

# INTATTENTION: A FULLY INTEGER ATTENTION PIPELINE FOR EFFICIENT EDGE INFERENCE

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## ABSTRACT

Deploying Transformer models on edge devices is limited by latency and energy budgets. While INT8 quantization effectively accelerates the primary matrix multiplications, it exposes the softmax as the dominant bottleneck. This stage incurs a costly dequantize → softmax → requantize detour, which can account for up to 65% of total attention latency and disrupts the end-to-end integer dataflow critical for edge hardware efficiency. To address this limitation, we present *IntAttention*, the first fully integer, plug-and-play attention pipeline without retraining. At the core of our approach lies *IndexSoftmax*, a hardware-friendly operator that replaces floating-point exponentials entirely within the integer domain. *IntAttention* integrates sparsity-aware clipping, a 32-entry lookup-table approximation, and direct integer normalization, thereby eliminating all datatype conversion overhead. We evaluate *IntAttention* and demonstrate consistent and substantial gains. Our method achieves up to **3.7x** speedup and **61%** energy reduction over FP16 baselines and **2.0x** faster than conventional INT8 attention pipelines on Armv8 CPUs. These gains are achieved with high-fidelity accuracy comparable to baselines across diverse language and vision models, enabling practical and efficient Transformer inference on commodity edge devices. *Code will be released in later version of this work.*

## 1 INTRODUCTION

Transformer-based models achieve state-of-the-art performance across natural language processing (Vaswani et al., 2017), computer vision (Dosovitskiy et al., 2021), and multimodal tasks (Radford et al., 2021). The core mechanism, multi-head self-attention, exhibits quadratic time and memory complexity with respect to sequence length ( $O(L^2)$ ). As the context length increases, attention becomes the dominant inference cost, substantially increasing latency and memory usage. In autoregressive language models, the pre-filling (prompt-processing) phase largely determines the time-to-first-token (TTFT), as the full key-value cache must be computed before generation begins (Kwon et al., 2023). Consequently, long prompts are computationally expensive, even though subsequent decoding is relatively fast.

Recent advances in compact and specialized models have accelerated the transition toward on-device inference. For instance, Google’s Gemma3-270M (Team et al., 2025) model targets energy-efficient deployment on smartphones, while studies such as QuestA demonstrate that reinforcement learning-based question augmentation can elevate a 1.5B

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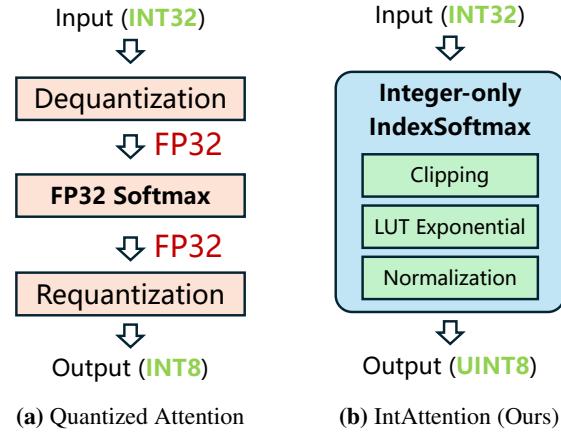


Figure 1. Comparison between conventional quantized attention and the proposed **IntAttention**, where **IntAttention** maintains an end-to-end integer dataflow from  $\mathbf{QK}^\top$  to  $\mathbf{PV}$ .

model to the performance level of 32B models on multiple reasoning benchmarks (Li et al., 2025). This migration shifts inference from cloud servers to mobile and embedded processors, where end-to-end latency and energy efficiency become primary constraints. Consequently, optimizing attention, particularly by reducing the computational cost of long-context processing, has become crucial for deploying practical large language models (LLMs) on edge hardware.

Previous studies commonly use low-precision floating-point formats such as BF16, FP16, FP8, and even FP4 (Mickevicius et al., 2022; Shah et al., 2024; Zhang et al., 2025b). However, these formats are neither universally supported nor energy-efficient on commodity edge hardware, which typically offers highly optimized integer computation pathways. Consequently, integer quantization, especially INT8, is the most practical and effective optimization strategy (Dettmers et al., 2022; Jacob et al., 2018). Motivated by this hardware constraint, we propose **IntAttention**. To the best of our knowledge, this work presents the **first fully integer, plug-and-play attention pipeline without retraining**. Designed for off-the-shelf edge processors, it executes attention entirely in the integer domain, eliminating redundant dequantization and requantization steps. Consequently, it functions as a drop-in replacement for conventional quantized attention within transformer-based inference pipelines.

Achieving an end-to-end integer attention pipeline is non-trivial. After applying dynamic INT8 quantization to the  $\mathbf{QK}^\top$  and  $\mathbf{PV}$  matrix multiplications, the remaining path that forms and applies attention weights becomes the dominant bottleneck. The standard softmax requires floating-point exponentials, row-wise normalization, and repeated data-format conversions. On edge processors, this dequantize  $\rightarrow$  softmax  $\rightarrow$  requantize detour can account for up to **65%** of the attention latency once the surrounding GEMMs are quantized as shown in Figure 2, thereby eroding much of the benefit of integer GEMMs acceleration.

