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ReLU Strikes Back: Exploiting Activation Sparsity in Large Language Models

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ABSTRACT

Large Language Models (LLMs) with billions of parameters have drastically transformed AI applications. However, their demanding computation during inference has raised significant challenges for deployment on resource-constrained devices. Despite recent trends favoring alternative activation functions such as GELU or SiLU, known for increased computation, this study strongly advocates for reinstating ReLU activation in LLMs. We demonstrate that using the ReLU activation function has a negligible impact on convergence and performance while significantly reducing computation and weight transfer. This reduction is particularly valuable during the memory-bound inference step, where efficiency is paramount. Exploring sparsity patterns in ReLU-based LLMs, we unveil the reutilization of activated neurons for generating new tokens and leveraging these insights, we propose practical strategies to substantially reduce LLM inference computation up to three times, using ReLU activations with minimal performance trade-offs.

1 Introduction

The widespread excitement surrounding Large Language Models (LLMs) has sparked significant interest in leveraging AI across diverse domains [5, 9, 6]. However, realizing the potential of LLMs is challenged by their significant computational and memory requirements during inference [60, 40, 3]. To enhance the inference efficiency[1], various techniques have been explored, including quantization [12, 50], speculative decoding [41], pruning [53, 71], and weight sparsification [20, 15]. Among these techniques, achieving activation sparsity offers a compelling advantage by providing a favorable balance between accuracy and speedup, especially on modern hardware like GPUs [51].

Notably, employing the Rectified Linear Unit (ReLU) activation function [22] in neural networks is recognized for inducing sparse activations and has been adopted in various prior works [27, 44, 48, 69]. To reaffirm this property, we employ the OPT model [80], utilizing ReLU, and measure the sparsity of activations in the Feed Forward Network (FFN) between the fully connected layers. As illustrated in Fig. 1a, all layers exhibit sparsity exceeding 90%. On average, across all layers, this activation sparsity results in substantial weight transfer (I/O) savings between the GPU and CPU, impacting 95% of the rows of the down projection layer's weights (Fig. 1b). This reduction directly translates to computation savings, as for these rows, the result of the matrix multiplication operation will be zero. Furthermore, unlike unstructured sparsity (e.g., weight pruning), this type of sparsity is more hardware-friendly due to zeroing more extensive and structured chunks, such as rows or columns [36, 51]. For OPT models, this sparsity reduces the computation required for inference from 6.6G FLOPS (Floating Point Operations Per Second) to 4.5G FLOPS per token, resulting in a 32% computation saving (Fig. 1c).

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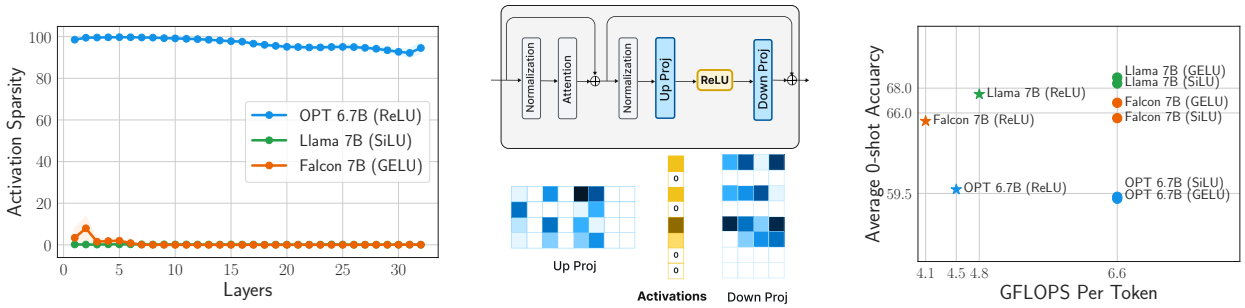
[1]In this work, we use FLOPS as a proxy for inference efficiency. In Appendix B, we demonstrate that for LLMs with activation sparsity, FLOPS can serve as a good approximation of real-world efficiency due to the structure inherent in activation sparsity (e.g., skipping the entire row corresponding to zero activations).



(a) Sparsity of different models (b) Sparsity for Efficiency (c) Accuracy vs. Computation

Figure 1: **(a)** Activation Sparsity of different pretrained models: ReLU-based OPTs show significantly higher sparsity. **(b)** Zeroed out entries after ReLU save compute in large semi-structured chunks (e.g., rows). **(c)** Comparison of inference efficiency and performance of the different models with different activation functions after fine-tuning: The choice of activation function does not significantly impact the accuracy, as any of GELU, SiLU, or ReLU can be used on all three models and achieve the same level of accuracy as the original activation function. However, using ReLU can provide an additional benefit of leading to activation sparsity and faster inference.

However, a recent trend has emerged, favoring variations of ReLU that are smoother but more complex [28, 64]. These alternatives have gained popularity due to their slightly faster convergence and improved final accuracy [66]. For example, PaLM [9] and Llama models [73] adopt SiLU[2] [28, 17, 64], while MPT [56] and Falcon models [2] use GELU [28]. Nonetheless, as demonstrated in Fig. 1c, when we finetune several pretrained LLMs with different activation functions, their performance does not change significantly (within a specific model), while ReLU models require much less computation.

In this paper, we re-evaluate using ReLU for LLMs. We are motivated by the pragmatic consideration that, in many real-world applications and computational platforms capable of supporting sparse vector-matrix multiplications, computational efficiency during *inference* outweighs the one-time computational cost incurred during training. We make the following contributions:

- We demonstrate that when trained from scratch, there is no significant difference in terms of performance between different activation functions. However, in terms of computational requirements during inference, ReLU activations prove significantly lighter (Sec. 3).
- Considering that many modern LLMs (e.g., Llama and Falcon) have been trained with non-ReLU activations, and it is not cost-effective to train them from scratch, we investigate fine-tuning these models with ReLU activations. We show that the models quickly regain their original performance across various reasoning and reading comprehension tasks (Sec. 4.1). Moreover, we show that by leveraging the activation sparsity of ReLU layers and inserting additional ReLU layers after normalization layers, we can further reduce inference FLOPS by up to threefold (Sec. 4.2).
- In addition to their computational benefits, we present two promising applications of activation sparsity that can inspire future work. Firstly, we demonstrate that LLMs with ReLU activations reuse a significant portion of already activated neurons during token generation, a phenomenon we term *aggregated sparsity* (Sec. 5.1). This reusability leads to an inference speedup for speculative decoding (Sec. 5.2). Additionally, we show that studying the pre-activations of pretrained LLMs can guide the selection of unconventional activation functions (e.g., *shifted ReLU*), achieving up to 90% sparsity while maintaining performance similar to ReLU activation (Sec. 5.3).

Overall, we believe our work represents a significant step toward leveraging the potential of sparse activation functions for faster and more efficient inference in large language models.

[2]To be more precise, the mentioned models use SwiGLU activation function, but in this work, we focus on the gating module that uses SiLU (Swish) function.

