FusedXpert: GPU Kernel for Fine-Grained Mixture of Experts

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1 Introduction

Recent advances in large language models (LLMs) have largely been driven by empirical scaling laws that relate a model's quality to its size, the amount of training data, and number of training steps [2, 3]. This partly motivates why the community has largely converged on the transformer architecture: they are quite general and typically scale well to large parameter counts and datasets.

The Sparsely-gated Mixture of Experts (MoE) has recently become a popular alternative to the dense feed-forward layers used in transformers [10]. The primary motivation is to further increase the model's parameter count, without a proportional increase in the number of floating point operations (FLOPs) [4, 10]. Using an MoE to scale the model size is a general trick and is not specific to language models: they are seeing a surge in use in broad application areas, including vision [7] and reinforcement learning [6].

There is an additional architectural trend towards *fine-grained MoEs*, which have many small experts. This has seen use in models like DeepSeek-V3, Llama 4, Qwen3, and OLMoE [1, 5, 14]. When doing inference or finetuning, routing tokens across a large number of experts can result in many small matrix multiplications of different sizes. One way to handle these small products is to use *grouped GEMMs*, as supported by libraries ike CUTLASS and cuBLAS to fuse a "group" of small matrix multiplications into a single kernel. Grouped kernels have a similar motivation to batched APIs.

In this work, we develop high-performance *single-GPU MoE kernels* using the triton DSL [12]. We implement kernels that fuse parts of the token routing with grouped GEMMs and grouped GLUs. This is an important application area as many researchers have had a noted difficulty with achieving real performance improvements when attempting to use MoEs [5]. This work prioritizes fine-tuning and inference, where inputs tend to be relatively small and all experts in a particular layer may fit on single GPU.

2 Background: MoE

When using a MoE in transformers, the dense feed forward layers are replaced by an MoE layer which consists of a *router* and e *experts*. The number of experts e typically varies from 8 up to 256. The router selects a subset of $k \ll e$ experts to route each token to. The number of FLOPs scales linear with k, but is constant with respect to e. Experts are typically simple MLPs. Many recent models like DeepSeek-V3 and Qwen3 choose to make all experts identical Gated Linear Units (GLU) [1, 8].

The specific details of an MoE can vary substantially. However, the general design has two main parts: 1. for each token, the router produces scores and 2. tokens are processed by the experts with the highest scores. One possible MoE is illustrated in Figure 1.

A simple way to implement an MoE is to 1. loop over all of the experts, 2. get the subset tokens that were routed to the current expert, 3. apply the expert to this subset of tokens, and 4. accumulate the output onto an output cache. This is how popular libraries like huggingface transformers implement MoEs [13]. The main issue with using a python for loop over the experts is that when using fine-grained MoEs, there can be a large number of small kernels that are executed serially. It is possible that the GPU will be underutilized if the number of tokens routed to an expert is too small.

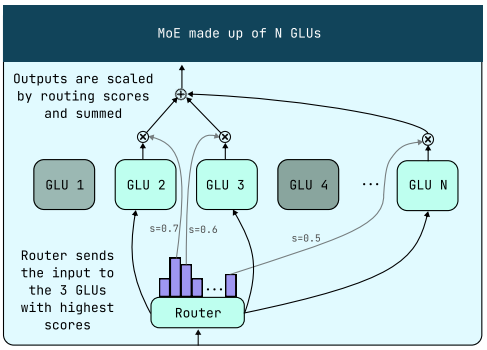

Figure 1: Diagram of an MoE. For each input token, the router produces a score for each expert. The token is then sent to the experts with the highest scores. The experts' outputs are scaled by the routing probabilities, and then accumulated.

3 MoE Routing Analysis

There is a phemonenon called "expert collapse" that may occur when training an MoE, in which the router begins prioritizing only one expert [10]. One common solution to this is to use an additional auxiliary loss to encourage the router to distribute tokens evenly across experts. In spite of this, as illustrated in figure 2, we find that the routing can still be quite biased when processing real datasets. This is important for constructing performant implementations of MoEs because the sizes matrix multiplications in each expert can vary substantially. This also highlights why using separate GEMM kernels for a fine-grained MoE can fail to achieve good performance.

4 Kernel Design

We briefly illustrate how an MoE can be implemented with grouped GEMMs and discuss where there are opportunities for fusion.

ROUTE(X, W_{router}, k)
1 $logits = XW_{router}$
2 $topk\text{-}scores, topk\text{-}indices =$ TOPK(SOFTMAX$(logits), k)$
3 $perm\text{-}tokens, groups =$ PERM-TO-EXPERTS$(tokens, topk\text{-}indices)$
4 **return** $perm\text{-}tokens, groups$

The router takes t tokens $X \in \mathbb{R}^t \times d$, a router weight $W_{router} \in \mathbb{R}^{d \times e}$, and the number of experts to route to, k. The PERM-TO-EXPERTS