To mitigate this bottleneck, we introduce *IndexSoftmax*, a lightweight approximation that replaces costly exponential evaluations with a compact lookup table and performs max-subtraction and clipping in the integer domain. *IndexSoftmax* preserves the relative structure of the attention scores and eliminates most per-element floating-point work.

Building on this, we integrate *IndexSoftmax* with integer normalization and direct requantization of the probability tensor. The resulting pipeline, **IntAttention**, takes INT32 logits from the  $\mathbf{QK}^\top$  GEMM, produces a quantized attention tensor  $\mathbf{P}$  in UINT8, and feeds  $\mathbf{P}$  into the integer  $\mathbf{PV}$  GEMM for value aggregation. This design eliminates the dequantize  $\rightarrow$  softmax  $\rightarrow$  requantize detour and preserves an end-to-end integer dataflow. Figure 1 contrasts a conventional quantized pipeline, which falls back to floating point in the softmax stage, with **IntAttention**, which remains integer from input to output.

To summarize, this work contributes:

- We introduce *IndexSoftmax*, a lookup-table-based approximation to softmax that is compatible with integer execution, and integrate it with integer normalization and probability quantization to form **IntAttention**.
- We show that **IntAttention** runs on off-the-shelf edge

processors, delivering up to **3.7x** speedup and up to **61%** lower energy consumption than an FP16 baseline, while preserving high-fidelity accuracy on both language and vision models.

## 2 BACKGROUND AND MOTIVATION

### 2.1 Attention and Dynamic Quantization

**Scaled Dot-Product Attention** We first recall the standard attention mechanism, which underlies our design. Let  $\mathbf{Q}, \mathbf{K}, \mathbf{V} \in \mathbb{R}^{L \times d}$  denote the query, key, and value with sequence length  $L$  and feature dimension per token  $d$  (Vaswani et al., 2017). The standard attention computes

$$\mathbf{A} = \mathbf{QK}^\top, \quad \mathbf{P} = \text{softmax}\left(\frac{\mathbf{A}}{\sqrt{d}}\right), \quad \mathbf{O} = \mathbf{PV}. \quad (1)$$

**Dynamic Quantizing  $\mathbf{Q}, \mathbf{K}, \mathbf{V}$**  To reduce latency and memory traffic on edge hardware, we adopt per-tensor symmetric INT8 quantization with zero point fixed at 0 for the three inputs  $\mathbf{Q}, \mathbf{K}, \mathbf{V}$  (Jacob et al., 2018). For a tensor  $\mathbf{X}$ , let  $\hat{\mathbf{X}} = \text{quant}(\mathbf{X})$ ; the scale factor and the quantized tensor are

$$s_X = \frac{\max(|\mathbf{X}|)}{127}, \quad (2)$$

$$\text{quant}(\mathbf{X}) = \text{clamp}\left(\left\lfloor \frac{\mathbf{X}}{s_X} \right\rfloor, -127, 127\right), \quad (3)$$

which enables low-precision matrix multiplications while preserving a simple dequantization model  $\mathbf{X} \approx s_X \hat{\mathbf{X}}$ , where  $\hat{\mathbf{X}} \in \mathbb{Z}^{\text{INT8}}$ . Applying Equation 3 to  $\mathbf{Q}, \mathbf{K}$ , and  $\mathbf{V}$  yields their quantized counterparts  $\hat{\mathbf{Q}}, \hat{\mathbf{K}}, \hat{\mathbf{V}}$  and the corresponding scales  $s_Q, s_K, s_V$ .

**Integer accumulation and scaling.** After quantization, the attention logits are computed fully in the integer domain using INT8  $\times$  INT8 multiplications with INT32 accumulation:

$$\hat{\mathbf{A}} = \hat{\mathbf{Q}} \hat{\mathbf{K}}^\top, \quad \alpha = \frac{s_Q s_K}{\sqrt{d}}, \quad \mathbf{A} \approx \alpha \hat{\mathbf{A}}. \quad (4)$$

Here  $\alpha$  rescales integer logits to the floating-point range. Substituting  $\mathbf{V} \approx s_V \hat{\mathbf{V}}$  into  $\mathbf{O} = \mathbf{PV}$  gives

$$\mathbf{O} \approx s_V \hat{\mathbf{O}} = s_V \mathbf{P} \hat{\mathbf{V}}. \quad (5)$$

With these definitions, the two heavy matrix multiplications ( $\mathbf{QK}^\top$  and  $\mathbf{PV}$ ) are executed in integer arithmetic. SageAttention demonstrates that carefully engineered INT8 kernels yield significant throughput gains with minimal loss of accuracy across diverse models (Zhang et al., 2025c). SageAttention2 further demonstrates that pushing similarity computation to INT4 for  $\mathbf{Q}$  and  $\mathbf{K}$  while keeping a slightly higher precision on the value path can remain near lossless and provides additional speedups on modern GPUs (Zhang et al., 2025a).