2 Related Works

Activation Functions in Transformers. The original Transformer architecture [74] was proposed with the ReLU activation function [22], following the popularity of ReLU at the time. Later, several studies aimed to improve the ReLU activation function by increasing its smoothness [28] and/or including parameterized gating mechanisms, such as GELU, SiLU, GLU, and SwiGLU [11, 64]. Earlier studies demonstrated the benefits of these alternatives to ReLU for transformers [66, 57], but on a small scale (e.g., they trained models up to a couple of 100M parameters with at most 35B tokens, while in this work, we train 1B parameter models on more than 100B tokens). However, we believe the impact of activation functions on performance is marginal, following scaling laws [37, 31], which state that architectural changes do not significantly impact performance.

Activation Sparsity. Existing research shows increased sparsity reduces inference and training times [44, 25, 70, 81, 47, 51]. For instance, Jaszczur et al. [36] uses ReLU and added a controller to both promote and predict sparsity, while other works only use prediction modules to predict the activation masks [51]. We note that the mentioned works assume the pretrained model has already been using a sparse ReLU activation, and hence, only training a separate module to predict sparsity could be enough. However, we note that most LLMs pretrained these days do not use ReLU, and we aim to bridge this gap. Moreover, these works focus only on a single transformer architecture while we focus on various architectures so our findings can be practical. Finally, we show that there is no need to train a separate prediction module that complicates the computation graph, and using efficient ReLU layers can be enough.

Speculative Decoding and Sparsity. Speculative decoding combats latency under memory constraints using a smaller model for token prediction and a larger model for verification [46, 41]. Investigating its integration with sparsity, we find activation sparsity exhibits a temporal pattern, enhancing speculative decoding. We provide guidelines for parameter selection when incorporating sparsity.

We defer other lines of related works that are orthogonal to our work, such as model compression techniques, sparse attention methods, and Mixture of Experts (MoE) to Appendix A.

3 Does the Activation Function Impact Performance?

This section first overviews our experimental setup, including models, data, and evaluations. Then, by training various models from scratch with different activation functions, we demonstrate that changing activation functions minimally impacts performance. However, the impact on inference efficiency is substantial.

3.1 Experimental setup

Models. We use open source pretrained models such as OPT [80], Llama (v1) [73], and Falcon [2] as they use different architectures and pretraining setup (e.g., attention/FFN structure/normalization, activation functions), allowing our study covers a wider range of models.

Datasets. We use the RefinedWeb dataset [59], for our pretraining in Sec. 3.2 and finetuning pretrained models in Sec. 4. We chose RefinedWeb because it is a high-quality subset of Common Crawl, which is often used in the pretraining phase of LLMs, including Llama, Falcon, and OPT. We also use the validation split of WikiText [54] for measuring the sparsity and recording preactivation distributions of various pretrained models. However, our conclusions hold for other datasets we have tested.

Training and Finetuning. For finetuning the pretrained models, we follow the original pretraining recipe, except we use a fixed learning rate of 1.5e-5 for Llama 7B, Falcon 7B, and OPT 6.7B models. In addition, we use the AdamW optimizer [52] for our finetuning with ZeRO stage 1 [62], where we shard the optimizer states across different GPUs. For pretraining OPT 1.3B models from scratch in Sec. 3.2, we follow the OPT training recipe.

Evaluation. For our *performance* evaluation, we use the few-shot tasks from Language Model Evaluation Harness [23]. We select these tasks such that they can measure various abilities of the models (e.g., reading comprehension, reasoning, etc.), and we aim to be consistent with other works in the literature to make the comparison easier. Consistent with the other sections, we compare activation sparsity as a measure of *efficiency*.

Further details regarding the relationship between activation sparsity, FLOPS, and inference efficiency are discussed in Appendix B.

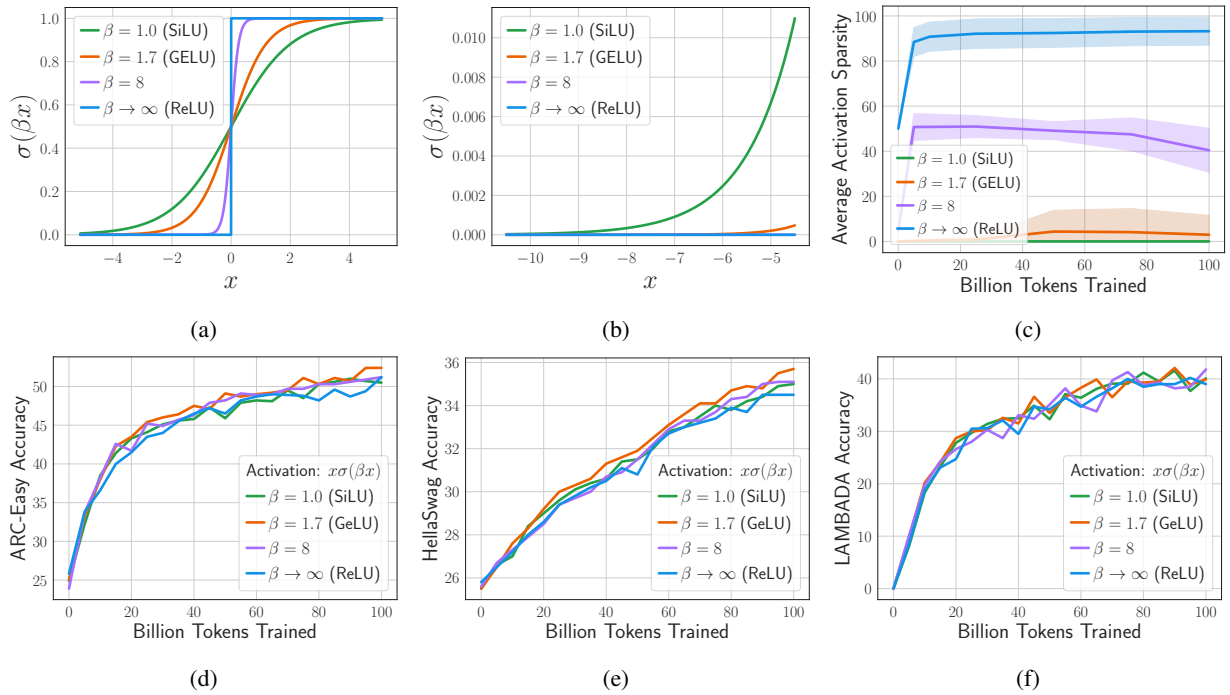


Figure 2: **(top)** (a) Shapes of different gating functions over [-5, 5]; (b) Continuation of (a) where SiLU is comparably larger compared to others; (c) Sparsity of the FFN with different activations: increasing β increases sparsity. **(bottom)** when trained from scratch, OPT 1.3 B models using different activation functions achieve similar performance.

3.2 Training from scratch: performance and sparsity

While the previous literature suggests that non-ReLU variants can improve the performance of transformers [66, 57], we argue the impact is marginal at best. To support our claim, we train the OPT 1.3B model from scratch on a hundred billion tokens of the RefinedWeb datasets with different activation functions, including ReLU, SiLU, and GELU. All these activation functions can be viewed as f(x) $= x \cdot \sigma(\beta x)$, where β controls the gating part (smoothed cutoff threshold) of the activation function (see Fig. 2a). For $\beta = 1$, we will have SiLU($x \cdot \sigma(x)$), and $\beta = 1.7$ is a good approximation of GELU. Finally, as $\beta \to \infty$, the activation function becomes closer to ReLU. To further explore the spectrum of ReLU to SiLUwe add another one with $\beta = 8$.

