# ConSmax: Hardware-Friendly Alternative Softmax with Learnable Parameters

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Abstract—The self-attention mechanism sets transformerbased large language model (LLM) apart from the convolutional and recurrent neural networks. Despite the performance improvement, achieving real-time LLM inference on silicon is challenging due to the extensively used Softmax in self-attention. Apart from the non-linearity, the low arithmetic intensity greatly reduces the processing parallelism, which becomes the bottleneck especially when dealing with a longer context. To address this challenge, we propose Constant Softmax (ConSmax), a softwarehardware co-design as an efficient Softmax alternative. ConSmax employs differentiable normalization parameters to remove the maximum searching and denominator summation in Softmax. It allows for massive parallelization while performing the critical tasks of Softmax. In addition, a scalable ConSmax hardware utilizing a bitwidth-split look-up table (LUT) can produce lossless non-linear operation and support mix-precision computing. It further facilitates efficient LLM inference. Experimental results show that ConSmax achieves a minuscule power consumption of 0.2 mW and area of 0.0008 mm<sup>2</sup> at 1250-MHz working frequency and 16-nm CMOS technology. Compared to state-ofthe-art Softmax hardware, ConSmax results in 3.35× power and  $2.75\times$  area savings with a comparable accuracy on a GPT-2 model and the WikiText103 dataset.

Index Terms—LLM, Transformer, Hardware-Software Co-Design, Softmax, ConSmax

## I. INTRODUCTION

Transformer-based LLM models [1, 2] have served as the foundation across a broad range of machine learning fields, from natural language processing [3, 4, 5] to computer vision [6, 7], etc. The enviable improvement can be attributed to the unique self-attention mechanism. Different from previous convolutional or recurrent network (CNN and RNN), this mechanism enhances LLMs to capture information across input contexts (i.e. tokens) regardless of their distance. The fabulous prospects in LLM have also driven efforts on specific accelerator design [8, 9, 10, 11]. However, accelerating LLM inference on silicon is challenging due to its low arithmetic intensity. It prevents the further applications of LLMs, especially on edge devices.

Softmax is the main factor exacerbating the inefficiency of LLMs for long contexts. Figure 1 details the LLM structure as well as the self-attention structure. The self-attention first transform the input token embeddings into separate representations termed Query (Q), Key (K) and Value (V). The inner

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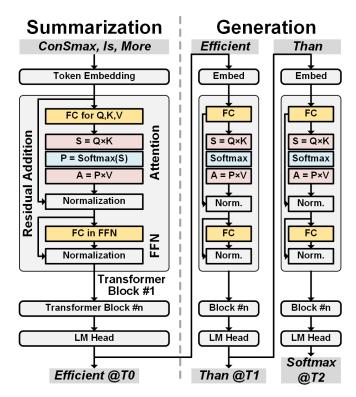


Fig. 1: LLM structure and processing flow with summarization and generation stages.

product is then computed between Q and K to determine the attention scores (S), reflecting the relevance between each pair of tokens. These scores are normalized as probabilities (P) and used to calculate weighted averages of V. The averaged result comprises the self-attention output. In addition to the mentioned matrix multiplications, the Softmax is the pivot to convert attention scores to probabilities. To compute the Softmax, the entire score vector should be allocated and iterated over to calculate the maximum score and score summation. Therefore, the after-Softmax  $P \times V$  should be blocked until the before-Softmax  $Q \times K$  and Softmax finish. Due to the low parallelism opportunity, Softmax reduces the hardware utilization of main-steam GPUs and TPUs, as well as the potential hardwares. Softermax [12] shows that the Softmax can lead more than 30% overhead of LLM latency, especially

at the longer input sequence found in state-of-the-art LLM models [2, 13, 14].

