM execution with tensor cores (Section 4.3.1). Based on *Tiled-CSL*, we then design the *sparse-to-dense transformation* approach carefully by using the distributed registers and shared memory as buffers for sparse data extraction (Section 4.1). Then, an efficient *two-level overlapping strategy of memory and computation* is introduced to coordinate the *sparse-to-dense transformation* on weights, the dense feature map data loading, and the tensor core operations with a full software pipeline (Section 4.2). Finally, we propose an *ahead-of-time sparse data reordering* approach to reduce shared memory bank conflicts (Section 4.3.3). In summary, this paper makes the following contributions:

- We propose Flash-LLM, the first cost-effective and highly efficient software framework for large generative model inference, opening up the scope of enabling unstructured sparsity exploration on high-performance tensor cores.
- We propose a general *Load-as-Sparse and Compute-as-Dense* approach to reduce memory footprint and increase the efficiency of

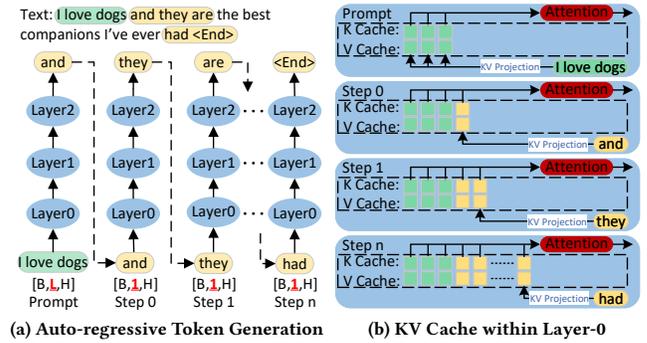


Figure 1: (a) Generative model inference; (b) KV-Cache.

the key skinny MatMuls by leveraging the insight of addressing the major memory bandwidth bottleneck in LLM inference.

- We propose an efficient software pipeline design to enable Flash-LLM by effectively leveraging our new sparse format, the sparse-to-dense transformation, and a two-level overlapping strategy.
- Flash-LLM is implemented and integrated into FasterTransformer for ease-of-use. Extensive evaluation results have shown that (1) at the kernel level, Flash-LLM outperforms the state-of-the-art solutions Sputnik and SparTA by an average of 2.9× and 1.5×, respectively. (2) At end-to-end framework level on OPT-30B/66B/175B models, for *tokens per GPU-second*, Flash-LLM achieves up to 3.8× and 3.6× improvement over DeepSpeed and FasterTransformer, with significantly lower inference cost.

2 BACKGROUND

2.1 Generative Model Inference

Inference Procedure of Modern Generative Models. Modern generative models’ inference is typically conducted in two phases: *prompt processing* and *token generation*. As illustrated in Figure 1a, the generative model first performs *prompt processing* to process user input sequences (*I love dogs*) and generates the first new token (*and*). Then the model turns into the *auto-regressive token generation* phase, where the single output token generated in step $i-1$ will be taken as input to generate the new token in step i iteratively.

In the *prompt processing* phase, multiple tokens within the input sequence will be processed at the same time, resulting in input tensors with shape $[B, L, H]$ (Figure 1a). B , L , and H indicate the *inference batch size*, *prompt sequence length*, and the *model hidden dimension*, respectively. Whereas in the *token generation* phase, only a single token will be taken as input thus forming the input tensors in the shape of $[B, 1, H]$. To prevent re-computations on KV vectors¹, a pre-allocated memory buffer (a.k.a. *KV-Cache* shown in Figure 1b) is usually used during token generation. At each step, a new KV pair is generated (in yellow) and written to the *KV-Cache*. **Inference Performance Hotspot of LLMs.** Figure 2 illustrates the typical decoder architecture of a single layer in modern attention-based generative models. There are four major *MatMuls*: *QKV Projection*, *Output Projection*, *MLP1*, and *MLP2*. Unlike encoder-centric non-generative language models (e.g., BERT [22]), generative model

¹K and V vectors of previous tokens are needed due to *attention* [55] mechanism.

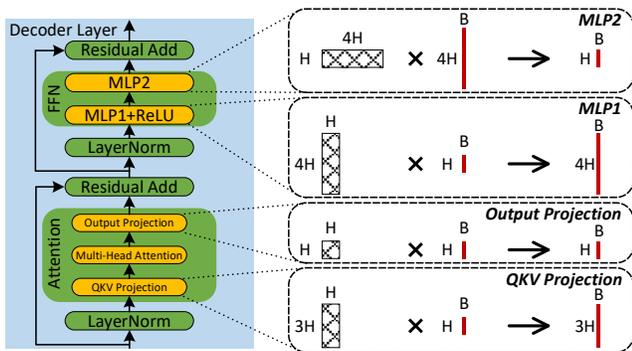


Figure 2: Decoder Layer Architecture. The H here means the hidden dimension aka. model dimension, which equals 12K for GPT-3. The B refers to the inference batch size which is typically small for real-time inference, e.g. 8, 16, or 32.

inference’s performance is heavily bounded by these four MatMuls. According to our experiments on OPT-66B [61] inference, these four MatMuls are the top contributors to the end-to-end inference latency (76.8%) and the overall GPU memory consumption (83.8%).

2.2 Matrix Multiply in LLM Inference

Skinny Matrix Multiply. The Matrix Multiply (MatMuls) in Figure 2 can be formalized as $C = A \times B$, where A is the weight matrix of shape $[M, K]$ and B is the feature map matrix of shape $[K, N]$. In this paper, we call these MatMuls “Skinny MatMuls”, as their N dimensions are much smaller than the M and K dimensions.²

Differences between Tensor/SIMT cores. SIMT cores are general-purpose execution units that handle a wide range of instructions for parallel execution. In contrast, tensor cores [36, 38] are specialized units, which provide significant acceleration for dense MatMuls. Conventional techniques leveraging SIMT cores for sparse MatMuls can not be directly applied to tensor cores as SIMT and tensor cores work at very different granularity. SIMT cores work on the granularity of scalar values. The per-element granularity makes it easy to do computation skipping at the element level for SpMM. However, tensor cores work at a much more coarse-grained granularity than SIMT cores, e.g. performing a MatMul between two matrices of shape 16×16 and 16×8 in a single instruction. Thus, tensor cores do not allow skipping arbitrary element-level computations.

3 OPPORTUNITIES AND INSIGHTS

3.1 Unstructured Sparsity on Tensor Cores

There are two typical types of pruning principles. The most flexible pruning strategy (*unstructured sparsity*) is to remove less salient elements without considering the distribution of the pruned elements in the weight matrix. Taking *magnitude pruning* for example, we rank all the elements in the matrix based on their absolute values and then remove the weights with the smallest magnitude. Another strategy (*structured sparsity*) is to prune the less salient weights, but at the same time, enforce some kind of structural criteria. For

²For these MatMuls, M and K are integer multiples of hidden size while N equals inference batch size (typically orders of magnitude smaller than hidden size).

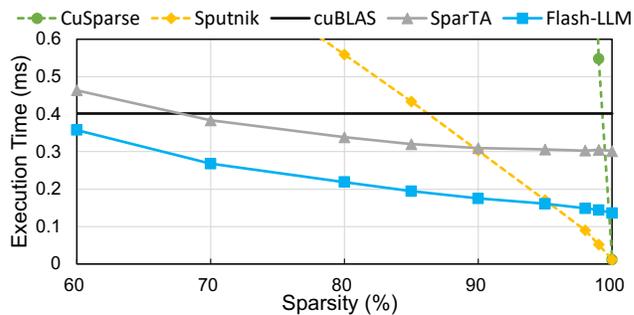


Figure 3: Performance of an unstructured SpMM ($M/K/N = \text{hidden_size}^4 / \text{hidden_size} / \text{batch_size} = 36K/9K/8$) under different designs on GPU. SIMT core centric designs are indicated with dash lines while tensor core centric designs are indicated with solid lines (including our solution Flash-LLM).

example, the weight matrices can be split into non-overlapping 8×1 vectors [4, 25] or 32×32 blocks [13], and then each vector/block is either kept or removed during pruning. In short, the major difference is that extra constraints must be satisfied for structured pruning compared to unstructured pruning. Even though structured sparsity is friendly for hardware acceleration, it suffers from more severe model accuracy degradation [8, 12, 14, 16, 51, 54] as it limits the freedom of deciding which element to prune. As shown in [28], compared to structured sparsity which has a 5% accuracy drop, unstructured sparsity only results in a 1% accuracy drop. In our experiments, model accuracy could be greatly preserved through finetuning-based unstructured pruning [15, 29] at 80% sparsity (e.g., the accuracy only decreases from 85.55% to 84.11% for OPT-30B).

However, the conventional techniques for supporting random unstructured sparsity in SpMM execution are not effective since they focus on leveraging SIMT cores without a sophisticated way of utilizing high-performance tensor cores. Figure 3 shows the performance comparison of different techniques for SpMM on an OPT-66B inference task with batch size 8. Note that the standard pruning for LLM inference typically requires a moderate level of sparsity (e.g., 80%) to preserve model quality while reducing memory footprint. CuSparse [40], the NVIDIA SpMM library, shows poor performance as it is mainly designed for scientific applications where matrices are extremely (99%+) sparse. Sputnik [10], the state-of-the-art SIMT-core-centric design for unstructured SpMM on deep learning tasks still cannot outperform cuBLAS(dense) until a high sparsity is reached.