As shown in the bottom row of Fig. 2, the performance of the models is very similar when using different activation functions. This is consistent with the scaling laws literature ([37, 31]), which suggests that the performance of sufficiently large models trained on sufficiently large data depends heavily on compute and data, not architectural details.

While the performance levels of the different activations are similar, their activation sparsity levels differ. Here, we define sparsity as the average sparsity level across all layers for each model. As shown in Fig. 2c, as we transition from SiLUto ReLU (increasing β), the sparsity also increases. This results from the different gating thresholds, as ReLU drops significantly more values compared to GELU and SiLU (see Fig. 2b). In Appendix D, we illustrate the evolution of the pre-activation distribution throughout training.

Overall, the results support our initial claim: non-ReLU activations result in a negligible performance gain (if any) but a substantial loss in sparsity and efficiency. While, at times, the performance of GeLU or SiLU might be slightly higher, ReLU can match it with slightly longer training. We acknowledge that to compensate for the small gap in performance, we need to pay the one-time cost of longer training. However, in return, we get a significantly more sparsity.

4 Relufication

While in the previous section, we have seen that the performance does not depend on the activation function, we note that most of the available pretrained LLMs are trained with activation functions other than ReLU. Hence, to incorporate the computational benefits of ReLU activations at inference time, we perform various architectural surgeries and study the consequences of such changes.

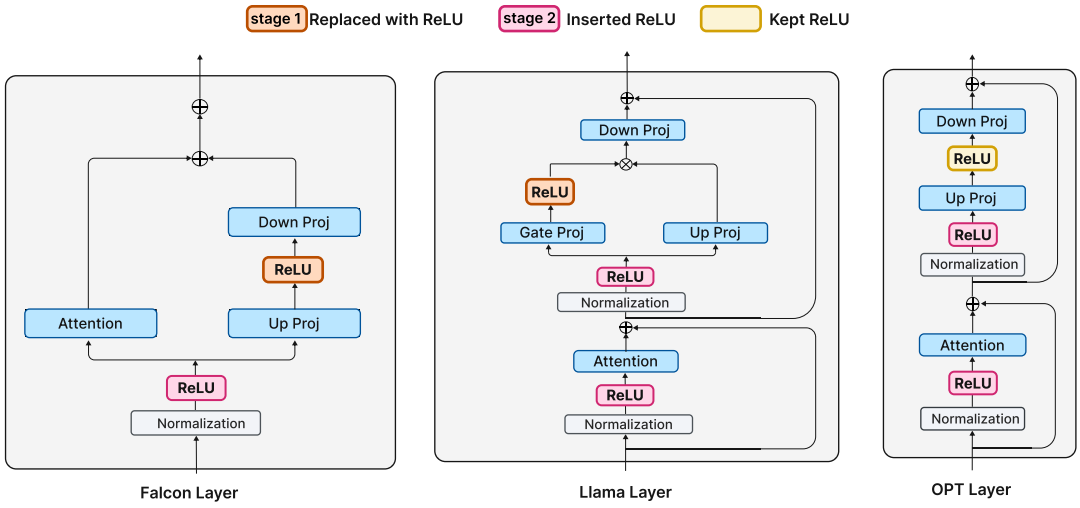
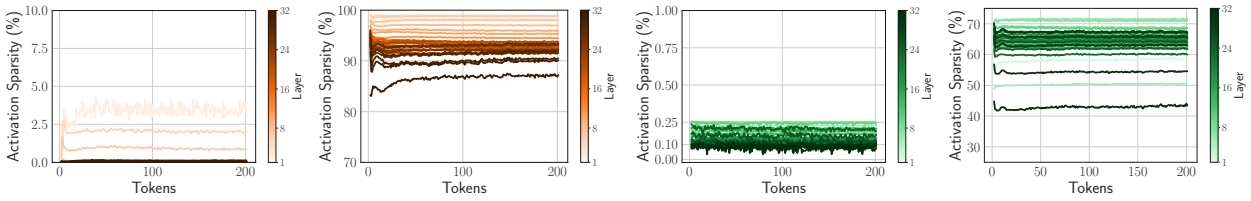


Figure 3: Architectural surgeries for *relufication*. In stage 1 we keep the existing ReLUs (in the case of OPT) or replace the activation function between up projection and down projections from GELU (Falcon) and SiLU (Llama) to ReLU. In stage 2, we insert new ReLUs after normalization layers.



(a) Falcon 7B (GELU) (b) Falcon 7B (ReLU) (c) Llama 7B (SiLU) (d) Llama 7B (ReLU)

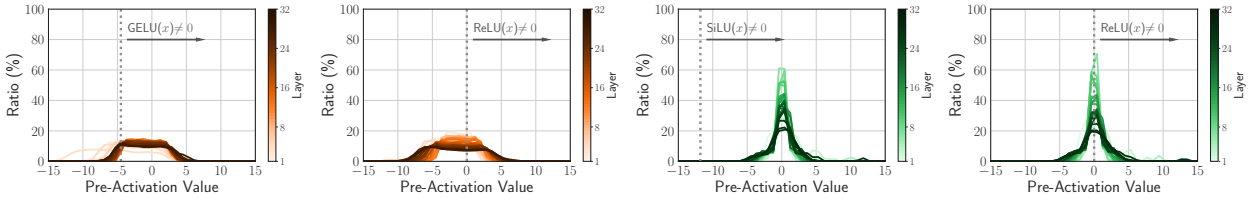
Figure 4: Activation sparsity of Falcon and Llama models improves significantly after *relufication*.

We present our findings about incorporating ReLU activations into the pretrained LLMs, a process we refer to as *relufication*. More specifically, we show that replacing the activation functions of pretrained LLMs with ReLU is possible, and the performance can be recovered very rapidly during finetuning. Moreover, we show that we can exploit the sparse ReLU activations, and by inserting additional ReLU layers after normalization layers, we can improve inference efficiency, as FLOPS indicates. Finally, we show these modifications, which are easy to implement, lead to lighter models at inference time while maintaining comparable performance to the original pretrained models.

4.1 Stage 1: replacing non-ReLU activations

The process of relufication for different pretrained architectures is shown in Fig. 3. This process can be done in multiple stages, as we describe here. The first and more intuitive stage replaces non-ReLU activations with ReLU in the FFN layer. For the Falcon and Llama models, this means replacing GELU and SiLU, respectively. We note that since OPT models already use ReLU activations, we keep those unchanged. After finetuning on 30 billion tokens of the RefinedWeb, Fig. 4 shows that the modified models have significantly more sparsity in their activations.

In addition to the drastic improvement in activation sparsity, we can make several notable observations. First, while the shape of preactivation depends on the pretraining dynamics and architecture, in Fig. 5, we show that it does not change significantly during the relatively short finetuning stage. As a result, we can predict the activation sparsity before finetuning, knowing it will not change significantly. Later in Sec. 5.3 we build on this observation and propose shifting the preactivation values before applying ReLU and further increasing the activation sparsity. The stability of the preactivation distribution may suggest that the behavior of the network does not change while creating sparse representations. Indeed, we show that after replacing the activation function with ReLU, finetuned models quickly recover their performance in Fig. 6. We believe optimizing this process even further (e.g., using better finetuning data) is an exciting follow-up direction.