While many previous designs exploit quantization [15, 16, 17, 18], weight sparsity [19, 20], token relevance sparsity [9, 10, 11, 21, 22, 23, 24] and workload partition [25, 26, 27, 28, 29] to optimize the matrix multiplications in LLM; however, these works are still plagued by Softmax due to the consequent low utilization. A few trailblazers [12, 30, 31] aim at Softmax optimization. They can be divided into two categories, namely computing approximation and workflow scheduling. Look-up tables (LUTs) [32, 33, 34] and Taylor expansions [35, 36] are two methods to approximate the nonlinear operations in Softmax. The former precomputes the results of exponents and reciprocals, while the latter uses piecewise functions to fit them. However, approximate computing always reduces the LLM accuracy and does not improve the Softmax parallelism. In contrast, workload scheduling focuses on Softmax parallelism. For example, SpAtten [11] computes  $Q \times K$ , Softmax and  $P \times V$  for a series of tokens in pipeline. It achieves a high efficiency on encoder-only BERT models [37] but still suffers from a low utilization on decoder-only GPT models, which are the representative of the currently prevalent LLM. On the other hand, partial Softmax, such as Flash Attention [28, 29], increases Softmax parallelism for both encoder and decoder utilizing LLMs. The main idea is to divide the score vector into several partial vectors, and then produce standard Softmax on them in parallel. Nevertheless, partial Softmax requires synchronization across partial vectors to determine the ultimate maximum score and score summation, which takes up around 20% runtime latency for selfattention computing [30].

In summary, previous Softmax-oriented works suffer from inefficiency for lack of high parallelism and accuracy. To address these challenges, there is a noteworthy observation that the the maximum score can be replaced by arbitrary values to scale the numerator and denominator in Softmax. In addition, the probability vector does not have to be a unit vector to ensure LLM accuracy. Therefore, the score summation to generate the Softmax denominator can be avoided. Inspired by the above insights, this paper proposes Constant Softmax (ConSmax), a software-hardware co-design as an efficient Softmax alternative. Marking a departure from prior approaches, ConSmax can increase computing parallelism and produce lossless normalization for LLM models. In short, the key contributions are listed as follows:

- We use two differentiable normalization parameters to replace the maximum score and denominator in the original Softmax, which avoids the data synchronization needed for maximum searching and score summation. These parameters are learnable during training and fixed during inference, which achieves inference efficiency.
- We propose a bitwidth-split ConSmax hardware to produce lossless non-linear functions and reduce the LUT overhead. In addition, the ConSmax hardware is scalable to support mix-precision computing, which is the prevalent feature in the state-of-the-art LLM models [13, 38].
- We extensively evaluate ConSmax on a GPT-2 model and the WikiText103 [39] dataset. Experimental results show

that ConSmax achieves a minuscule power consumption of 0.2 mW and area of 0.0008 mm² at 1250-MHz working frequency and 16-nm CMOS technology. Compared to state-of-the-art Softmax hardware, ConSmax results in more than  $3.35\times$  power and  $2.75\times$  area savings.

The rest of the paper is organized as follows. Section II reviews the transformer-based LLM mechanisms and the Softmax bottleneck in LLM inference. Section III describes the proposed efficient ConSmax algorithm. Section IV presents the overall architecture of ConSmax hardware and the integration to LLM accelerators. Experimental results are demonstrated in Section V, and Section VI concludes this paper.

#### II. BACKGROUND

# A. Large Language Model

1) Structure: Figure 1 illustrates the LLM structure. It typically contains three main architectural components: the embedding layer, the transformer block and the language model (LM) head. At the foundation of LLM model is the embedding layer, consisting of token embedding and positional encoding, which encode the discrete input tokens to high-dimensional representations. Token embedding captures the semantic meaning, while positional encoding records the relative positioning order. The corresponding outputs are added together to generate the final embedded features. In contrast, at the very end is the LM head, which has the opposite function as the embedding layer. It receives the transformer outputs and converts them back into linguistic tokens by predicting the next-token probabilities.