We observe that existing sparse MatMul kernels are usually slower than their dense counterpart (cuBLAS[39]). The reason is that cuBLAS have leveraged the tensor cores, while sparse MatMul kernels are leveraging SIMT cores in state-of-the-art solutions. Note that A100 GPU [36] can provide $16\times$ higher computational throughput using tensor cores than using SIMT cores for mixed-precision dense MatMuls. Although Sputnik can effectively leverage SIMT cores for unstructured sparsity processing, its performance is still limited by the peak performance of SIMT cores.

Due to the clear peak performance discrepancy between SIMT and tensor cores, there is a strong demand for high-performance

unstructured SpMM support for LLM inference. However, it is *non-trivial to enable high-performance unstructured SpMM onto the highly restrictive tensor cores as tensor cores do not allow skipping arbitrary scalar-level computations (described in Section 2.2)*. Previous SpMM works are based either on highly structured sparse matrices [4, 13, 18] (not random unstructured sparsity), or for extremely high sparsity ratio [57] (i.e., >95%), rather than unstructured sparsity at a moderate sparsity ratio range for high accuracy. SparTA[65] leverages sparse tensor cores [32] for major computations. However, it cannot effectively exploit high sparsity as sparse tensor cores only support 50% sparsity (i.e., 2:4 sparsity). As shown in Figure 3, the performance of SparTA is lower than Flash-LLM especially as the sparsity increases.

3.2 Design Opportunities

Given that tensor cores can only support highly structured computations, it is not practical to directly map the unstructured sparse computations to tensor cores. The unique design opportunity here is that *we can still achieve significant speedups without skipping any computations compared to dense MatMuls, according to the workload characteristics of modern LLMs*. The reason is that MatMuls in modern LLMs inference are skinny and the execution of skinny MatMuls is limited by off-chip memory bandwidth instead of arithmetic throughput of tensor cores. The benefit of not skipping computation related to the pruned weights is that the computation will be preserved as dense and structured. Based on this insight, we proposed the **Load-as-Sparse Compute-as-Dense (LSCD)** approach. Specifically, weight matrices are loaded from global memory in sparse format with reduced size to mitigate the bandwidth bottleneck. The corresponding dense format of weights is then reconstructed in runtime before being consumed by tensor cores for dense computations. We describe how off-chip memory transactions become the performance bottleneck in Section 3.2.1, and how much improvement can be achieved with LSCD in Section 3.2.2.

3.2.1 Performance Bottleneck of Skinny MatMuls in LLM Inference. We analyze the performance bottleneck of skinny MatMuls execution starting from dense MatMul workloads in LLMs. According to our profiling results for OPT-66B [61], the average utilization of tensor cores is around 5.0%, 10.1%, 19.9%, and 39.7% under typical batch sizes of 8, 16, 32 and 64 as shown in Figure 4, while the bandwidth of global memory is already fully saturated. The underlying cause for this is that the compute intensity (i.e., FLOP/Byte) of skinny MatMul is very low. For a MatMul described in Section 2.2, the total operations conducted are $2MNK$ floating-point operations (FLOP), and the corresponding data read is $2(MK + KN)$ bytes with FP16 data type. Thus, the computational intensity (CI) is:

$$CI = \frac{M \times N}{M + N} \quad (1)$$

According to Equation 1, it is easy to demonstrate that the overall CI of a MatMul can be easily restricted by either a small M or N dimension. For instance, for a skinny MatMul where N is 16, CI will have a strict upper bound of 16 no matter how big the M dimension is. Note that in generative LLM models, the N dimension equals the inference batch size which is usually very small in production environments. Thus, the CI is strongly bounded by the N dimension in real-time LLM inference. According to the roofline model [58],

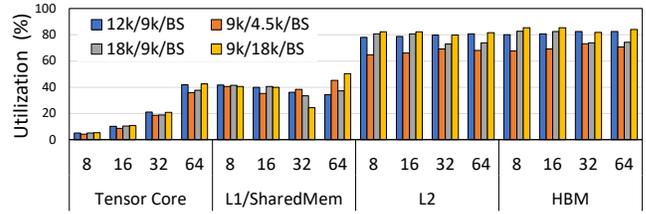


Figure 4: GPU utilization Breakdown. The MatMuls profiled in this figure are the most time-consuming parts during OPT-66B inference (with 2 GPUs) at batch sizes 16, 32, 64, and 128.

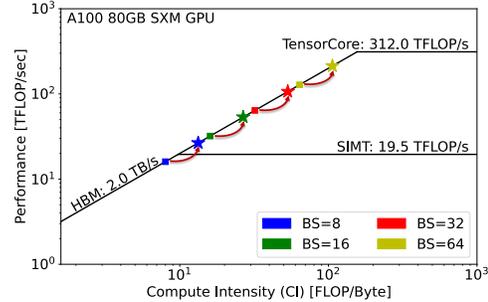


Figure 5: Roofline model for skinny MatMuls. The solid Squares refer to the CI and the performance upper bound for dense solutions (e.g. cuBLAS), while the solid Stars represent the improved CI and the new performance bound with our LSCD. Note that each axis is displayed on a logarithmic scale.

the performance of a kernel with low computational intensity will be easily bounded by memory bandwidth.

3.2.2 Load as Sparse, Compute as Dense. Given that the bottleneck of skinny MatMul comes from memory access/memory bandwidth rather than arithmetic computation, we propose the basic idea of *Load-as-Sparse and Compute-as-Dense* here which leverages the performance boost from reduced memory access while enabling the efficient use of tensor cores for unstructured sparsity (refer to Section 4 for details). Under this idea, given the sparsity ratio β , the computational intensity can be improved to:

$$CI_{SparseLoad}^3 = \frac{M \times N}{M \times (1 - \beta) + N} \quad (2)$$

Figure 5 shows the CIs and their corresponding achievable tensor core performance of a typical MatMul (M : 48k, N : BS, K : 12k) in OPT-175B model inference with different batch sizes. According to the figure, MatMuls in generative model inference with different batch sizes all face memory wall issues. As a result, the dense MatMuls kernels can only achieve 5.1%, 10.3%, 20.5%, and 40.1% peak performance of tensor cores bounded by insufficient global memory bandwidth. These theoretical values are consistent with our actual measurements in Figure 4. In theory, with *Load-as-Sparse and Compute-as-Dense* approach under 40% sparsity, the tensor cores utilization can be improved to 8.5%, 17.1%, 34.2%, and 68.2%.

³It’s worth noting that we do not take sparse index overhead into the theoretical consideration here. In practice, the real CI would be a bit lower than this equation.

4 DESIGN METHODOLOGY

Flash-LLM leverages both SIMT cores and tensor cores effectively for efficient unstructured SpMM computation. The flexible SIMT cores are exploited for *Sparse-to-Dense Transformation* (i.e., *Load-as-Sparse*) while tensor cores are used for compute-intensive tensor computations (i.e., *Compute-as-Dense*). We give an overview of the high-level optimizations of Flash-LLM in Section 4.1. Then we describe the design of Flash-LLM’s computation pipeline in Section 4.2. We illustrate the novel sparse format and the memory access techniques in Section 4.3. Finally, we described the end-to-end inference system enabled by our Flash-LLM in Section 5.

4.1 Design Overview

We use the tiling-based approach for the SpMM computations in Flash-LLM, shown in Figure 6a. Each thread block (TB) is in charge of calculating a tile (e.g., the green tile in the shape of $M_{TB} * N_{TB}$) in the output matrix C . For each iteration, each thread block loads A_{Tile} (shape $[M_{TB}, K_{TB}]$) in sparse and B_{Tile} (shape $[K_{TB}, N_{TB}]$) in dense from global memory. A_{Tile} is then transformed to dense format with *Sparse-to-Dense Transformation* shown in Figure 6b and stored in shared memory while B_{Tile} is directly stored in shared memory. Finally, each thread block consumes the dense data in shared memory and generates the output tile. Figure 6b shows the overall kernel behavior of Flash-LLM from the microarchitecture aspect. Shared memory is used as the workspace for *Sparse-to-Dense Transformation*, where all threads within the thread block work together collaboratively to load sparse encoding (SE)⁴ of A_{Tile} from global memory and extract them to shared memory with the dense format. Specifically, the basic idea of *Sparse-to-Dense Transformation* is extracting non-zero elements from the sparse encoding to their corresponding locations in the dense format on shared memory while other locations are padded with zeros. We use the distributed registers as the intermediate buffer to store the sparse encoding before extracting them to shared memory. We do not use shared memory as this intermediate buffer to avoid the turn-around shared memory access of the sparse encoding.

4.2 Computation Pipeline Design of Flash-LLM

Given that each thread consumes a large fraction of the overall registers/shared memory as buffers for tiling, the thread-level parallelism (TLP) is inherently low. Thus, it is important to optimize the instruction-level parallelism. We describe the software pipeline of Flash-LLM in this section where the memory accesses and tensor core computations are processed in parallel efficiently.

4.2.1 Two-level Overlapping of Memory and Computation. It requires several stages to load the sparse encoding from the global memory to shared memory in dense format for each A_{Tile} . Specifically, it requires loading sparse encoding from global memory to the distributed registers (*gmem2reg* stage), resetting the shared memory buffer with zero (*rst_smem* stage), and extracting the sparse encoding from registers to shared memory (*extract* stage). As for B_{Tile} , which is already in dense format, it can be loaded directly from global memory to the shared memory buffer (*ld_dense* stage).

⁴We refer to the data of A in the sparse format as *sparse encoding*. Each tile of the weight matrix is encoded into sparse encoding with fewer bytes than the dense format.

Finally, the *smem2tc* stage loads the A_{Tile} and B_{Tile} from shared memory to registers for tensor core computations.