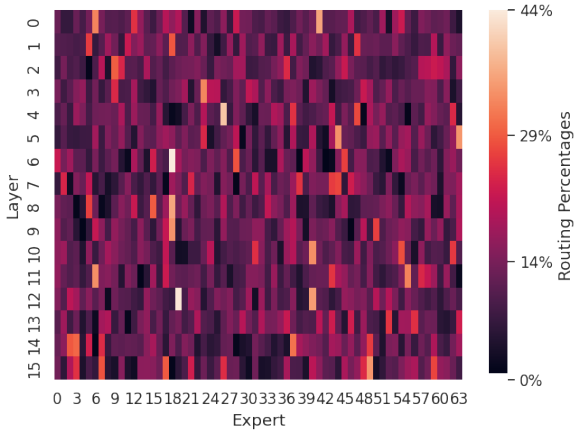

Figure 2: Olmoe router distribution on wikitext. The router in each of the sixteen layers can be heavily skewed. Some experts receive over 40% of the tokens, while others receive less than 1%.

function produces the new array, *perm-tokens*, which contains the routed tokens. Each group corresponds to one expert. I.e., $perm\text{-}tokens[groups[e] : groups[e+1]]$ contains the tokens routed to expert e. The *groups* array defines the extent of each group. So, $groups[e+1] - groups[e]$ is the number of tokens routed to expert e. These are the groups that can be processed by grouped GEMMs. The described MoE uses GLUs [9].

MoE-Grouped-GEMM($perm\text{-}tokens, groups, W_{up}, W_{gate}, W_{down}$)

1 up = Grouped-gemm($perm\text{-}tokens, groups, W_{up}$)
2 $gate$ = Grouped-gemm($perm\text{-}tokens, groups, W_{gate}$)
3 $gated = up \times \text{silu}(gate)$
4 $down$ = grouped-gemm($gated, groups, W_{down}$)
5 out = scale-and-acc($down, groups$)
6 **return** out

There are a number of improvements that can be made to this high-level implementation:

(1) The token permutation can be fused with the grouped GEMMs that produce *up* and *gate* [11].
(2) The two grouped GEMMs producing up and gate can be fused, as the process the same input.
(3) The SiLU activation can then be fused with the GEMMs.

The scale-and-acc function appears to be difficult to fuse. It is left unfused in our current implementation.

5 Results and Discussion

We present performance results for our implementation. The implementations for each model are tested against their corresponding implementation on huggingface transformers [13]. However, as the implementations on hugging transformers have relatively poor performance, we exclude them from our results. We use ScatterMoE as our baseline [11]. Our experiments are run one Nvidia A30 GPU. All models use the bfloat16 data type. Results are shown in Figure 3.

The unfused MoE clearly becomes the slowest, while ScatterMoE and our fused implementation scale similarly. As with our fused implementation, ScatterMoE fuses some of the routing operations into its GEMM kernels. The main culprit for the unfused MoEs poor performance is the output scaling and reduction, shown in Figure 1. This has a poor memory access pattern. Fusing routing with the grouped GEMM is effective at hiding the latencies of some of these memory accesses.

We note that ScatterMoE performs poorly on very small inputs because it does not tune the M-dimension of the GEMM tile size. The number of tokens per expert may be extremely small and if the tile size is too large, it is necessary to pad the tile with zeros, resulting in extra computation.

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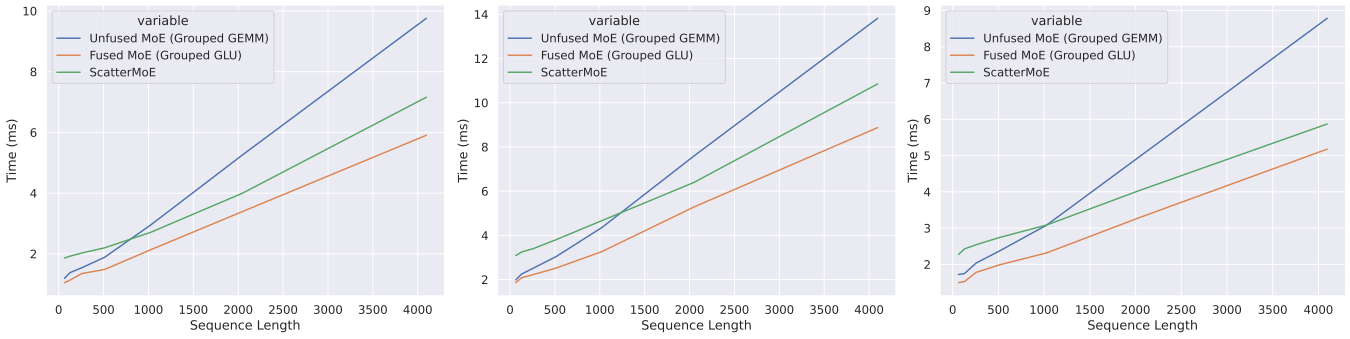

(a) OLMoE-1B-7B **(b) Ernie4-21B-A3B** **(c) Qwen3-30B-A3B**

Figure 3: Performance results on OLMoE, Ernie 4.5, and Qwen3. We compare three versions: 1. An MoE relying on a triton implementation of a grouped GEMM, with no other operations fused. 2. Our described MoE implementation that fuses the GLU operations. 3. The baseline ScatterMoE, which fuses routing operations with a GEMM, but does not fuse the GLU or activation functions.

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