(a) Falcon 7B (GELU) (b) Falcon 7B (ReLU) (c) Llama 7B (SiLU) (d) Llama 7B (ReLU)

Figure 5: The preactivation distribution of pretrained models for Falcon and Llama does not change significantly during the short finetuning stage of relufication. The dashed line shows the cutoff point before which the output is almost zero.

Table 1: Comparing zero-shot performance across several tasks: After *relufication*, the activation sparsity of models increases significantly, hence increased efficiency measured by FLOPS. Within each group, the performance levels are comparable.

Model (stage)	Input Sparsity (%)			FLOPS (G)	Zero-Shot Accuracy (%)									
	QKV	DownProj	UpProj		Avg	Arc-E	Arc-C	Hellaswag	BoolQ	PIQA	LAMBADA	TriviaQA	WinoGrande	SciQ
OPT 1.3B	0	96	0	1.3	50.7	57.3	22.9	41.3	57.0	71.8	56.0	6.1	58.9	84.6
OPT 2.7B (s2)	50	96	35	1.1	53.1	60.3	26.8	44.9	55.4	73.9	57.6	12.4	59.6	86.7
OPT 2.7B	0	96	0	1.8	54.5	63.3	29.2	45.8	57.6	74.2	61.4	12.3	60.8	85.9
OPT 6.7B (s2)	50	97	40	2.8	58.6	66.5	32.2	49.1	63.0	76.4	63.3	23.8	63.1	90.3
OPT 6.7B	0	97	0	4.5	59.8	68.0	32.4	50.2	68.4	75.8	67.2	20.9	65.3	90.2
Falcon 7B (s2)	56	95	56	2.2	64.8	73.6	38.6	55.3	68.4	78.9	67.6	40.4	67.1	93.4
Falcon 7B (s1)	0	94	0	4.1	65.2	72.2	39.1	55.4	70.6	78.4	69.2	40.5	67.5	93.1
Falcon 7B	0	1	0	6.6	66.8	74.6	40.2	57.7	73.5	79.4	74.5	40.4	67.2	94.0
Llama 7B (s2)	51	65	67	2.9	66.4	73.8	39.6	54.8	69.9	77.9	70.7	48.5	68.6	93.8
Llama 7B (s1)	0	62	0	4.8	67.1	75.2	40.1	55.2	73.4	77.7	71.5	49.6	67.1	94.2
Llama 7B	0	0	0	6.6	68.4	75.5	42.1	69.9	74.8	78.7	73.1	49.9	69.8	95.4

4.2 Stage 2: Pushing for more sparsity

In the previous stage, we replaced non-ReLU activations to gain more sparsity. This leads to the input of *down projection* layer being sparse, roughly 30% of the total computation. However, there are other matrix-vector multiplications in the decoder layer of transformers besides the down projection. For instance, before the *up projection* and *gate projections* of FFN layer, and *QKV projections* in the attention layer (see Fig. 3). Together, the mentioned matrix-vector multiplications consume about 55% of the total computation.

To this end, we utilize the fact that in modern transformer layers, the input to both the attention and FFN layers come from a normalization layer, e.g., LayerNorm [4] or RMSNorm [78]. These layers can be viewed as a specific form of MLP, where, instead of applying arbitrary learnable parameters, they learn to scale inputs. Therefore, we apply ReLU to obtain sparse activations after normalization layers which we call the *second stage* of relufication in Fig. 3.

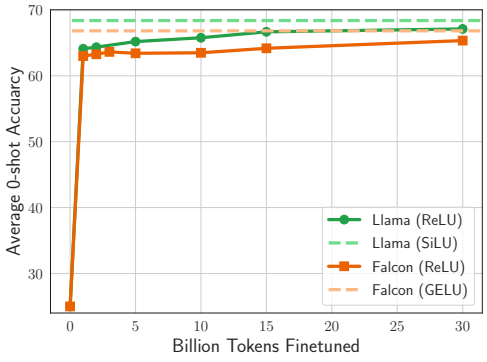


Figure 6: Evolution of zero-shot accuracy during finetuning: The model quickly recovers most of its lost performance due to the architecture surgery.

Tab. 1 shows that different stages of the relufication process do not significantly reduce zero-shot accuracy while using significantly less compute. The sparsity is broken down into three categories: up, down, and QKV projections. Notably, the input to QKV is less sparse than FFN projections, which opens an interesting avenue for future research. We note that the small gap in performance between the original vs. relufied models may be partially due to the finetuning process and not necessarily the activation function. Our finetuning is applied only for 30B and 50B tokens for stages 1 and 2, respectively. Putting into prospect and comparing it with 1T tokens of Llama, for example, this is equivalent to 3-5% of the original training duration. As discussed in Sec. 3.2, according to the scaling properties of LLMs, the gap will be further bridged by additional finetuning steps.

Table 2: MMLU five-shot accuracy. Models finetuned with different activation functions have similar performance.* Denotes we replace the SiLU function in Llama's SwiGLU activation function with ReLU.

Model	Activation	FLOPS(%)	Avg	Humanities	STEM	Social Sciences	Other
Falcon 7B	SiLU	100	26.4	24.8	27.4	27.2	26.2
Falcon 7B	GELU	100	27.7	28.1	26.0	28.0	29.4
Falcon 7B	ReLU	62	27.9	26.0	26.5	31.8	27.9
Llama 7B	SiLU*	100	35.1	37.9	30.2	37	37.1
Llama 7B	GELU	100	35.9	38.4	29.4	37.6	39.5
Llama 7B	ReLU	72	34.7	34.8	31.2	36.3	37.8

We also assess the in-context learning ability of the relufied models with the Massive Multitask Language Understanding (MMLU) [29] benchmark in Tab. 2. Our results show that when we augment the original LLMs with different activations and finetune, the few-shot performance does not change significantly either. Moreover, Sec. E in the appendix shows that a larger but relufied model performs better than an original smaller model of the same FLOPS. Overall, the results affirm that the proposed relufication procedure can decrease the inference FLOPS at various stages and rates while maintaining on-par performance on various tasks.

5 Applications

In this section, we discuss promising directions motivated by our investigation in Sec. 4. First, we introduce *aggregated sparsity*, showing that ReLU networks reuse previously activated neurons when generating tokens. Hence, we can leverage this to increase the generation speed. Next, we relate aggregated sparsity with speculative decoding to further improve speculative decoding's inference time. Finally, we briefly discuss a promising direction of using the *shifted ReLU* activation function to improve the sparsity further.

5.1 Aggregated Sparsity: reusing previously activated neurons

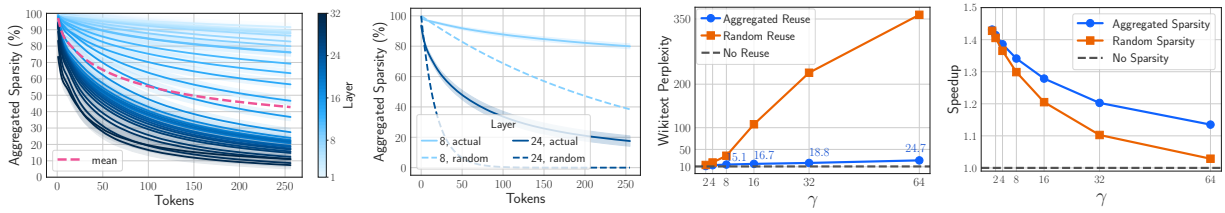
A consequence of using only a small subset of neurons for each token is that if these neurons are shared to some degree, the model still does not use all of the neurons until many tokens are processed. We refer to this as *aggregated sparsity*, which we defined as the ratio of neurons that have not been used up to processing the first t token. Note that this metric will always be non-increasing. Intuitively, it measures the unused capacity of feed-forward neurons for processing a specific prompt.