As shown in Figure 6c, Flash-LLM exploits a two-level overlapping of the above memory and computation stages for efficient execution. On one hand, it leverages double-buffering to overlap off-chip memory loads with tensor core computation, called *inter-iteration overlapping*. On the other hand, it overlaps the stages of off-chip memory load within *Sparse-to-Dense transformation* for more efficient memory activities, called *intra-iteration overlapping*. The horizontal axis of Figure 6c represents the execution time while the vertical axis represents the on-chip buffers. It uses two shared memory buffers for A_{Tile} (corresponds to A1 and A2) and B_{Tile} (corresponds to B1 and B2), and one register buffer reused in different iterations (corresponds to SE). Specifically, SE in Iteration-1/3 (SE in Iteration-2/4) and A1 (A2) correspond to the *Sparse-to-Dense transformation* process of A_{Tile} on the first (second) set of buffer, and B1 (B2) corresponds to the data movement of B_{Tile} on the first (second) set of buffer. As for *inter-iteration overlapping*, as shown in Iteration-2 in Figure 6c, while reading from the first set of buffers (A1 and B1) and executing tensor core computations, Flash-LLM loads and extracts data from global memory to the second set of buffers (A2 and B2). As for *intra-iteration overlapping*, the activities of A1 and B1 are processed in parallel, and the *gmem2reg* and *rst_smem* stages on A_{Tile} are also processed in parallel. In this way, the sparse/dense data loading and tensor core operations are overlapped efficiently.

A critical design for *Sparse-to-Dense transformation* is explicitly using registers as data buffers between global memory and shared memory. In Flash-LLM, the sparse encoding movement from global memory to shared memory is explicitly split into two stages, i.e. LDG (loading data from global memory to registers) instructions during *gmem2reg* and STS (storing data to shared memory from registers) instructions during *extract* as shown in Figure 6c. On one hand, the split two-stage design helps to increase instruction-level-parallelism (ILP) to hide high global memory access latency. Note that each pair of LDG and STS instructions has load-use dependency. If we do not split the *gmem2reg* and *extract* into two stages but launch each pair of LDG and STS instructions in the adjacent cycles (e.g. directly storing to shared memory after loading from global memory), each GPU thread will execute instructions in the order of $LDG_0, STS_0, LDG_1, STS_1, \dots$ without effective ILP. By splitting the two instructions into two stages as in Figure 6c, the execution order will be $LDG_0, LDG_1, \dots, STS_0, STS_1, \dots$ and results in a high ILP of global memory load. On the other hand, splitting the data movement into *gmem2reg* and *extract* enables the overlapping opportunity between *gmem2reg* and *rst_smem*. Note that STS instructions within *extract* should not be launched before the completion of *rst_smem* stage. Otherwise, the data written by STS instructions might be overwritten by *rst_smem* incorrectly. The execution of *gmem2reg* and *rst_smem* can be overlapped once the *gmem2reg* contains no shared memory write (all STS instructions are assigned to the *extract* stage), which further increases ILP.

4.2.2 Minimum Range of Synchronizations and Memory Barriers. Given the complex pipeline in Figure 6c, it requires a set of thread

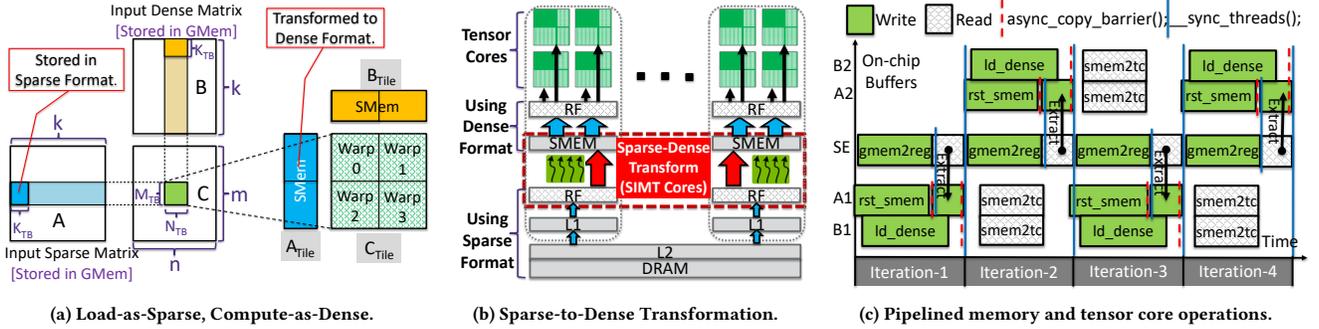


Figure 6: Design Overview.

synchronizations and memory barriers to ensure correctness. Flash-LLM inserts the minimum range of synchronizations and memory barriers to ensure correctness while keeping the overlapping.

To prevent the data written by *extract* from being overwritten incorrectly by *rst_smem*, Flash-LLM inserts the explicit thread-block level synchronization between the two stages to ensure that all the threads have finished their work resetting the A1/A2 buffer in shared memory, shown as the first blue line in each iteration in Figure 6c. Meanwhile, it also requires another synchronization to ensure that all data movements and tensor core operations of the current iteration are completed before starting the next iteration, shown as the second blue line in each iteration. Take Iteration-1 as an example, it must be ensured that all threads have finished writing the A1 and B1 shared memory buffers before we start Iteration-2, as the data in A1 and B1 will be used by tensor cores in Iteration-2. Besides, we have to make sure that all threads have finished reading the data from the SE buffer for *extract* in Iteration-1 before letting the SE buffer be overwritten by the *gmem2reg* in Iteration-2.

In addition to the synchronizations, it also requires memory barriers after asynchronous copy activities of global-to-shared data movement. Flash-LLM makes use of the asynchronous copy primitives for the overlapping of data movement and other activities. Note that the asynchronous copy primitive *cp.async*, starting from NVIDIA Ampere GPU [36], allows moving data from global memory to shared memory in the background asynchronously while executing other computations in the foreground. Specifically, both the *rst_smem* and *ld_dense* stages use the *cp.async* primitives. To enable a fine-grained pipeline execution, Flash-LLM uses different *async-copy* barriers for *rst_smem* and *ld_dense* stages. As shown in Figure 6c, the *extract* stage waits for the completion of only *rst_smem*, while the final thread-block barrier of each iteration waits for the completion of all previous *cp.async* operations. In this way, the *extract* stage could be overlapped with the *ld_dense* stages.

4.2.3 Overall Implementation. Algorithm 1 shows the implementations of the pipelined computation in Flash-LLM. In line 3, the software pipeline will be initialized, preparing the data of A_{Tile} and B_{Tile} on shared memory for the tensor core computations of the first iteration in the main loop. The main iterations described in Figure 6c are implemented in lines 7-28. For each iteration, it issues the instructions for the asynchronous data loading for the

Algorithm 1 Flash-LLM SpMM kernel pseudo code.

```

1: Inputs: SparseMatrix A, Matrix B
2: Output: Matrix C
3: Initialize_Pipeline();
4: offset = subArray(A.offset);
5: int start_prefetch = offset[1];
6: int nnz_prefetch = offset[2] - offset[1];
7: for int id = 0; id < K_Global/K; id ++ do
8:   //Prefetch startIdx and nnz.
9:   int start = start_prefetch;
10:  int nnz = nnz_prefetch;
11:  start_prefetch = offset[id + 2];
12:  nnz_prefetch = offset[id + 3] - offset[id + 2];
13:  //Set pointers for double-buffer.
14:  half* smem_w = smem + ((id + 1)%2) * OFFSET;
15:  half* smem_r = smem + (id%2) * OFFSET;
16:  //Launch Asynchronous Memory Operations.
17:  ▶ rst_smem
18:  cp_async_commit();
19:  CopyGlobal2Reg(A.nz + start, nnz)
20:  CopyGlobal2Shared(smem_w, B.data)
21:  cp_async_commit();
22:  //Math Computations.
23:  Pipelined_Shared2Reg_TensorCoreOps(smem_r);
24:  //barrier: initSharedMem()
25:  cp_async_wait<-1>(); __syncthreads();
26:  ExtractRegister2Shared(smem_w)
27:  //barrier: copyGlobal2Shared().
28:  cp_async_wait<0>(); __syncthreads();
29: results_Reg2Global(C.data);

```

next iteration and does the tensor core computation of the current iteration in a double buffer manner. Specifically, one A_{Tile} for the next iteration will be loaded and extracted from global memory to shared memory (*rst_smem*, *gmem2reg*, and *extract*), and one dense B_{Tile} will be loaded directly from global memory (*ld_dense*). The *rst_smem* stage is in line 17, where each thread issues *cp.async* operation to set buffer A to zeros. In line 19, *gmem2reg* is accomplished, where sparse encoding is loaded from global memory to the distributed registers. The *ld_dense* stage is in line 20, where the data for B_{Tile} is loaded from global memory to shared memory buffer with *cp.async* operations. After launching these asynchronous memory operations, tensor core operations are launched in line 23. Note that we load dense matrices from shared memory to registers using *ldmatrix.sync* instruction and utilize tensor cores for the core computations by explicitly launching *mma.sync* instruction in the function *Pipelined_Shared2Reg_TensorCoreOps()*.

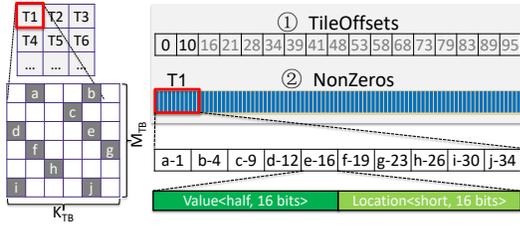


Figure 7: Tiled-CSL Format for sparse matrices.