Between the embedding layer and LM head, a stack of transformer blocks forms the LLM bulk. Each block can be further divided into a multi-head self-attention layer and a feed-forwarding layer. The self-attention layer allows each token to attend to every other token, thus drawing global information across input tokens regardless of their distance. This self-attention is applied multiple times as multi-head self-attention. All attention heads work in parallel to model linguistic dependencies from multiple representation subspaces. The feed-forward layer further projects the attention output through two linear transformations. It provide additional representational ability to LLM models.

2) **Workflow:** For language generation tasks, the LLM model works between summarization stage and generation stage. The summarization stage provides the initial prompt context to condition the LLM model, while the generation stage uses the context to produce a continuation.

Both working stages reuse the same model structure but with different workflow. In the summarization stage, the self-attention layer receives a bunch of input tokens and extracts the key and value representations for them in parallel. The extracted representation matrix is reused in the generation stage. In contrast, each generation iteration only processes one single input token instead of the entire sequence. The current key and value vectors are concatenated to the key and value matrices from the summarization stage, respectively. The query vector produces self-attention with the new key and value matrix to produce a new output token. Then the generation stage

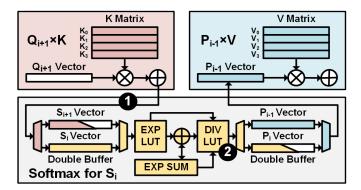


Fig. 2: Self-attention inference on hardware with tokenpipeline workflow.

iteratively feeds output tokens from the previous iteration as input to generate subsequent output tokens.

# B. Softmax Bottleneck in LLM Inference

The operations in LLM models can be roughly divided into linear matrix-matrix or vector-matrix multiplications, and non-linear functions such as Softmax. The former can accelerated well in the mainstream GPUs/TPUs, while the latter will cause a decrease in hardware utilization. Nevertheless, most recent transformer-aware accelerators still target optimizations on matrix multiplications. It is commonly achieved by the model compression techniques, such as knowledge distillation [40], quantization [15, 17, 18], sparsification [10, 11, 22, 20] and workload partition [25, 27, 28, 30], etc. These works perform high efficiency in the LLM summarization stage. But unfortunately, Softmax is still a bottleneck in the generation stage due to the low computing parallelism.

Figure 2 shows the structure of the typical transformer accelerators [10, 11]. For generality, the peripheral modules such as the sparsity detector in these works are omitted. This kind of accelerator produces  $Q \times K$ , Softmax and  $P \times V$  in a pipeline manner. Note that the original Softmax requires data synchronization to generate the maximum factor and denominator. Therefore, for each token, the Softmax module should allocate all Q×K results and block the P×V calculation until Softmax finishes. To increase computing parallelism, these cascaded modules process different tokens in pipeline, which is called as token-pipeline workflow. For example, Q×K module is for Token<sub>i+1</sub>, while Softmax and P×V modules target at Token<sub>i</sub> and Token<sub>i-1</sub>, respectively. Within each operation, the partial result is stored in double buffering and interleaved to the next module when ready. Token-pipeline flow facilitates summarization stage, where LLM model receives plenty of tokens from the input prompt. However, as mentioned in Section II-A, the generation stage cannot fill up the pipeline because the LLM only involves single input token. Only one of the three modules is working at the same time, leading to a reduced hardware utilization.

Beside the low parallelism, Softmax also suffers from the hardware-unfriendly non-linear operations such as exponents and reciprocals. To accommodate Softmax on silicon, one can utilize LUTs as well as Taylor expansions to approximate Softmax as piece-wise linear functions. This method works well for CNN and RNN acceleration, where Softmax accounts for a minimal portion as the final classification layer. However, this prerequisite is no longer valid for transformer-based LLM models, which employ Softmax as the key component in self-attention mechanism. On the one hand, the LLM accuracy will deteriorate with such approximated Softmax. On the other hand, the computing parallelism is not improved.