Here in Fig. 7a we show that for the OPT-6.7B model, on average, about 50% of all the neurons will be unused across the first 150 tokens of prompts coming from the WikiText dataset. Our empirical results hold for other ReLU models and other datasets. Additionally, in Fig. 7b, we show that this pattern is far from random activation of neurons during the token generation with a rate equal to the average rate of activation usage per token. Let s_i be the activation sparsity of layer i averaged over all tokens. Then, the probability of an activation not used in generating the first t tokens in uniformly random selection is s_i^t . Fig. 7b shows this quantity for two layers $i = 8, 24$ for the first 256 tokens in dashed line. It also shows the real (observed) number of activations being used in the solid line. The fact that the random aggregated sparsity (referred to as random sparsity) is lower than the observed aggregated sparsity (we refer to it as aggregated sparsity) shows a clear pattern of reusing activations.

We can benefit from the overlapping activations by utilizing previously loaded weights from the down projection layer for upcoming tokens. To test this, we initiate with reading 128 tokens. For the subsequent 128 tokens, we intermittently avoid loading new weights for every γ token. Using $\gamma = 16$ as an example, tokens 129-145 are generated conventionally. However, for tokens 146-161, we retain the existing weight without introducing any new weight. This pattern continues, with every next set of γ tokens alternating between conventional generation and weight reuse. In Fig. 7c, we observe only a slight increase in perplexity when using this approximation to address the memory and I/O-intensive nature of LLM inference. This figure contrasts the perplexity obtained from reused activations and random selections. The reuse strategy aligns well with the baseline, whereas random selection notably increases perplexity, highlighting the effectiveness of reusing the already loaded activations for subsequent tokens.

5.2 Activation sparsity and speculative decoding

As highlighted in Sec. 5.1, activation reuse happens for multiple consecutive tokens. When multiple consecutive tokens are processed together, we can save the I/O (i.e., transferring weights to GPU/CPU as discussed in Appendix B)



(a) (b) (c) (d)

Figure 7: **(a)** Aggregated sparsity of different layers and their mean. **(b)** Aggregated sparsity during token generation and comparison with a random sparsity. **(c)** Perplexity, based on the number of tokens for which loaded weights from previous tokens are reused. The dashed line represents no reuse, the solid blue line shows the case with activation reuse according to aggregated sparsity, and the orange line depicts the perplexity when activations are reused according to a random sparsity. **(d)** The inference speedup of speculative decoding with aggregated sparsity and with random sparsity. Speedup equal to 1.0 is the standard version of speculative decoding.

associated with activations that are not used in any of them. If the reuse was not happening, and the sparsity of all tokens was purely random, the aggregated sparsity would shrink exponentially and quickly diminish. Speculative decoding [46] is a related technique that uses a smaller model M_q to propose γ tokens and a larger model M_p to verify those tokens and select matching ones. It improves the runtime of the model by avoiding running M_p sequentially.

To improve speculative decoding, aggregated sparsity can trim down the portion of the model that needs to be run. Instead of running the full model, only the non-sparse parts need to be evaluated, which will reduce I/O and compute latency. Suppose the average aggregated sparsity of M_p for γ tokens is $\bar{s}_{\text{agg}}(\gamma)$, and cost of running M_q over M_p is c. Then the expected latency speedup when going from standard speculative decoding to sparse speculative decoding is $\frac{c\gamma+1}{c\gamma+(1-\bar{s}_{\text{agg}}(\gamma))}$.

Fig. 7d compares sparse speculative decoding to the standard version for OPT 6.7B model. As a case study, for $\gamma = 16$, the sparse version has a 1.27x speedup over the standard speculative decoding. If the aggregated sparsity was random over different tokens, the speedup would have been only 1.20x. Note that even random sparsity will lead to speedup over standard speculative decoding. This further shows the value of relufication. However, the speedup due to random sparsity would diminish quickly in comparison to aggregated sparsity as we go for larger γ. For example, for $\gamma = 64$ the speedup is almost negligible, while the speedup for the aggregated sparsity is around 1.14x. Further discussion and details are postponed to Appendix C, where we compare sparse speculative decoding, standard speculative decoding, and autoregressive decoding and discuss optimal γ in the case of sparse speculative decoding.

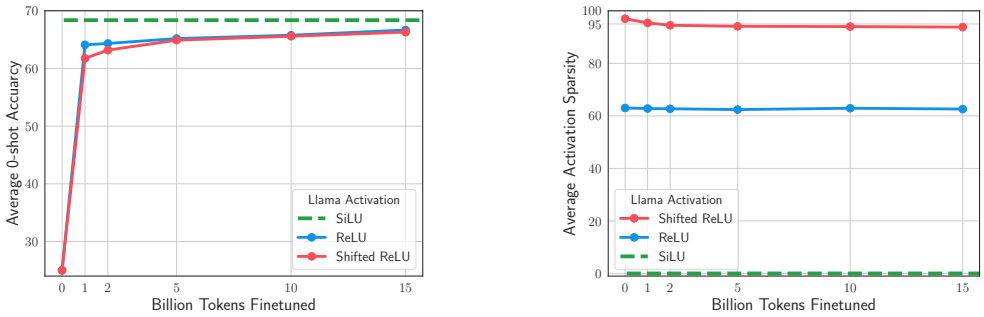
5.3 The shifted ReLU activation

Our work in this section is motivated by the observation from Sec. 4, where, comparing Fig. 4d with Fig. 4b revealed that the relufied Llama has much less sparsity (65%) than the relufied Falcon model (95%). In addition, we build on two of our previous findings. First, the preactivation distribution of the relufied Llama (Fig. 5c) includes a considerable mass after the cutoff value at zero. Second, the shape of the preactivation distribution does not change before and after the relufication process (Fig. 5c and Fig. 5d).

Therefore, we may be able to shift the preactivation distribution to the left to put more volume before the cutoff at 0. To this end, for preactivation input x, rather than applying $\text{ReLU}(x)$, we use $\text{ReLU}(x - b)$ where $b \in \mathbb{R}$ is a constant scalar. We propose to set the value b based on the preactivation distribution. For instance, based on the distribution in Fig. 5d, setting $b = 1$ and hence using $\text{ReLU}(x - 1)$ as our activation function will result in dropping 95% of the preactivations and make it significantly sparser. Another benefit of this approach is simplicity, as this does not require changing the loss function or the training regime.

Figure 8a shows that the shifted ReLU activation function has on-par accuracy with the ReLU activation function. Moreover, similar to our observation in Sec. 4, the shifted ReLU activation quickly recovers the lost performance due to the drastic change of activation function, while it also maintains a very high-level activation sparsity during the finetuning stage. The gap between shifted ReLU and ReLU is wider in the early stages of training, and it narrows down when more tokens are seen.