The first async-copy barrier in Figure 6c is in line 25, guaranteeing that all asynchronous operations launched in line 17 are completed while the operations launched in line 20 can still be in progress. The *extract* stage is in line 26, where the data in registers are extracted to the shared memory buffer for A_{Tile} . Finally, the async-copy barrier and thread-block synchronization are called in line 28 to make sure that all threads have completed their work in this iteration.

Different from dense MatMul where the data size to be loaded from global memory can be inferred by the tile sizes, the size of sparse encoding is determined by the number of non-zeros (nnz) within A_{Tile} , which is unpredictable. Before loading the sparse encoding of each tile, Flash-LLM identifies its start offset in global memory and its size. Such information is maintained in *TileOffsets* array, which is stored in global memory (more details in Section 4.3). To avoid instruction stalls caused by long latency global memory access, this metadata should be pre-fetched. In lines 5-6 and lines 11-12, the start offset and the size of sparse encoding are pre-fetched. At the beginning of each iteration, the start offset and the size of the current A_{Tile} are updated using the value pre-fetched in advance.

4.3 Sparse Encoding and Runtime Parsing

4.3.1 Tiled-CSL Format. The design of the sparse format for A matrix is essential for efficient sparse data storage and *Sparse-to-Dense Transformation*. We propose a tile-by-tile sparse encoding format to support the optimizations in Section 4.2 effectively. The non-zero elements are organized tile-by-tile, where each tile maintains its non-zero elements accompanied by the sparse index. As shown in Figure 7, the non-zeros of each tile within the sparse matrix are encoded into a small array, and combining all tiles will form the overall array (*NonZeros Array*). The *TileOffsets Array* maintains the starting offset of each tile in *NonZeros Array*. The number of non-zero elements for each tile is the difference of two adjacent elements in *TileOffsets Array*. For each tile in *NonZeros Array*, each element is stored along with its location within the tile. As shown in Figure 7, each non-zero weight is a 16-bit float-point and each location is encoded into a 16-bit short integer.

4.3.2 Register to Shared Memory Extraction. As described in Algorithm 2, each thread extracts nnz_thread non-zero values from its sparse encoding buffer $Reg[]$ to the shared memory buffer A with a loop. The $v()$ and $idx()$ functions are used to extract the value (high 16 bits) and its location (low 16 bits). There are some special considerations when using registers as intermediate buffers for sparse encoding. Different from shared memory and global memory, GPU

registers are not addressable. Forcing an array defined in CUDA into registers requires that, all the indices used to access the array can be determined statically at compile-time. Otherwise, the array will be stored in global memory instead. In line 1 of Algorithm 2, `#pragma unroll` is used to notify the GPU compiler to fully unroll the main loop, so that all the indices used to access the $Reg[]$ can be determined statically. Note that adding such compiling directive alone is not enough as a loop with a variable number of iterations can not be fully unrolled. Thus, we use a constant value $\#REG$ (the upper bound of the number of iterations, typically 32/64 in Flash-LLM) in line 2 instead of using the variable value nnz_thread .

Algorithm 2 ExtractRegister2Shared

```

1: #pragma unroll
2: for int i = 0; i < #REG; i ++ do
3:   if i ≥ nnz_thread then
4:     break
5:   A[idx(Reg[i])] = v(Reg[i])

```

4.3.3 Ahead of Time Sparse Data Reordering. There are two types of shared memory access for the sparse weight matrix A , including the data reading in *smem2tc* stage and the data writing in *extract* stage. It is essential to avoid bank conflict⁵ for good performance. However, the random sparsity makes it challenging to avoid bank conflict for both *smem2tc* and *extract* stages.

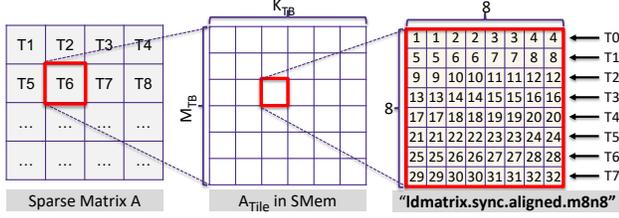
As for *smem2tc*, it makes use of *ldmatrix* intrinsic for efficient data loading from shared memory for tensor core computation. Figure 8a shows the behavior of *ldmatrix* where eight threads collectively load an 8×8 matrix in FP16 from shared memory. This 8×8 matrix reading can be served by a single shared memory wavefront⁶ if there is no bank conflict. The bank-conflict-free memory load of *ldmatrix* requires that all scalars within the 8×8 matrix can be read from disjoint memory banks. Figure 8a shows an example shared memory data layout demonstrating the bank assignment (bank ID ranging from 1 to 32) to achieve bank-conflict-free *ldmatrix*, where each scalar is assigned a bank ID according to its location in A_{Tile} .

However, this memory layout requirement will easily cause bank conflict of shared memory writing during *extract* stage due to the random position of the non-zeros in matrix A . In other words, we can guarantee the bank-conflict-free reading according to the layout requirement of *ldmatrix*, but will cause bank-conflict writing during *extract*. Figure 8b gives an example, where each non-zero value should be stored in a target shared memory bank (SMem-Bank) according to their relative position within A_{Tile} to meet the requirement of bank-conflict-free *ldmatrix*. As the distribution of NonZeros is random, the target SMemBank for each NonZero value is also random. As a result in Figure 8b, all WARPs (the NonZeros in the same color are processed by the same WARP) suffer from bank conflict and lead to multiple shared memory wavefront (SMem WF).

To reduce the bank conflict, we propose the *ahead of time sparse data reordering* approach. The basic insight is that the bank-conflict-free *ldmatrix* already determines the target bank of each data element, we can thus reorder the data elements in each *Tiled-CSL* tile

⁵Shared memory is divided into multiple memory banks that can be accessed simultaneously. Bank conflict means multiple addresses of a memory request map to the same memory bank, causing serialized accesses.

⁶A *wavefront* is the maximum unit of work that can pass through the GPU hardware pipeline per cycle. At most 1,024 bits can be loaded per wavefront for shared memory.



(a) "Ldmatrix" intrinsic loads an 8x8 matrix from shared memory each time.

NonZeros	0.1	0.3	-1.1	7.4	-0.9	1.1	3.4	1.4	-0.7	0.5	3.2	0.2	1.5	-0.9	-0.5	0.3	-1.1	-0.3	3.1	1.7	...	
Locations
SMemBank	1	4	4	1	3	3	2	4	3	2	2	2	1	2	3	1	3	4	1	4	...	

2 SMem WF. 2 SMem WF. 3 SMem WF. 2 SMem WF. 2 SMem WF.

(b) Bank conflicts during *ExtractRegister2Shared*. (WARP size and SMem banks are reduced from 32 to 4 for simplicity.)

NonZeros	0.1	3.4	-0.9	0.3	7.4	0.5	1.1	-1.1	1.5	3.2	-0.7	1.4	0.3	0.2	-0.5	-0.3	3.1	-0.9	1.1	1.7	...	
Locations
SMemBank	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	...	

1 SMem WF. 1 SMem WF. 1 SMem WF. 1 SMem WF. 1 SMem WF.

(c) No conflict after Sparse Data Reorder.

Figure 8: Ahead of time sparse data reordering.

so that elements correspond to different banks could be organized into the same WARP for *extract*. Specifically, we iteratively select the sparse element that corresponds to different memory banks when generating the NonZeros sub-array for each *Tiled-CSL* tile. Figure 8c shows an ideal case after data reordering where only one shared memory wavefront is needed to serve one WARP executing *extract*. Note that the data reordering here only changes the layout of the sparse data but does not change the content of the corresponding dense matrix. In short, it is a way to change the layout on global memory for more efficient shared memory access.

Algorithm 3 Tiled-CSL_Gen_AOTSparseDataReordering

```

1: Input: Matrix A in size  $M \times K$ ;
2: Output1: vector<vector<unsigned int>> NonZeros;
3: Output2: vector<int> TileOffsets;
4: vector<unsigned int> NZ_Bucket[32];
5: for int i = 0; i < M/128; i ++ do
6:   for int j = 0; j < K/64; j ++ do
7:     // classifying NonZeros.
8:     half *TilePTR = A + i * 128 * K + j * 64;
9:     for int x = 0; x < 128; x ++ do
10:      for int y = 0; y < 64; y ++ do
11:        val = TilePTR[x * K + y];
12:        short loc = location_in_SMem(x, y);
13:        int BankID = (x%8) * 4 + (y%8)/2;
14:        NZ_Bucket[BankID].push_back(val, loc);
15:     // iteratively picking 32 NonZeros as a group.
16:     int NNZ = count_NNZ(NZ_Bucket);
17:     for int g = 0; g < NNZ/32; g ++ do
18:       vector<unsigned int> NZ_group;
19:       for int b = 0; b < 32; b ++ do
20:         int id = BankID_Max(NZ_Bucket);
21:         NZ_Group.push_back(NZ_Bucket[id].back());
22:         NZ_Bucket[id].pop_back();
23:       NonZeros.push_back(NZ_group);
24:       TileOffset.push_back(NNZ);

```

Algorithm 3 shows the algorithm to generate *Tiled-CSL* format from the pruned weight matrix with *ahead of time sparse data reordering* applied. The input is the sparse matrix A with M rows and K columns in dense format, where some elements are already set to 0 through model pruning. The outputs are *NonZeros* and *TileOffsets*, the key components of *Tiled-CSL* format. *NonZeros* are split into groups each of which contains 32 non-zeros. At lines 7-24, the *Tiled-CSL* format of one tile (128×64) will be generated. At lines 11-14, each non-zero within matrix A will be encoded into a 32-bit word containing (*val, loc*). Besides, non-zeros are distributed to 32 different buckets ($NZ_Bucket[32]$ at line 4) according to their target shared memory bank ID ranging from 0 to 31 as calculated in line 13. In line 16, the total number of non-zeros (NNZ) is counted. At line 19-22, one group of non-zeros are formed by iteratively picking non-zeros from $NZ_Bucket[id]$ where $NZ_Bucket[id]$ is the bucket with the most non-zeros not processed at that time.