# C. Key Ideas of ConSmax

In summary, the Softmax operation bottlenecks existing LLM accelerators because of the low computing parallelism and hardware-unfriendly non-linear operations. To address these challenges, we propose ConSmax, a software-hardware co-design as efficient Softmax alternative. Our work is orthogonal to previous works, contributing:

- 1) High Computing Parallelism: Instead of the well-optimized matrix multiplication, we thoroughly analyze the Softmax bottleneck in LLM acceleration. The differentiable normalization parameters in ConSmax replaces the maximum factor and denominator in the original Softmax, It improves the computing parallelism by avoiding the maximum score searching and score summation.
- 2) Lossless Computing and Scalability: A bitwidth-split ConSmax hardware can produce lossless non-linear operations as well as reduces the LUT overhead. In addition, the ConSmax hardware is hierarchical and scalable to support mixprecision computing, which is the widely used in state-of-the-art LLM models.

## III. CONSMAX ALGORITHM

Although Softmax operation accounts for a relatively small portion of the overall self-attention layer, Softmax is much more challenging to design into efficient hardware than matrix-multiplication. Therefore, it can incur significant overhead if not handled appropriately. In this section, we propose the ConSmax algorithm, which helps avoid data synchronization and, hence, increase computing parallelism in Softmax.

### A. Convert Softmax to ConSmax

The Softmax operation in Figure 3(a) requires the entire score vector to calculate the maximum score and score summation. However, generating all scores at the same cycle is unreasonable, especially since the current LLM models allow thousands to hundreds of thousands of input tokens [2, 13, 14] (such as 8K to 128K tokens). Therefore, the potential hardware should buffer the exponent results for all score elements before Softmax can proceed. Note that the exponent operation would explode the numerical range. It results in more memory consumption to maintain the precision of these intermediate results. To increase Softmax parallelism, the key problem is how to compute each partial Softmax result without requiring maximum score and summation results from other partial Softmax computations.

According to the mathematical formula, Softmax operation works as a normalization function, where the maximum value

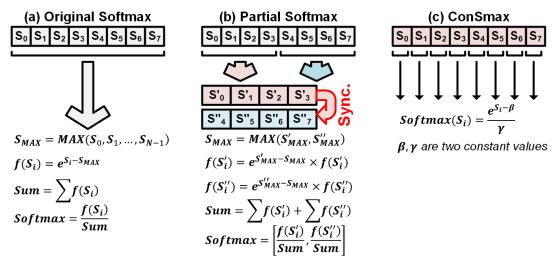


Fig. 3: Comparing ConSmax with (a) original Softmax and (b) partial Softmax.

is used as the scaling factor to avoid data overflow. There is a noteworthy observation that the scaling factor can be an arbitrary value rather than using the maximum value theoretically. Therefore, the Softmax operation is converted as:

$$Softmax(S_i) = \frac{e^{S_i - S_{max}}}{\sum_i e^{S_i - S_{max}}} = \frac{e^{S_i - \beta}}{\sum_i e^{S_i - \beta}}$$
(1)

where  $S_i$  is the i-th score element and  $\beta$  could be arbitrary value. Further, the denominator could also be arbitrary as long as it meets the normalization function. Therefore, we replace the denominator with another constant value as  $\gamma$  to propose the final ConSmax as:

$$ConSmax(S_i) = \frac{e^{S_i - \beta}}{\gamma}$$
 (2)

However, the scaling factor cannot be random values due to the overflowing of the exponential computation. For example, the overflow occurs with the case where  $S_i >> \beta.$  In contrast, the exponential result infinitely tends to be zero if  $S_i << \beta,$  leading to numerical precision loss. Similarly, the denominator cannot be arbitrary since it normalizes the exponential score to probability distribution. Take the most extreme case as an example, where  $\gamma \to 0$  or  $\gamma \to +\infty.$  Conversely, the probability results leads to infinity or zero, which cannot distinguish the token relevance.