A deeper investigation of ReLU-variants that can promote sparsity without sacrificing performance is an appealing future direction. Moreover, it will be interesting to study the impact of the shifted ReLU for stage-2 of our relufication process where the sparsity level is usually not very high.



(a) (b)

Figure 8: The effect of shifted ReLU on Llama model. **(a)** The performance is almost the same as the original ReLU. **(b)** Shifted ReLU (i.e., ReLU$(x-1)$) is much sparser than the original ReLU.

6 Conclusion

In this study, we conducted a large-scale investigation of the activation functions, and we have shown that the choice of activation functions during pretraining and finetuning does not have a significant impact on performance while using ReLU can provide an additional benefit of leading to activation sparsity and more efficient inference. To bridge the gap between existing pre-trained models and our work, we have *relufied* several models to incorporate the ReLU activation function into the architecture of these already pre-trained models. We have shown that across several zero-shot and few-shot tasks, the ReLU-based LLMs perform similarly to their non-ReLU models at a significantly reduced computation. In addition, after observing sparsity patterns in ReLU LLMs, we explored a few promising directions to improve the token generation speed through *aggregated sparsity* and achieve greater efficiency using ReLU-based activation functions like *shifted ReLU*.

We believe our work is among the few studies that investigate changes in the architectural components of LLMs on a large scale. We hope our findings motivate the community to further investigate the advantages of well-structured activation sparsity, ultimately enhancing the efficiency of these models.

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Appendix

A Extended Related Works

Activation Functions. ReLU, introduced by [22], remains a predominant activation function for deep neural networks and was notably utilized in the original transformers work [74]. SwiGLU [66] has been shown to enhance performance when replacing ReLU in feedforward layers and is a feature in models like Llama [73]. Narang et al. [57] conducted an extensive comparison of various activation functions, such as GeLU, SiLU [28, 17], ELU [10], SeLU [42], and GLU variants [11], identifying certain advantages over ReLU. Our paper and results differ from theirs by training billion scale models and data as opposed to their smaller scale ones. Furthermore, our results indicate that extended training can diminish the performance gap between ReLU and these other functions, also leading to savings in computational costs.

Activation Sparsity. A body of prior research [44, 25, 70] has demonstrated that increasing sparsity can lead to reductions in both inference and training times. Dejavu [51] and [47] observed pronounced sparsity in activations when using the ReLU function in feedforward layers. These studies propose that predicting this sparsity can further boost inference speeds. Similarly, [36] employed ReLU activations and introduced a controller to actively promote sparsity. Notably, these studies predominantly focus on networks employing ReLU activations, leaving out those with alternative activation functions. In contrast, our approach modifies networks by substituting other activation functions with ReLU. We then fine-tune these networks to achieve activation sparsity in the MLP layer post-ReLUfication. We further illustrate that inserting ReLU prior to the QKV and Feedforward layers can substantially reduce FLOPS, albeit at a minor cost to accuracy. Unlike the aforementioned studies, we do not utilize a sparsity predictor to minimize FLOPS.

ReLU in Attention Mechanisms. Beyond the activation function in the MLPs of large language models, a softmax activation is often employed within the attention module. Prior studies have indicated that it's feasible to replace this softmax with ReLU without compromising accuracy [75, 68, 32]. This avenue of research is distinct from our approach of Relufication, which specifically focuses on activations preceding weight multiplications.

Model compression for efficient inference Quantization, pruning and distillation are the main three techniques for compressing neural networks [82]. Quantization has been used to reduce model size and faster inference [13, 50, 58, 12, 49, 45, 14, 39, 7, 76]. The quantized model occupies less space reducing the memory latency [21, 38]. Reluification is orthogonal to quantization and reduces the amount of memory required to be loaded and can further decrease the memory latency. Distillation [33, 30, 24, 55, 1] is another technique to train smaller models. This is orthogonal to using ReLU activations as any activation can be used in distillation methods. Sparsifying or pruning weights of neural networks [20, 35, 79, 71, 65, 53] can reduce computation and inference time. Weight sparsity is usually unstructured and hard to implement for hardware, but the sparsity induced by ReLU can easily be implemented as a matrix multiplication of non zero rows. Weight sparse models can be combined with our relufication for further decrease in compute.

Mixture of Experts. Mixture of Experts (MoE) LLMs usually subdivide the feed-forward layer into multiple experts. A router is then employed to selectively and sparsely activate these experts [67, 19, 72]. Similar to our work, MoE is a form of activation sparsity but in a group form and can be seen as a subset of sparse activation. Subsequent studies have further refined the inference and training methodologies for MoE models [61, 34, 77, 16, 43, 63, 83, 8, 26]. MoE can be also combined with Relufication, having sparsity inside FFN of each expert.

Another line of work is MoEfication of networks that have sparse activations by subdividing neurons [81]. Relufication can also help MoEfication be applicable to a wider range of networks by increasing sparsity of FFNs. For a more in depth review of mixture of expert models we refer the reader to [18].

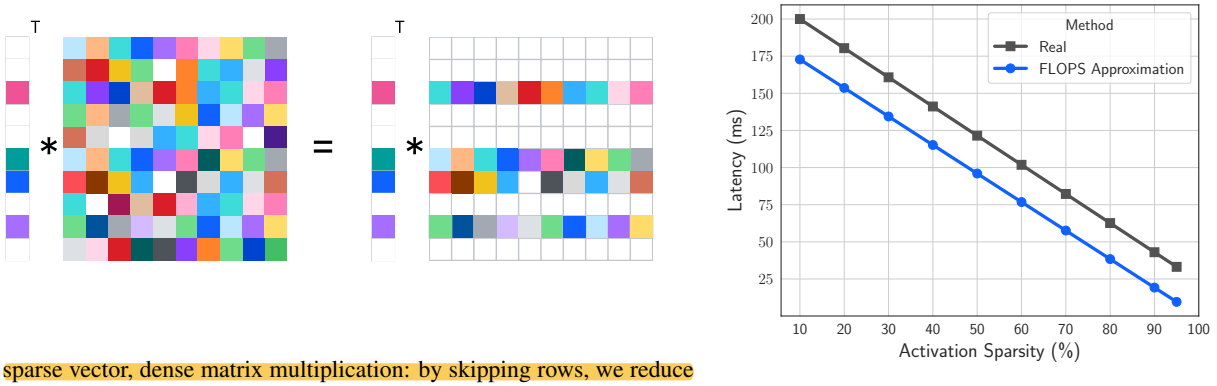
Speculative Decoding and Sparsity. Speculative decoding is a method that aims to improve model latency when faced with memory bandwidth constraints [46, 41]. It involves using a smaller model to predict the next tokens, with a larger model subsequently verifying multiple tokens in a single operation. In this work, we examine the direct effects of incorporating sparsity into speculative decoding. We show that adding sparsity can lead to performance improvements in speculative decoding. Additionally, we provide guidelines on selecting parameters for speculative decoding when sparsity is introduced.

B Discussion on Activation Sparsity and Inference Efficiency

The primary motivation behind our work is to enhance *efficiency*, and we believe it is essential to provide a precise definition of this term. Throughout the main text, we predominantly use FLOPS as our efficiency metric. In this

section, we argue why, in the presence of *activation sparsity*, FLOPS can serve as a suitable proxy for measuring various efficiency metrics.