5 IMPLEMENTATION

We provide a set of C++ APIs for high-performance Flash-LLM kernel. We integrate Flash-LLM kernel into FasterTransformer [37], enabling high-efficiency distributed inference with sparsified weight matrices. Specifically, we extended its corresponding class definition (i.e. *DenseWeight* class) to support the *Tiled-CSL* format. Besides, we extended its library wrapper (i.e., *cuBlasMMWrapper* class) to support calling either the dense MatMul library or Flash-LLM SpMM kernel. Flash-LLM can also be easily integrated into other deep learning frameworks through library calls with Flash-LLM API. We also provide a weight reformatting tool to generate sparse matrices in *Tiled-CSL* format given the dense PyTorch model.

In our implementation, the size of M_{TB} in Figure 6a is 128 or 256, K_{TB} is 64, and N_{TB} is 8/16/32/32 when the N dimension of MatMul (inference batch size) is 8/16/32/64. For larger N dimensions, the N_{TB} is 64. The thread block size is 128. These configurations work well for the workloads we evaluated in Section 6. The configuration tuning is not in the research scope of this paper.

6 EVALUATION

We evaluate the performance of Flash-LLM on two levels: kernel-level benchmarking and model-level evaluation. The evaluation is conducted on the NVIDIA A100-SMX8-80GB platform (128-core Intel Xeon Platinum 8369B CPU @2.90GHz, 8 NVIDIA A100 GPU @80GB), with Ubuntu 18.04 and CUDA 11.8. We enable auto-mixed precision (AMP) for all evaluations. We mainly do experiments on NVIDIA A100 GPUs. However, the method we proposed is also a good reference for the kernel design of TPU and Intel CPUs that are equipped with customized hardware for matrix multiplication.

6.1 Kernel Performance

Workloads, baselines, and settings. We evaluate Flash-LLM on MatMuls under different shapes, coming from the four MatMuls described in Section 2.1 within OPT-30B, OPT-66B, and OPT-175B [61] given four different batch sizes (8, 16, 32, and 64). For each MatMul shape, we evaluate the kernel latency under 70%, 80%, and 90% of random sparsity in the weight matrices. The baselines we compare include cuSPARSE [40], Sputnik (commit: 46e380c) [10, 11], SparTA (commit: 1f61a36) [64, 65], and cuBLAS [39]. CuSPARSE is part of

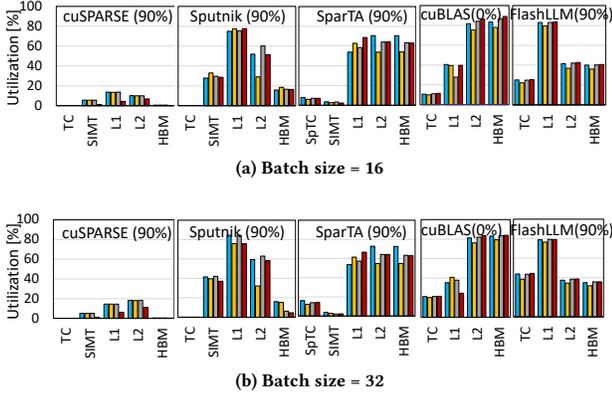


Figure 10: Kernel utilization breakdown with four MatMul shapes (indicated with different colors) from OPT-66B.

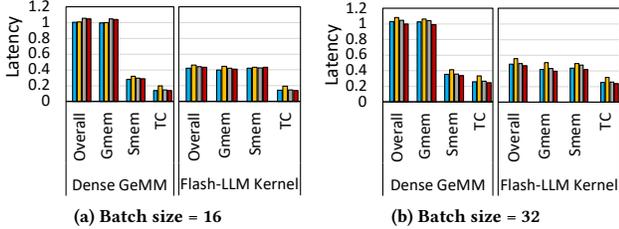


Figure 11: Latency breakdown of Dense and Flash-LLM Kernels (normalized to cuBLAS[39] kernel latency).

Although the Smem latency is increased due to the extra shared memory access required by the *extract* in Figure 6c, it does not prevent Flash-LLM kernel from achieving better performance than cuBLAS. It is a good trade-off between global memory and shared memory utilization. What’s more, Flash-LLM shows similar latency with dense GeMM kernel in terms of tensor core operations as we do not skip any computations. However, tensor core operations are not the bottleneck for the overall kernel performance.

Performance on more MatMul shapes. As discussed in Section 3.2.1, we mainly want to mitigate the inefficiency caused by Skinny MatMuls in common LLM inference. For more comprehensive understanding evaluations, we provide kernel performance on more shapes even when the shape is not common for LLM inferences. As shown in Figure 12, Flash-LLM becomes slower than cuBLAS if the N dimension is larger than 256, noting the memory footprint of Flash-LLM is still smaller than dense counterparts. The reason behind this is twofold. First, the inefficiency of cuBLAS is no longer significant as the N dimension is large enough, which makes cuBLAS more performant. Second, Flash-LLM has more complicated kernel designs and extra shared memory access, which slows it down a little bit. We also notice that Sputnik becomes much slower than other tensor-core-based designs as the N dimension increases. Even though SIMT-core-based solutions such as Sputnik

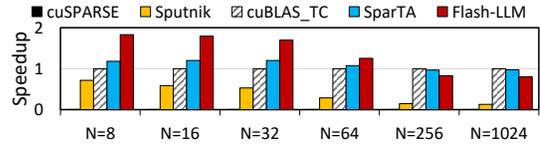


Figure 12: Kernel speedups over cuBLAS [39] GeMM kernel with different shapes (36K/9K/N, sparsity=80%).

Table 1: Peak GPU memory usage (GB).

Batch Size	8	16	32	64	128
Ours-1GPU	34.7	40.8	52.9	77.1	OOM
FT-1GPU	62.7	68.7	OOM	OOM	OOM
DS-1GPU	64.1	70.9	OOM	OOM	OOM
FT-2GPU	65.6	71.7	83.9	108.3	OOM
DS-2GPU	68.3	75.7	90.6	120.4	OOM

can skip computations exploiting sparsity, such computational savings still can not make up for the huge performance gap between SIMT cores and tensor cores.

6.3 End-to-End Model Evaluation

Baselines. We include NVIDIA FasterTransformer (FT) (git commit: 9770d30) [37] and DeepSpeed (DS) [1] as baselines, the state-of-the-art inference frameworks supporting model parallelism [49] to fit large models that would otherwise not fit in GPU memory.

Workloads. We benchmark the end-to-end inference latency of the OPT models [61], including OPT-30B, OPT-66B, and OPT-175B. To accommodate only the model parameters in the dense format, 60/132/350GB GPU memory is required for OPT-30B/66B/175B. Note that SOTA GPUs only have 80GB of memory each, at least 1/2/8 GPUs are required⁷ for the inference of OPT-30B/66B/175B. Besides, extra GPU memory is required to store the KV-Cache (refer to Figure 1b, with its size positively related to inference batch size) during runtime. According to Table 1, existing inference frameworks can easily run out of GPU memory during the inference of OPT-30B for batch sizes larger than 16 if storing the model in dense format. For all experiments, the input/prompt sequence length is 64 and the output/generated sequence length is 512.

Metric. We propose the metric *tokens per GPU-second* to indicate the normalized inference throughput with the consideration of both execution time and hardware cost (i.e., the number of GPUs used). It is calculated with the following equation:

$$Performance = \frac{N_{token}}{\sum_{i=1}^{N_{GPU}} T_i} \quad (3)$$

N_{token} means the number of tokens generated, whereas N_{GPU} and T_i mean the GPU number and the time spent on the i ’th GPU for execution. We use this metric to evaluate the system’s performance. Note that for real-time inference serving, the inference throughput is the higher the better once the inference latency is less than a specific threshold.

6.3.1 Case Study: OPT-30B. Model Pruning. To show that the pruned model has comparable performance with the original model,

⁷The number of GPUs must be a power of 2 for model parallelism[6].

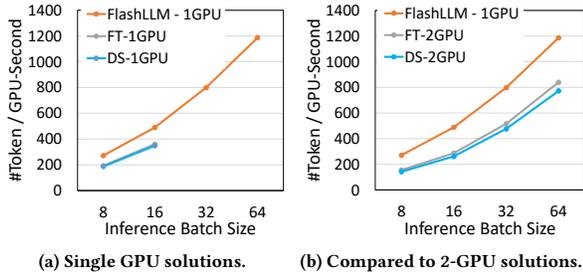


Figure 13: OPT-30B Inference Throughput.

we evaluate the accuracy of the pruned model with OPT-30B [61] and GPT-NEOX-20B [2, 5] on Recognizing Textual Entailment task in SuperGLUE [56]. To achieve better accuracy, we adopt the popular pruning method Taylor Pruning [33] to prune these models and keep the front quarter and the last quarter feedforward input layers dense. Based on that, we achieve 80% sparsity on OPT-30B and GPT-NEOX-20B with only 1.44% and 0.72% accuracy decrease, respectively. Specifically, accuracy decreases from 85.55% to 84.11% on OPT-30B, and from 83.03% to 82.31% on GPT-NEOX-20B.