To obtain the optimal scaling and denominator, we set the  $\beta$  and  $\gamma$  as learnable parameters. The training phase ensures that these parameters evolve in response to the practical dataset. In addition, the pair of  $\beta$  and  $\gamma$  is distinct across different self-attention head. It enables a more flexible and tailored approach to normalization. The next problem is how to initialize the  $\beta$  and  $\gamma$  for training. The optimization of  $\beta$  and  $\gamma$  is integral to the efficacy of the ConSmax function, offering a promising avenue in LLM efficiency improvement. This exploration can be done through a hyperparameter tuning process, where various combinations of initial values are tried during the warming-up iterations. The one leading to the best performance (e.g., lowest validation loss) is chosen.

Lastly, note that the pretrained denominator cannot ensure that probability vector is a unit vector. The experimental results in Section V show that this constraint will not degrade LLM accuracy, as long as the probability distribution can exaggerate the small differences in input scores. In addition, the ConSmax in Equation 2 can be rewritten as:

$$ConSmax(S_i) = \frac{e^{S_i - \beta}}{\gamma} = C \times e^{S_i}, where \ C = \frac{e^{\beta}}{\gamma}$$
 (3)

We merge  $\beta$  and  $\gamma$  into one constant value for inference, but retain them as independent parameters during training to guard against exponential overflow.

## B. Comparison with Partial Softmax

Softermax [12] and Flash Decoding++ [30] are two Softmax alternatives to reduce memory consumption and improve computing parallelism. Similarly, they employ the partial Softmax technique, where the global maximum factor is replaced by the local one. More specifically, the main idea is to divide the score vector to several partial vectors and then produce Softmax on each partial vector separately.

Although these works improve Softmax parallelism, they require additional synchronization among different partial vectors. As shown in Figure 3(b), the synchronization recomputes the previous partial Softmax with the updated maximum factor. In contrast, ConSmax avoids any synchronization, which sets ConSmax apart from these previous works.

# IV. CONSMAX HARDWARE

Based on the algorithm in Section III, we delve into the intricacies of the customized ConSmax hardware. The bitwidth-split LUT architecture can produce lossless non-linear functions and scale for mix-precision computing. In addition, we also detail how to integrate the ConSmax hardware into state-of-the-art transformer accelerators. Thanks to the synchronization free property, ConSmax can increase parallelism in both LLM summarization and generation stages.

**Proprietary EDA** ConSmax Softermax Softmax Consmax Softermax Softmax Process 130nm 16nm Max Frequency (MHz) 1250 1111 909 666.67 333.33 285.71 Area (mm<sup>2</sup>)<sup>a</sup> 0.0008 0.0022 0.011 0.007 0.029 0.18 Power (mW)b 0.2 0.67 1.5 2.69 8.5 51 0.2 1.5 25.5 178.5 Optimum Energy per op(pJ) 0.7 Opensource EDA ConSmax Softmax Softermax Softmax Softermax Consmax Process 16nm 130nm 2000 500 166.67 87.72 Max Frequency (MHz) 1000 142.86 Area (mm<sup>2</sup>)<sup>a</sup> 0.0009 0.0019 0.011 0.015 0.033 0.2

2.82

1.4

10.2

2.7

1.82

16.7

TABLE I: ConSmax Hardware Performance Comparison with Softermax, Softmax

0.683

Optimum Energy per op(pJ)

Power (mW)

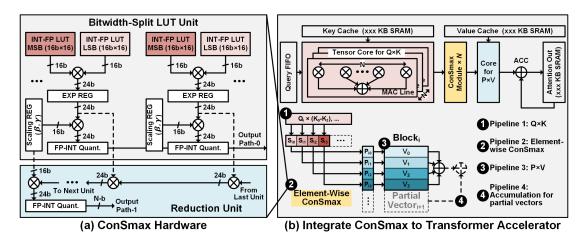


Fig. 4: (a) Bitwidth-split ConSmax hardware unit and (b) Integrate ConSmax hardware to transformer accelerator.