Firstly, it is important to be reminded of the two major factors contributing to the efficiency of Large Language Models (LLMs): (1) the total amount of computation and (2) input/output (IO) transfer—i.e., transferring parameters from RAM to CPU/GPU for calculations. Notably, for today's large models, factor (2) acts as the major bottleneck during the inference phase. We refer the reader to the detailed analysis by Liu et al. [51]. Ultimately, for a specific target device and assuming an efficient implementation, we believe that the most practical measure of efficiency is *latency* (e.g., the average time to generate a token). However, each device possesses its unique properties, necessitating a more ubiquitous proxy metric.



(a) sparse vector, dense matrix multiplication: by skipping rows, we reduce both the weight transfer (i.e., loading these rows for computation) and computation (i.e., the result will be zero).

(b) Comparing FLOPS versus real latency for OPT model (FFN).

Figure 9: For LLMs that have sparse activations, FLOPS is a good approximation of the real latency.

We argue that the way we calculated *FLOPS* in our paper and is greatly influenced by *activation sparsity* can reasonably approximate *efficiency*. Here are our reasons:

- **Reduced Computation**: As shown in Fig. 9a, with activation sparsity, we have a sparse vector-dense matrix multiplication at inference, while this will be a sparse-matrix-dense matrix multiplication during training. It is important to note that this is a semi-structured sparsity (unlike magnitude weight pruning), and we can leverage the fact that we are transferring weights in large chunks (i.e., *rows*). Modern accelerators already support sparse operations[3] and we can build on these existing tools.
- **Reduced IO Transfer**: During inference, weights need to be transferred to the device cache for computation (e.g., from RAM to CPU cache or GPU VRAM to GPU cache). This step constitutes the main bottleneck during token generation. For instance, approximately 99.3% of the total latency is attributed to IO, as indicated by Liu et al. [51]. However, by storing matrices in a row-major order, we can *skip loading* unnecessary rows as the output will be zero.

Overall, as depicted in Figure 9b based on the calculations by Liu et al. [51], we demonstrate that for the OPT model on an NVIDIA A100 node, counting FLOPS provides a reasonable approximation to and is highly correlated with the time needs to generate tokens, especially, for LLMs with activation sparsity.

C Activation Sparsity and Speculative Decoding

Speculative decoding [46] is a technique that uses a smaller model M_q to propose γ tokens and a larger model M_p to verify those tokens and selects matching ones. This technique improves the runtime of the model by avoiding running M_p sequentially per all tokens. To further improve the speculative decoding inference, we can leverage sparsity as follows.

Latency model. We assume a simple conceptual model for latency in speculative decoding. Following Deja Vu [51] latency can be broken down into compute and I/O latency. The compute latency is negligible to I/O. Also, notice that the Speculative decoding is meant for the constraints that memory bandwidth is the bottleneck. Therefore we only compare I/O latency between sparse and non-sparse models. If the average aggregated sparsity of M_p for γ

[3]For example, both cuSPARSE on NVIDIA CUDA® and Accelerate on Apple devices.

tokens is $\bar{s}_{\text{agg}}(\gamma)$, and runtime of M_p is T, we approximate the latency of running M_p for γ consecutive tokens with $(1-\bar{s}_{\text{agg}}(\gamma))T$. As discussed in the previous section, this is a good approximation of real latency.

Theoretical latency improvement. Assume the smaller model M_q operates c times faster than the cumbersome model M_p. As per the primary text, token acceptances are assumed to follow an independent and identically distributed (i.i.d.) behavior. Denote α as the expected probability of a token generated by M_q being approved by M_p. The following theorems hold:

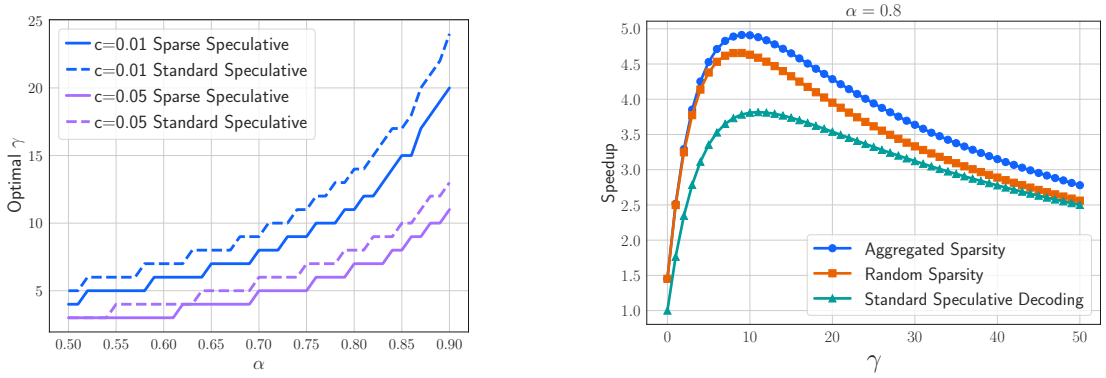
Theorem 1. *The expected improvement factor in latency for speculative decoding with sparsity, over standard speculative decoding is* $\frac{c\gamma+1}{c\gamma+(1-\bar{s}_{agg}(\gamma))}$.

Proof. The amount of time required to run sparsified model is quantified as $Tc\gamma + (1-\bar{s}_{\text{agg}}(\gamma))T$. It is the time of running a smaller model plus a larger model's non-sparse portion. Run time of speculative decoding without sparsity is $Tc\gamma + T$. The number of generated tokens in both is the same. Therefore the relative speedup of using sparsity is given by: $\frac{Tc\gamma+T}{Tc\gamma+(1-\bar{s}_{\text{agg}}(\gamma))T}$. □

Theorem 2. *The expected improvement factor in latency, when combining sparsity with speculative decoding against normal (autoregressive) decoding using only* M_p*, is* $\frac{1-\alpha^{\gamma+1}}{(c\gamma+(1-\bar{s}_{agg}(\gamma)))(1-\alpha)}$.

Proof. Similar to theorem above $Tc\gamma + (1-\bar{s}_{\text{agg}}(\gamma))T$ gives the time required for sparse speculative decoding. According to the original paper, the standard speculative decoding yields an average of $\frac{1-\alpha^{\gamma+1}}{1-\alpha}$ tokens generated per each run [46]. Thus, the anticipated run time when generating tokens with sparsity during speculative decoding becomes $\frac{(c\gamma+(1-\bar{s}_{\text{agg}}(\gamma)))(1-\alpha)}{1-\alpha^{\gamma+1}}T$. Given the runtime for producing a single token via an autoregressive approach is T, the inverse of this fraction gives the desired results. □

Optimal γ. The optimal γ for speculative decoding can be found by optimizing the speedup factor equation in Theorem 2. When sparsity is not present, the equation can be solved numerically, but for reluified networks, the aggregated sparsity for different γ's will affect the final results. We have found optimal γs based on $\bar{s}_{\text{agg}}(\gamma)$ for OPT 6.7B and presented the results in figure 10a. The chosen γ for sparse speculative decoding is smaller than standard speculative decoding since higher γ will result in less sparsity. The gap in γ is always less than 20%. Also, in figure 10b, it can be seen for the specific case of $\alpha = 0.8, c = 0.02$, the sparse speculative decoding has the highest speed-up factor over autoregressive at $\gamma = 10$s vs standard version's optimal point which happens for $\gamma = 12$. Sparse speculative decoding at $\gamma = 12$ is better than standard speculative decoding at $\gamma = 12$, while sparse speculative decoding at $\gamma = 10$ beats both. Another observation from 10b is for the case of purely random sparsity, the benefit of sparse speculative decoding would diminish over standard speculative decoding in higher γs. In contrast, the benefits of aggregated sparsity would last for larger values of γ.