Results. As shown in Figure 13a, Flash-LLM achieves 3.4× and 3.3× higher performance than DeepSpeed (DS) and FasterTransformer(FT) with a single GPU. DS and FT can at most achieve 348 and 359 *tokens per GPU-second* with a single A100 GPU. If further increase the inference batch size, DS/FT will run out of memory as inference tasks with larger batch sizes need more GPU memory to store the cached-KV and activations. In contrast, Flash-LLM achieves up to 1187 *tokens per GPU-second* on batch size 64. It is because the memory used for storing model weights is reduced with the *Tiled-CSL* format, and thus more Cached-KV and activations can be accommodated. We also compare the performance of Flash-LLM to DS and FT with two-way *model-parallelism*[49], with which DS and FT can support batch size 64. As shown in Figure 13b, FT and DS achieve similar performance in terms of *tokens per GPU-second*. Compared to DS/FT, Flash-LLM achieves 1.91×/1.75×, 1.87×/1.70×, 1.67×/1.55×, and 1.54×/1.41× higher performance at batch sizes 8, 16, 32, and 64 respectively. The detailed GPU memory usage of Flash-LLM, FT, and DS are shown in Table 1.

Breakdown. To figure out why Flash-LLM can achieve better performance, we conduct the time breakdown of end-to-end inference shown in Figure 14a. Note that we conduct all the end-to-end breakdowns in this paper leveraging the NSight System [44]. Compared to FT-2GPU (FasterTransformer with 2 GPU used), Flash-LLM with 1 GPU can achieve lower normalized inference latency⁸ mainly because of (1) the more efficient MatMul execution and (2) the elimination of cross-GPU communication overhead.

6.3.2 Case Study: OPT-66B Model. Result As shown in Figure 15a, Flash-LLM achieves 3.8× and 3.6× higher token generation throughput than DS and FT with two GPUs. DS and FT can at most achieve 139 and 144 *tokens per GPU-second* with batch size

⁸To also consider inference cost and compare the inference efficiency with different system configs (e.g. different numbers of GPUs may be used), we sum the execution time on all used GPUs as the normalized latency.

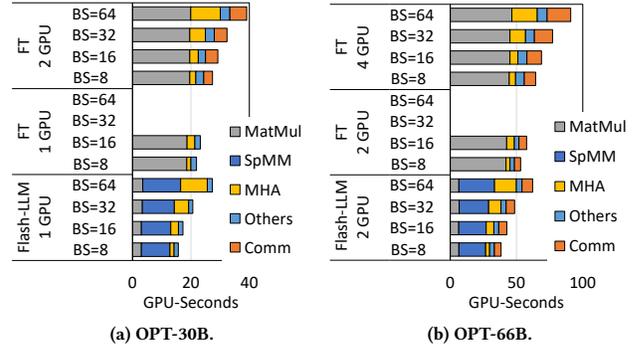


Figure 14: Inference Time Breakdown. (MHA: multi-head attention, Comm: cross-GPU communications)

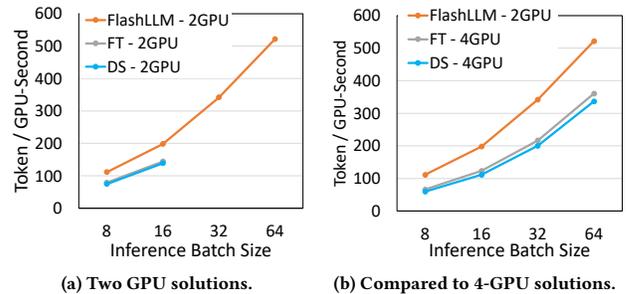


Figure 15: OPT-66B Inference Throughput.

16 as they will run out of memory if further increasing the batch size. In contrast, Flash-LLM achieves up to 522 *tokens per GPU-second* at batch size 64. We also compare the performance of Flash-LLM to DS-4GPU/FT-4GPU where Flash-LLM still uses two GPUs, while DS-4GPU/FT-4GPU uses four GPUs to enable bigger batch sizes for the baselines. Compared to DS-4GPU/FT-4GPU, Flash-LLM achieves 1.85×/1.68×, 1.78×/1.61×, 1.7×/1.58×, and 1.55×/1.45× higher performance of *tokens per GPU-second* at batch sizes 8, 16, 32, and 64 respectively.

Breakdown. We conduct the time breakdown of end-to-end inference with FT and Flash-LLM for OPT-66B as shown in Figure 14b. Compared to FT-4GPU (FasterTransformer with 4 GPU used), Flash-LLM with two GPUs can achieve lower normalized latency than FT-4GPU mainly because of (1) the reduction of MatMul time and (2) the reduction of cross-GPU communication overhead.

6.3.3 Case Study: OPT-175B Model. Results & Breakdown We successfully run the inference of OPT-175B models with Flash-LLM using 4 A100 GPUs. In contrast, the weight of OPT-175B can not fit into 4 A100 GPUs with traditional solutions. Thus, we do not show the performance of FT/DS using 4 GPUs here as they all run out of GPU memory. In addition, we failed to run OPT-175B with DS using 8 GPUs. Figure 16a compares the performance of Flash-LLM and FT where we only use 4 GPUs while FT uses 8 GPUs. Compared to FT-8GPU, Flash-LLM achieves 2.0×, 1.9×, 1.7×, and 1.5× higher performance at batch sizes 8, 16, 32, and 64 respectively.

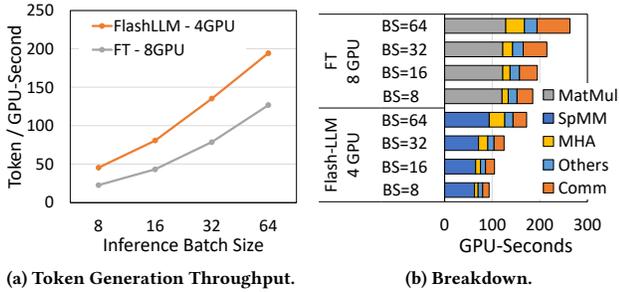


Figure 16: OPT-175B Inference

As shown in Figure 16b, both the MatMul time and the cross-GPU communication time are significantly reduced using Flash-LLM.

7 RELATED WORK AND DISCUSSION

The parallel and distributed ML task execution is widely used for model training [6, 7, 19–21, 24, 26, 27, 30, 31, 35, 46, 49, 60, 62]. With the growth of the model size, people start to support the LLM inference through tensor parallelism [21, 49] to put parameters onto distributed devices [1, 37]. However, the distributed execution of model inference introduces high communication costs and high economic investment. Some works support LLM inference on a single GPU through memory offloading of data onto CPU memory and even disk [1, 48]. The offloading approach only works for latency non-sensitive applications (e.g. offline inference with large batch size), rather than the online inference tasks demanding very low latency. In this work, we enable efficient LLM inference execution with fewer GPUs through efficient SpMM execution.

Model pruning is a common approach to reducing parameter numbers. The structured sparsity is to enforce a structured distribution of non-zero elements during pruning, which usually could be friendly to hardware acceleration. NVIDIA Ampere GPU [36] supports 2:4 structured sparsity [32] to execute on tensor cores. CuSPARSE[40] can support structured SpMM on tensor cores based on the Blocked-ELL [13] format, which is a coarse-grained structured sparsity where model parameters are pruned in the granularity of squared blocks (e.g. 32×32). Some works prune the model parameters in the granularity of vectors to form the structured sparse format and make use of GPU tensor cores [4, 18, 25]. While tensor cores can be enabled with certain structured sparsity, the major concern is that deep learning models pruned with structured sparsity usually suffer from more severe model accuracy degradation than unstructured sparsity [8, 12, 14, 16, 51, 54].

The unstructured sparsity is to prune the elements without forming a structured distribution, which is usually hard to accelerate on modern hardware architectures. STOREL [47] and TACO [23] are CPU-based designs that can support SpMM with unstructured sparsity. Instead, Flash-LLM mainly focuses on the GPU-based SpMM with unstructured sparsity, as GPU is more widely used for large-scale deep-learning tasks since it usually has higher memory bandwidth, computational throughput, and energy efficiency. The typical approach to execute the unstructured SpMM on GPU is through SIMT cores, e.g. cuSPARSE[40], ASpT[17], and Sputnik[10]. Under a

moderate level of sparsity (<90%), Sputnik significantly outperforms cuSPARSE and ASpT, but it struggles to beat its dense counterpart cuBLAS [39] as it cannot utilize tensor cores. TC-GNN [57] supports unstructured sparsity with tensor cores, which is customized for GNN where the sparsity ratio is extremely high (e.g. >99%) and is not efficient for generative models requiring moderate-level sparsity. SparTA [65] proposes to utilize both sparse tensor cores [32] and SIMT cores to support unstructured sparsity by splitting the original sparse matrix into a 2:4 structured sparse matrix for tensor core execution (by cuSPARSELt [41]) and an unstructured sparse matrix for SIMT core execution (by Sputnik[10]). However, if the sparse ratio is high, it has to excessively pad zeros to the 2:4 sparse matrix. Besides, if there are too many non-zeros that can not meet the 2:4 requirement, the SIMT kernel would cause high latency and slow down the overall processing. Flash-LLM supports the moderate-level sparsity on tensor cores efficiently and does not require the 2:4-like distribution. SparseTIR [59] supports unstructured sparsity with tensor cores by splitting sparse matrices into 8×1 column vectors and omitting the vectors containing only zeros. It can not work well under moderate sparsity (e.g., 80%) as very few vectors can be skipped. It can not outperform the dense baseline cuBLAS until the sparsity is higher than 95%, while Flash-LLM can outperform cuBLAS since 60% sparsity.