## A. Lossless and Scalable ConSmax Hardware

Figure 4(a) illustrates the proposed ConSmax hardware with a two-level structure. Level-1 consists of several bitwidth-split ConSmax units to process ConSmax operations in parallel. The reduction unit in Level-2 can allocates the basic ConSmax units to support mix-precision computing. For brevity, Figure 4(a) just contains two ConSmax units to produce two 8-bit results or one 16-bit result at the same time.

1) Bitwidth-Split ConSmax Unit: each unit consists of four components as bitwidth-split LUTs, floating-point (FP) multipliers, FP-to-Integer (INT) converter and necessary buffers. Given an 8b-INT score from Q×K, the LUT first produces exponent and dequantizes the result to 16b-FP simultaneously. Therefore, the exponential result can be stored in a limited bitwidth with a higher precision. Instead of using a large LUT to enumerate all of the 256 combinations, we split the 8-bit input into two slices as MSB-INT4 and LSB-INT4. Each slice is paired with one 16-entry LUT. The partial sums from two LUTs are merged in the downstream multiplier. In this way, the bitwidth-split LUTs can produce the lossless exponential operation for all input combinations with a trifling LUT overhead.

In contrast to the simple shift and addition used for integral bitwidth alignment, the partial sum reduction between floatingpoint fragments is relatively complicated:

$$e^{S_{INT8}} = e^{(MSB_{INT4} <<4) + LSB_{INT4}}$$
$$= e^{2^4 \times MSB_{INT4}} \times e^{LSB_{INT4}}$$
(4)

42.2

255.3

10.5

73.5

To avoid the implementation of non-linear  $(e)^{2^4}$  in hardware, the MSB-LUT projects  $e^{2^4*x}$  for MSB-INT4, while LSB-LUT just maps  $e^x$ . After exponent, the ConSmax normalization is applied as Equation 3. The pretrained  $\beta$  and  $\gamma$  are merged and multiplied with the exponential result in another multiplier.

2) **Reduction Unit**: The mix-precision computing is a prevalent model compression technique for efficient LLM inference [13], wherein different operators of the model can be assigned with different precision. Therefore, this feature necessitates the support of mix-precision computing in the ConSmax hardware. To achieve this, the reduction unit allocates several basic LUT units with respect to the precision requirement. As shown in Figure 4(a), the 16-bit score element is first divided to two 8-bit slices. Then each ConSmax unit receives one slice and produce ConSmax separately. The reduction unit reads the generated partial sums and reduces them using a summation chain.

## B. Integrate ConSmax Hardware to Transformer Accelerator

Figure 4(b) details the integration of ConSmax hardware to dedicated transformer accelerators. Two tensor cores and

<sup>0.3</sup> <sup>a</sup> Power for 16nm is tested with 500MHz, for 130nm is tested with 80MHz.

<sup>&</sup>lt;sup>b</sup> Area is measured at Max Frequency.

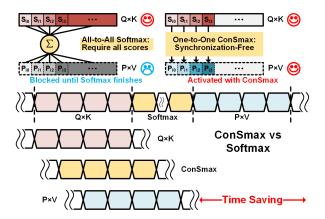


Fig. 5: Synchronization-free ConSmax leads to high parallelism and time savings.

the inserted ConSmax hardware produce  $Q \times K$ , ConSmax normalization and  $P \times V$  in pipeline. If the input sequence is too large to generate the entire score results at once, the score vector is divided into partial vectors and multiplied with the paired value elements. The partial results are then accumulated in series.