(a) (b)

Figure 10: (a) optimal γ for sparse speculative decoding (b) speed up of sparse speculative decoding and standard speculative decoding over autoregressive decoding when $\alpha = 0.8$ and $c = 0.02$

D Pre-activation Distribution of OPT models trained from scratch

The distribution of pre-activation inputs is suspected to be the main factor determining the amount of sparsity. As we saw in Sec. 4.1, the pre-activation distribution for Llama and Falcon differs a lot. One may wonder that if we control for the training data and optimization algorithm, would the shapes of the distribution differ? To this end, we train OPT 1.3B models from scratch using our four variants of the activation function and depicted the pre-activation distribution along the training in Fig. 11. They start from the exact figure but gradually diverge. From SiLU to ReLU (increasing β), the pre-activation distribution becomes more concentrated around 0 and would be almost uni-modal. Further investigations on the dynamics of pre- and post-activations and their relation to efficiency and accuracy are left as an exciting future direction for research.

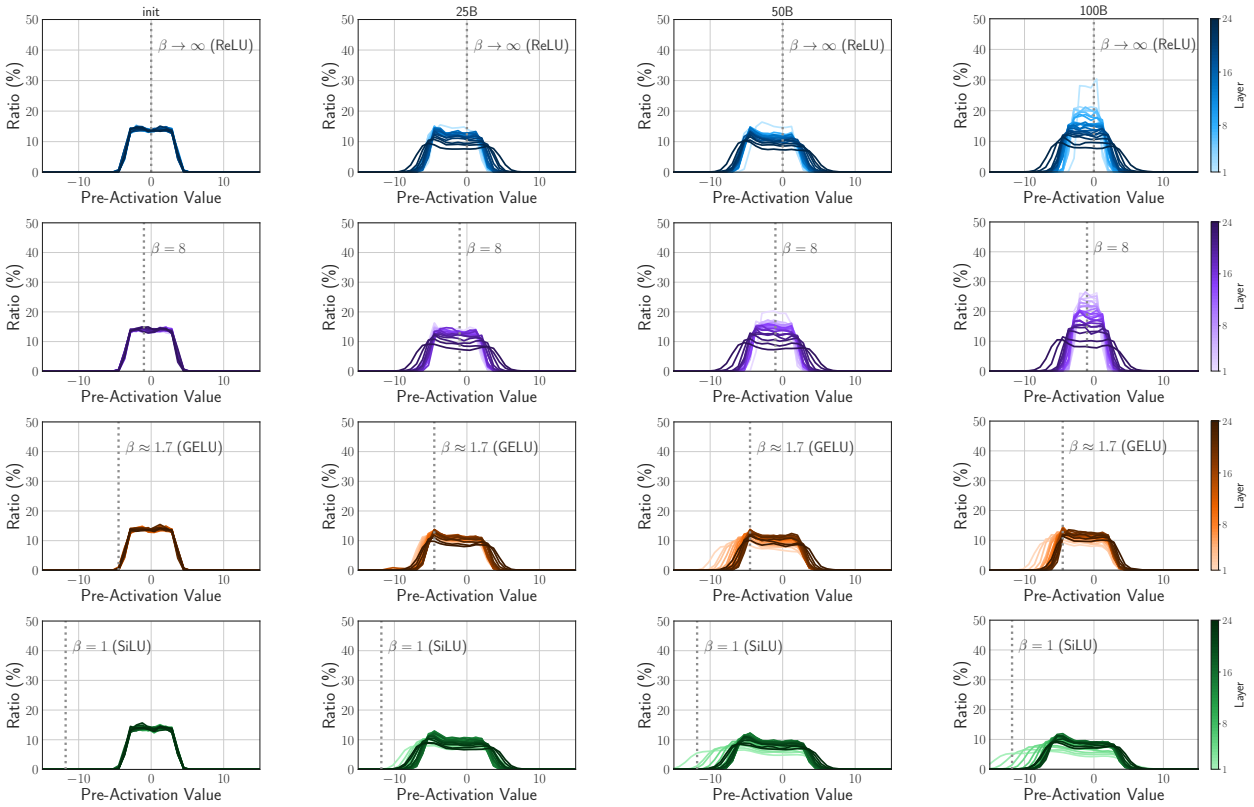


Figure 11: Pre-activation distributions of various OPT 1.3B models with all four types of activations trained from scratch at various number of seen tokens during training.

E Is a sparsified large model better than dense smaller ones?

When it comes to deploying efficient models, one may naturally use an original smaller-size (dense) model. The argument would be the performance of the relufied larger model might be already equal to or less than the smaller dense model. To study the above question, we plotted the performance vs. efficiency of the original and the relufied OPT models in Fig. 12. Taking the relufied OPT 6.7B model as an example, it operates at 2.8 GFLPOPs per token. Interpolating the blue line (that can be seen as a scaling plot of the OPT model), a dense model with equivalent FLOPS falls more than 2% short in zero-shot performance.

Similarly, compared to the relufied OPT 2.7B model, the equivalent (in FLOPS) dense model performs almost 2% lower. Indeed, the fact that the relufied models lie well above the scaling graph of the original OPT models, shows the effectiveness of relufication processes as a method to get better but more efficient models. As a side benefit, it makes the efficiency spectrum of the available LLMs more continuous. For example, consider a combination of hardware and use case that only allows deploying LLMs with lower than 3 GFLOPS during inference. Going with standard pretrained models, the only available option is OPT 2.7B with almost 1 GFLOPS, as the 6.7B does not satisfy the hardware constraint. In this situation, our relufied model not only falls in the limited inference budget but is also very

close to the next largest available model in terms of accraucy. An exciting and timely direction for future research is finding methods, that, given an LLM (or a family of LLMs), are able to produce the best performing model matching the specified inference computation budget.

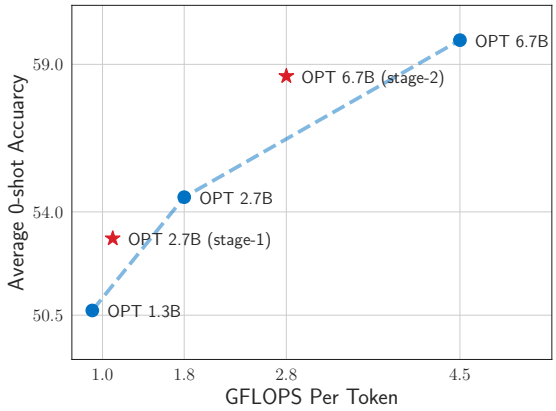


Figure 12: Performance of sparse large models vs. dense smaller models: The relufied large models (red stars) are above the scaling curve of original dense models (blue circles and dashed line).