The fine-tuning-based pruning [15, 29] can achieve moderate-level sparsity with good accuracy, while the post-training pruning [8] can only achieve quite low sparse ratios. Flash-LLM aims to optimize the SpMM with the moderate-level sparsity (e.g. 60%-90%) generated with the fine-tuning-based pruning. The fine-tuning-based pruning usually consumes a high fine-tuning cost, which as a result becomes one limitation of Flash-LLM.

Model quantization [16] is another approach to reduce the memory and computation for ML models, by transforming the data type into lower bits (e.g., 8-bits, 4-bits) [9, 25]. Model pruning and quantization are two orthogonal and complementary approaches to model compression. This paper mainly focuses on supporting model pruning, which is orthogonal to model quantization.

8 CONCLUSION

We propose Flash-LLM, a library for efficient large generative model inference through unstructured sparsity with tensor cores. We observe that MatMuls in generative models inference are usually skinny, and are bounded by off-chip memory access. We propose the *Load-as-Sparse and Compute-as-Dense* approach for tensor core SpMM, reducing the global memory footprint and addressing the memory access bottleneck without skipping any computation for sparse MatMuls. We propose an effective software pipeline for unstructured SpMM with tensor cores, efficiently leveraging on-chip resources for sparse data extraction and coordinating sparse data extraction, dense data loading, and tensor core computation in an overlapped manner. Flash-LLM outperforms cuBLAS/Sputnik/SparTA by $1.4 \times / 3.6 \times / 1.4 \times$, $1.7 \times / 3.0 \times / 1.4 \times$, $2.1 \times / 2.0 \times / 1.6 \times$ under 70%, 80% and 90% sparsity. We integrate Flash-LLM kernels into FasterTransformer for end-to-end generative model inference. For *tokens per GPU-second*, Flash-LLM achieves up to $3.8 \times$ and $3.6 \times$ improvement over DeepSpeed and FasterTransformer on OPT-30B/66B/175B models with significantly lower inference cost.

REFERENCES

- [1] Reza Yazdani Aminabadi, Samyam Rajbhandari, Ammar Ahmad Awan, Cheng Li, Du Li, Elton Zheng, Olatunji Ruwase, Shaden Smith, Minjia Zhang, Jeff Rasley, et al. 2022. DeepSpeed-inference: enabling efficient inference of transformer models at unprecedented scale. In *Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis*. 1–15.
- [2] Sid Black, Stella Biderman, Eric Hallahan, Quentin Anthony, Leo Gao, Laurence Golding, Horace He, Connor Leahy, Kyle McDonell, Jason Phang, Michael Pieler, USVSN Sai Prashanth, Shivanshu Purohit, Laria Reynolds, Jonathan Tow, Ben Wang, and Samuel Weinbach. 2022. GPT-NeoX-20B: An Open-Source Autoregressive Language Model. In *Proceedings of the ACL Workshop on Challenges & Perspectives in Creating Large Language Models*. <https://arxiv.org/abs/2204.06745>
- [3] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.
- [4] Zhaodong Chen, Zheng Qu, Liu Liu, Yufei Ding, and Yuan Xie. 2021. Efficient tensor core-based GPU kernels for structured sparsity under reduced precision. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis*. 1–14.
- [5] EleutherAI. 2022. GPT-NeoX-20B. Retrieved October 14, 2023 from <https://huggingface.co/EleutherAI/gpt-neox-20b>
- [6] Hugging Face. 2023. *Model Parallelism*. Retrieved October 14, 2023 from <https://huggingface.co/docs/transformers/v4.15.0/parallelism>
- [7] Shiqing Fan, Yi Rong, Chen Meng, Zongyan Cao, Siyu Wang, Zhen Zheng, Chuan Wu, Guoping Long, Jun Yang, Lixue Xia, Lansong Diao, Xiaoyong Liu, and Wei Lin. 2021. DAPPLE: A pipelined data parallel approach for training large models. In *Proceedings of the 26th ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming*. 431–445.
- [8] Elias Frantar and Dan Alistarh. 2023. Massive Language Models Can Be Accurately Pruned in One-Shot. *arXiv preprint arXiv:2301.00774* (2023).
- [9] Elias Frantar, Saleh Ashkboos, Torsten Hoefler, and Dan Alistarh. 2022. GPTQ: Accurate Post-Training Quantization for Generative Pre-trained Transformers. *arXiv preprint arXiv:2210.17323* (2022).
- [10] Trevor Gale, Matei Zaharia, Cliff Young, and Erich Elsen. 2020. Sparse gpu kernels for deep learning. In *SC20: International Conference for High Performance Computing, Networking, Storage and Analysis*. IEEE, 1–14.
- [11] Trevor Gale, Matei Zaharia, Cliff Young, and Erich Elsen. 2020. *sputnik github*. Retrieved October 14, 2023 from <https://github.com/google-research/sputnik/>
- [12] Aidan N Gomez, Ivan Zhang, Siddhartha Rao Kamalakar, Divyam Madaan, Kevin Swersky, Yariv Gal, and Geoffrey E Hinton. 2019. Learning sparse networks using targeted dropout. *arXiv preprint arXiv:1905.13678* (2019).
- [13] Scott Gray, Alec Radford, and Diederik P Kingma. 2017. Gpu kernels for block-sparse weights. *arXiv preprint arXiv:1711.09224* 3 (2017), 2.
- [14] Song Han, Huizi Mao, and William J Dally. 2015. Deep compression: Compressing deep neural networks with pruning, trained quantization and Huffman coding. *arXiv preprint arXiv:1510.00149* (2015).
- [15] Song Han, Jeff Pool, John Tran, and William Dally. 2015. Learning both weights and connections for efficient neural network. *Advances in neural information processing systems* 28 (2015).
- [16] Torsten Hoefler, Dan Alistarh, Tal Ben-Nun, Nikoli Dryden, and Alexandra Peste. 2021. Sparsity in Deep Learning: Pruning and growth for efficient inference and training in neural networks. *J. Mach. Learn. Res.* 22, 241 (2021), 1–124.
- [17] Changwan Hong, Aravind Sukumaran-Rajam, Israt Nisa, Kunal Singh, and P Sadayappan. 2019. Adaptive sparse tiling for sparse matrix multiplication. In *Proceedings of the 24th Symposium on Principles and Practice of Parallel Programming*. 300–314.
- [18] Guyue Huang, Haoran Li, Minghai Qin, Fei Sun, Yufei Ding, and Yuan Xie. 2022. Shf-BW: Accelerating Deep Neural Network Inference with Tensor-Core Aware Weight Pruning. In *Proceedings of the 59th ACM/IEEE Design Automation Conference (San Francisco, California) (DAC '22)*. Association for Computing Machinery, New York, NY, USA, 1153–1158. <https://doi.org/10.1145/3489517.3530588>
- [19] Yanping Huang, Youlong Cheng, Ankur Bapna, Orhan Firat, Dehao Chen, Mia Chen, HyoukJoong Lee, Jiquan Ngiam, Quoc V Le, Yonghui Wu, et al. 2019. Gpipe: Efficient training of giant neural networks using pipeline parallelism. *Advances in neural information processing systems* 32 (2019).
- [20] Xianyan Jia, Le Jiang, Ang Wang, Wencong Xiao, Ziji Shi, Jie Zhang, Xinyuan Li, Langshi Chen, Yong Li, Zhen Zheng, Xiaoyong Liu, and Wei Lin. 2022. Whale: Efficient Giant Model Training over Heterogeneous GPUs. In *2022 USENIX Annual Technical Conference, USENIX ATC 2022, Carlsbad, CA, USA, July 11-13, 2022*, Jiri Schindler and Noa Zilberman (Eds.). USENIX Association, 673–688.
- [21] Zhihao Jia, Matei Zaharia, and Alex Aiken. 2019. Beyond Data and Model Parallelism for Deep Neural Networks. *Proceedings of Machine Learning and Systems* 1 (2019), 1–13.
- [22] Jacob Devlin Ming-Wei Chang Kenton and Lee Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of NAACL-HLT*. 4171–4186.
- [23] Fredrik Kjolstad, Shoab Kamil, Stephen Chou, David Lugato, and Saman Amarasinghe. 2017. The Tensor Algebra Compiler. *Proc. ACM Program. Lang.* 1, OOPSLA, Article 77 (oct 2017), 29 pages. <https://doi.org/10.1145/3133901>
- [24] Alexandros Koliouisis, Pijika Watcharapichat, Matthias Weidlich, Luo Mai, Paolo Costa, and Peter Pietzuch. 2019. CROSSBOW: Scaling Deep Learning with Small Batch Sizes on Multi-GPU Servers. *Proceedings of the VLDB Endowment* 12, 11 (2019).
- [25] Shigang Li, Kazuki Osawa, and Torsten Hoefler. 2022. Efficient quantized sparse matrix operations on tensor cores. In *Proceedings of the International Conference on High Performance Computing, Networking, Storage and Analysis*. 1–15.
- [26] Shen Li, Yanli Zhao, Rohan Varma, Omkar Salpekar, Pieter Noordhuis, Teng Li, Adam Paszke, Jeff Smith, Brian Vaughan, Pritam Damania, et al. 2020. PyTorch Distributed: Experiences on Accelerating Data Parallel Training. *Proceedings of the VLDB Endowment* 13, 12 (2020).
- [27] Youjie Li, Amar Phanishayee, Derek Murray, Jakub Tarnawski, and Nam Sung Kim. 2022. Harmony: Overcoming the Hurdles of GPU Memory Capacity to Train Massive DNN Models on Commodity Servers. *Proc. VLDB Endow.* 15, 11 (jul 2022), 2747–2760.
- [28] Mingbao Lin, Yuxin Zhang, Yuchao Li, Bohong Chen, Fei Chao, Mengdi Wang, Shen Li, Yonghong Tian, and Rongrong Ji. 2022. 1xn pattern for pruning convolutional neural networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2022).
- [29] Zhuang Liu, Mingjie Sun, Tinghui Zhou, Gao Huang, and Trevor Darrell. 2018. Rethinking the value of network pruning. *arXiv preprint arXiv:1810.05270* (2018).
- [30] Xupeng Miao, Xiaonan Nie, Yingxia Shao, Zhi Yang, Jiawei Jiang, Lingxiao Ma, and Bin Cui. 2021. Heterogeneity-aware distributed machine learning training via partial reduce. In *Proceedings of the 2021 International Conference on Management of Data*. 2262–2270.
- [31] Xupeng Miao, Yujie Wang, Youhe Jiang, Chunan Shi, Xiaonan Nie, Hailin Zhang, and Bin Cui. 2022. Galvatron: Efficient Transformer Training over Multiple GPUs Using Automatic Parallelism. *Proc. VLDB Endow.* 16, 3 (nov 2022), 470–479.
- [32] Asit Mishra, Jorge Albericio Latorre, Jeff Pool, Darko Stolic, Dusan Stolic, Ganesh Venkatesh, Chong Yu, and Paulius Micikevicius. 2021. Accelerating Sparse Deep Neural Networks. *arXiv:2104.08378* [cs.LG]
- [33] Pavlo Molchanov, Arun Mallya, Stephen Tyree, Iuri Frosio, and Jan Kautz. 2019. Importance estimation for neural network pruning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 11264–11272.
- [34] Avaniika Narayan, Ines Chami, Laurel Orr, and Christopher Ré. 2022. Can Foundation Models Wrangle Your Data? *Proc. VLDB Endow.* 16, 4 (dec 2022), 738–746.
- [35] Xiaonan Nie, Xupeng Miao, Zilong Wang, Zichao Yang, Jilong Xue, Lingxiao Ma, Gang Cao, and Bin Cui. 2023. FlexMoE: Scaling Large-scale Sparse Pre-trained Model Training via Dynamic Device Placement. *arXiv preprint arXiv:2304.03946* (2023).
- [36] NVIDIA. 2020. *NVIDIA A100 Tensor Core GPU Architecture*. Retrieved October 14, 2023 from <https://images.nvidia.com/aem-dam/en-zz/Solutions/data-center/nvidia-ampere-architecture-whitepaper.pdf>
- [37] NVIDIA. 2022. *NVIDIA Faster-Transformer*. Retrieved October 14, 2023 from <https://github.com/NVIDIA/FasterTransformer>
- [38] NVIDIA. 2022. *NVIDIA H100 Tensor Core GPU Architecture*. Retrieved October 14, 2023 from https://www.hpctech.com.jp/catalog/gtc22-whitepaper-hopper_v1.01.pdf
- [39] NVIDIA. 2023. *cuBLAS Docs*. Retrieved October 14, 2023 from <https://docs.nvidia.com/cuda/cublas/index.html>
- [40] NVIDIA. 2023. *cuSPARSE Library*. Retrieved October 14, 2023 from <https://docs.nvidia.com/cuda/cusparsel/index.html>
- [41] NVIDIA. 2023. *cuSPARSELT Library*. Retrieved October 14, 2023 from <https://docs.nvidia.com/cuda/cusparselt/>
- [42] NVIDIA. 2023. *CUTLASS 3.2*. Retrieved October 14, 2023 from <https://github.com/NVIDIA/cutlass>
- [43] NVIDIA. 2023. *Nsight Compute Profiling Guide*. Retrieved October 14, 2023 from <https://docs.nvidia.com/nsight-compute/ProfilingGuide/#introduction>
- [44] NVIDIA. 2023. *Nsight System*. Retrieved October 14, 2023 from <https://developer.nvidia.com/nsight-systems>
- [45] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog* 1, 8 (2019), 9.
- [46] Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, and Yuxiong He. 2020. Zero: Memory optimizations toward training trillion parameter models. In *SC20: International Conference for High Performance Computing, Networking, Storage and Analysis*. IEEE, 1–16.
- [47] Maximilian Schleich, Amir Shaikhha, and Dan Suciu. 2023. Optimizing Tensor Programs on Flexible Storage. *Proceedings of the ACM on Management of Data* 1, 1 (2023), 1–27.
- [48] Ying Sheng, Lianmin Zheng, Binhang Yuan, Zhuohan Li, Max Ryabinin, Daniel Y Fu, Zhiqiang Xie, Beidi Chen, Clark Barrett, Joseph E Gonzalez, et al. 2023. High-throughput generative inference of large language models with a single gpu. *arXiv preprint arXiv:2303.06865* (2023).