Compared to the token-pipeline in Section II-B, ConSmax-integrated accelerators leads to high parallelism and significant time saving. As shown in Figure 5, the  $P \times V$  is blocked until the original Softmax finishes. In contrast, thanks to the synchronization-free property, the ConSmax enables elementwise pipeline instead of token-pipeline. Therefore, the accelerator can fill up all processing module even with single tokens. It not only speeds up LLM summarization, but more importantly, promotes LLM generation.

# V. EXPERIMENTAL RESULT

# A. Experiment Setup

For software performance, we evaluate ConSmax on a small GPT-2 model [41, 42] and the WikiText103 [39] dataset. The benchmark model contains 6 transformer layers with 6 self-attention heads. Embedding features size is set to 384. The default context length is set to 256. We substitute RMSNorm [43] for LayerNorm in post-norm. We train for 30,000 iteration steps. For the ConSmax evaluation, we replaced Softmax in each attention block with ConSmax. We report validation loss for the language generation task. This metric measures the ability of the transformer language model on text generation. A lower validation loss value indicates better performance.

A ConSmax prototype in Verilog is implemented in 16nm and 130nm CMOS technology. We synthesize ConSmax with both proprietary Design Compiler and open-source EDA toolchains. The generated netlist is used to evaluate the power and area consumption.

# B. Software Performance

In Figure 6, we compared the variation losses associated with Softmax and the proposed ConSmax. Initially, it is observed that the variation loss for the ConSmax is marginally

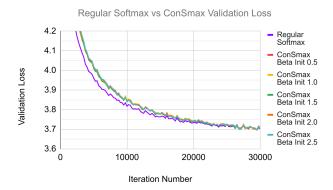


Fig. 6: Validation Loss of GPT-2 models with Softmax and ConSmax, showing convergence of validation losses.

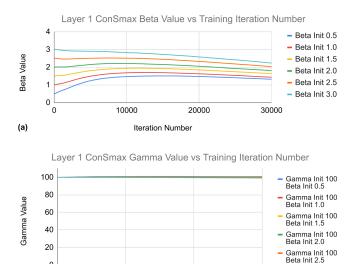


Fig. 7: Evolution of  $\beta$  and  $\gamma$  throughout training, each training run using a different starting value for  $\beta$  (as  $\gamma$  has been observed to have low % change). Spread of  $\beta$  values has been found to decrease with training.

Iteration Number

20000

30000

Gamma Init 100 Beta Init 3.0

10000

(b)

higher compared to Softmax. Nevertheless, this discrepancy diminished over time. After approximately 2000 iterations, the variation losses for Softmax and ConSmax models converge, demonstrating a similar trend in their performance metrics. There is only a 2.3% loss degeneration for ConSmax after the first 2000 iterations and less than 0.9% after the first 10000 iterations.

Figure 7 illustrates the evolution of  $\beta$  and  $\gamma$  throughout training for layer 1 of the 6-layer GPT-2 model employing the ConSmax technique.

As the training proceeds, it is noteworthy that both  $\beta$  and  $\gamma$  exhibit a converging trend to stabilize at constant values. These stabilized values are then expected to be utilized as fixed constants during the inference phase.

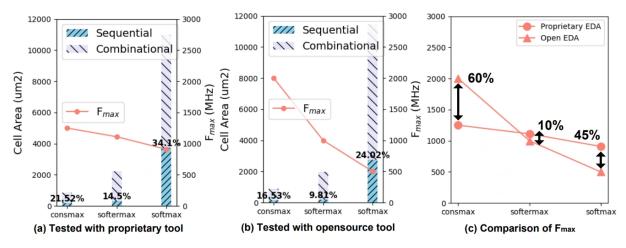


Fig. 8: Cell area comparison of Consmax, Softermax and Softmax in 16nm process (a) tested in proprietary EDA tool, (b) tested in opensource EDA tool and (c) comparison of  $F_{max}$  using different EDA tool for 3 designs.

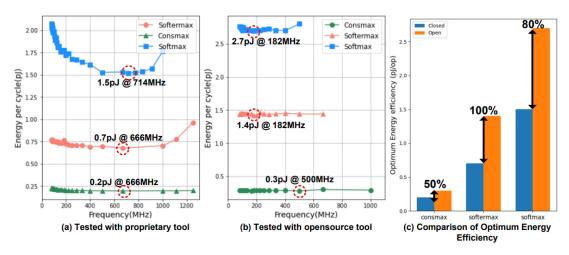


Fig. 9: Energy efficiency comparison of Consmax, Softermax and Softmax in 16nm process (a) tested in proprietary EDA tool, (b) tested in opensource EDA tool and (c) comparison of Energy efficiency using different EDA tool for 3 designs.

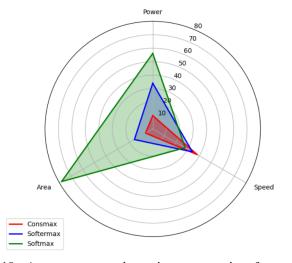


Fig. 10: Area, power, and maximum operating frequency (fmax) normalized and compared for Consmax, Softermax, and Softmax implementations.

## C. Hardware Performance

We have carried out a comparative study of our proposed ConSmax against the baseline Softmax and Softermax[12]. The power and area consumption are evaluated under 16nm and 130nm CMOS. In order to render a thorough comparison, we have established the testing environment in both commercial EDA and open-source EDA tool.

The feature size for Softmax, Softermax and Consmax are set to 8 for all the experiments.

Table I summarizes ConSmax hardware performance and compares it with Softmax and Softermax hardware. Under 16nm CMOS technology, 500-MHz working frequency and 0.8-V power supply, one ConSmax hardware only consumes 0.2mW power and  $0.0008 \text{mm}^2$  area. Compared to the Softermax counterpart, ConSmax achieves  $3.35 \times$  power, and  $2.75 \times$  area savings. Compared to Softmax counterpart, Consmax achieves  $7.5 \times$  power, and  $13.75 \times$  area savings. With a lower 80-MHz working frequency and 130 nm CMOS, ConSmax achieves  $3.2 \times$  power and  $4.14 \times$  area savings compared to Softermax. As well as  $23.2 \times$  power and  $25.7 \times$  area savings

compared to Softmax With opensource EDA, the ConSmax shows similar performance improvement by  $4.13 \times$  power and  $2.11 \times$  area reductions.

Figure 8 presents a comparison of the silicon area utilized by three different designs when operated at their maximum frequencies. In comparison with Softermax and Softmax, Consmax exhibits a reduced area footprint along with an increased maximum operating frequency. This finding is consistent across both open-source and proprietary EDA tools.

Furthermore, as depicted in Figure 9, an optimal energy consumption per cycle has been identified for each of the designs. At an operating frequency of 666 MHz, Consmax is projected to attain an energy efficiency of 0.2 pJ. When benchmarked against Softermax, this represents a significant energy saving of  $3.5 \times$ , and a  $7.5 \times$  energy saving in comparison to Softermax ans Softmax respectively.

Figure 10 provides a visual representation of the power, area, and speed normalized for the three designs, evaluated at their respective peak operating frequencies. It is evident that Consmax achieves a superior speed while incurring lower power and area costs, underscoring its potential for highly efficient design applications.

#### VI. CONCLUSION

This paper presents ConSmax, a software-hardware codesign for efficient Softmax acceleration. ConSmax improves Softermax computing parallelism by avoiding the data synchronization, which produces maximum score and score summation. In addition, the bitwidth-split ConSmax hardware is lossless and scalable to calculating non-linear functions. The experiments show that ConSmax achieves a minuscule power consumption of 0.2 mW and area of 0.0008 mm² at 1250-MHz working frequency and 16-nm CMOS technology. Compared to state-of-the-art Softmax hardware, ConSmax results in 3.35× power and 2.75× area savings with a comparable accuracy on GPT-2 model and the WikiText103 dataset.

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