- [49] Mohammad Shoeybi, Mostofa Patwary, Raul Puri, Patrick LeGresley, Jared Casper, and Bryan Catanzaro. 2019. Megatron-lm: Training multi-billion parameter language models using model parallelism. *arXiv preprint arXiv:1909.08053* (2019).
- [50] Shaden Smith, Mostofa Patwary, Brandon Norick, Patrick LeGresley, Samyam Rajbhandari, Jared Casper, Zhun Liu, Shrimai Prabhunoye, George Zerveas, Vijay Korthikanti, Elton Zhang, Rewon Child, Reza Yazdani Aminabadi, Julie Bernauer, Xia Song, Mohammad Shoeybi, Yuxiong He, Michael Houston, Saurabh Tiwary, and Bryan Catanzaro. 2022. Using DeepSpeed and Megatron to Train Megatron-Turing NLG 530B, A Large-Scale Generative Language Model. arXiv:2201.11990 [cs.CL]
- [51] Mingjie Sun, Zhuang Liu, Anna Bair, and J. Zico Kolter. 2023. A Simple and Effective Pruning Approach for Large Language Models. arXiv:2306.11695 [cs.CL]
- [52] Immanuel Trummer. 2022. From BERT to GPT-3 Codex: Harnessing the Potential of Very Large Language Models for Data Management. *Proc. VLDB Endow.* 15, 12 (aug 2022), 3770–3773.
- [53] Shreshth Tuli, Giuliano Casale, and Nicholas R. Jennings. 2022. TranAD: Deep Transformer Networks for Anomaly Detection in Multivariate Time Series Data. *Proc. VLDB Endow.* 15, 6 (feb 2022), 1201–1214.
- [54] Karen Ullrich, Edward Meeds, and Max Welling. 2017. Soft weight-sharing for neural network compression. *arXiv preprint arXiv:1702.04008* (2017).
- [55] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017).
- [56] Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2019. Superglue: A stickier benchmark for general-purpose language understanding systems. *Advances in neural information processing systems* 32 (2019).
- [57] Yuke Wang, Boyuan Feng, Zheng Wang, and Yufei Ding. 2023. TC-GNN: Accelerating Sparse Graph Neural Network Computation Via Dense Tensor Core on GPUs. arXiv:2112.02052 [cs.LG]
- [58] Samuel Williams, Andrew Waterman, and David Patterson. 2009. Roofline: an insightful visual performance model for multicore architectures. *Commun. ACM* 52, 4 (2009), 65–76.
- [59] Zihao Ye, Ruihang Lai, Junru Shao, Tianqi Chen, and Luis Ceze. 2023. SparseTIR: Composable abstractions for sparse compilation in deep learning. In *Proceedings of the 28th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 3*. 660–678.
- [60] Xiaodong Yi, Shiwei Zhang, Ziyue Luo, Guoping Long, Lansong Diao, Chuan Wu, Zhen Zheng, Jun Yang, and Wei Lin. 2020. Optimizing distributed training deployment in heterogeneous GPU clusters. In *CoNEXT '20: The 16th International Conference on emerging Networking EXperiments and Technologies, Barcelona, Spain, December, 2020*, Dongsu Han and Anja Feldmann (Eds.). ACM, 93–107.
- [61] Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, Todor Mihaylov, Myle Ott, Sam Shleifer, Kurt Shuster, Daniel Simig, Punit Singh Koura, Anjali Sridhar, Tianlu Wang, and Luke Zettlemoyer. 2022. OPT: Open Pre-trained Transformer Language Models. arXiv:2205.01068 [cs.CL]
- [62] Zhen Zhang, Shuai Zheng, Yida Wang, Justin Chiu, George Karypis, Trishul Chilimbi, Mu Li, and Xin Jin. 2022. MiCS: near-linear scaling for training gigantic model on public cloud. *Proceedings of the VLDB Endowment* 16, 1 (2022), 37–50.
- [63] Lianmin Zheng, Zhuohan Li, Hao Zhang, Yonghao Zhuang, Zhifeng Chen, Yanping Huang, Yida Wang, Yuanzhong Xu, Danyang Zhuo, Eric P. Xing, Joseph E. Gonzalez, and Ion Stoica. 2022. Alpa: Automating Inter- and Intra-Operator Parallelism for Distributed Deep Learning. In *16th USENIX Symposium on Operating Systems Design and Implementation, OSDI 2022, Carlsbad, CA, USA, July 11-13, 2022*, Marcos K. Aguilera and Hakim Weatherspoon (Eds.). USENIX Association, 559–578.
- [64] Ningxin Zheng. 2022. *SparTA github*. Retrieved October 14, 2023 from https://github.com/microsoft/SparTA/tree/sparta_artifact
- [65] Ningxin Zheng, Bin Lin, Quanlu Zhang, Lingxiao Ma, Yuqing Yang, Fan Yang, Yang Wang, Mao Yang, and Lidong Zhou. 2022. {SparTA}::{Deep-Learning} Model Sparsity via {Tensor-with-Sparsity-Attribute}. In *16th USENIX Symposium on Operating Systems Design and Implementation (OSDI 22)*. 213–232.