## 2.2 Emerging Bottleneck in Quantized Attention Pipelines

**Numerically stable softmax.** We adopt the standard maximum subtraction strategy to ensure numerical stability in the exponential. Given  $\mathbf{A} \in \mathbb{R}^{L \times L}$ , define the row-wise maximum vector  $\mathbf{m} = \text{rowMax}(\mathbf{A})$ . The stable softmax can then be written compactly as

$$\mathbf{P} = \frac{\exp(\mathbf{A} - \mathbf{m})}{\text{rowSum}(\exp(\mathbf{A} - \mathbf{m}))} \quad (6)$$

where both *rowMax* and *rowSum* operate along the row dimension. This transformation preserves the exact softmax while constraining all exponential inputs to  $(-\infty, 0]$ , thus preventing numerical overflow and improving stability.

**Cost drivers on edge hardware.** The  $O(L^2)$  complexity of softmax persists even when  $\mathbf{QK}^\top$  and  $\mathbf{PV}$  are accelerated. On edge hardware with limited thread-level parallelism, the exponential and the division dominate latency. A single  $\exp(\cdot)$  typically expands to tens of floating point operations per element, and the normalization still incurs row-wise divisions. In quantized pipelines, this cost is further amplified because INT32 logits must be dequantized to FP32 before softmax, and the resulting probabilities must be requantized for the value projection, which interrupts an otherwise contiguous integer dataflow.

**Measured breakdown and implication.** Figure 2 reports the measured time share of the dequantize → softmax → requantize path. In FP32, the share is about 13% to 19% across sequence lengths. With FP16 GEMMs it increases to about 23% to 30% yet remains secondary. After switching GEMMs to INT8, their latency drops while the softmax path is essentially unchanged, so its share rises to **57% to 65%** and becomes the dominant cost. Therefore, once the multiplications are quantized, the probability normalization path is the next component that must be optimized to unlock further end to end speedups.

**Context in prior work.** Multiple GPU-oriented efforts have shown that softmax becomes the limiting stage once the surrounding matrix multiplications are heavily optimized. FlashAttention related kernels tile queries and keys, fuse attention with online softmax, and aggressively reduce memory traffic (Dao et al., 2022a;b). FlashAttention-3 goes further by driving GEMMs with FP8 Tensor Cores and then hiding the dominant softmax cost using warp specialization and ping–pong scheduling that overlaps GEMM and softmax through double buffering (Shah et al., 2024). TurboAttention extends this line of work by addressing not only the softmax bottleneck but also the dequantization overhead that arises in quantized attention. It unifies these optimizations through *FlashQ*, which enables quantized

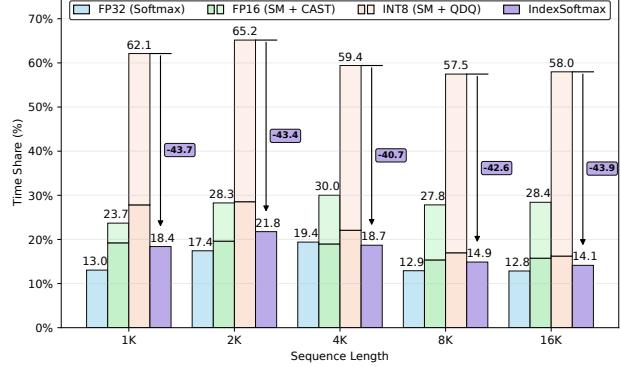


Figure 2. Breakdown of time share for the dequantize → softmax → requantize path across different precisions. Once GEMMs are accelerated to INT8, this path emerges as the dominant latency and becomes the next optimization target.

execution of matrix multiplications, and a sparsity-based Softmax approximation that avoids FP32 dequantization during exponentiation(Kang et al., 2025).

These results confirm that the softmax and quantization-related path is a real bottleneck. However, all of these optimizations rely on massive GPU parallelism and specialized floating-point hardware. On edge devices, which lack high-throughput floating-point units and deep warp-level concurrency but provide efficient integer units, the same path remains largely scalar and costly. This motivates the need for a lightweight, plug-and-play, and integer-friendly softmax replacement to further accelerate attention inference on edge hardware.

## 2.3 Acceleration Strategies

As the softmax and its associated floating-point conversions overhead have become the dominant bottlenecks in quantized attention, recent research has focused on accelerating this stage through three main strategies:

**Hardware-oriented softmax co-design.** Approaches such as Softermax and ConSmax redesign the softmax operator alongside dedicated accelerator logic. Softermax replaces  $e^x$  with  $2^x$  and uses fixed-point integer shifters for exponentiation and normalization (Stevens et al., 2021). ConSmax removes explicit max-finding and normalization by training fixed scaling constants, allowing inference to be implemented with table lookups and multiplications (Liu et al., 2024). These co-designs achieve high throughput and energy savings, but only work on specialized hardware and require operator changes, which limits their adoption on generic edge processors.

**Input-aware quantization and LUT-based softmax.** Methods like EXAQ and TurboAttention accelerate softmax without changing model operators or hardware. EXAQ

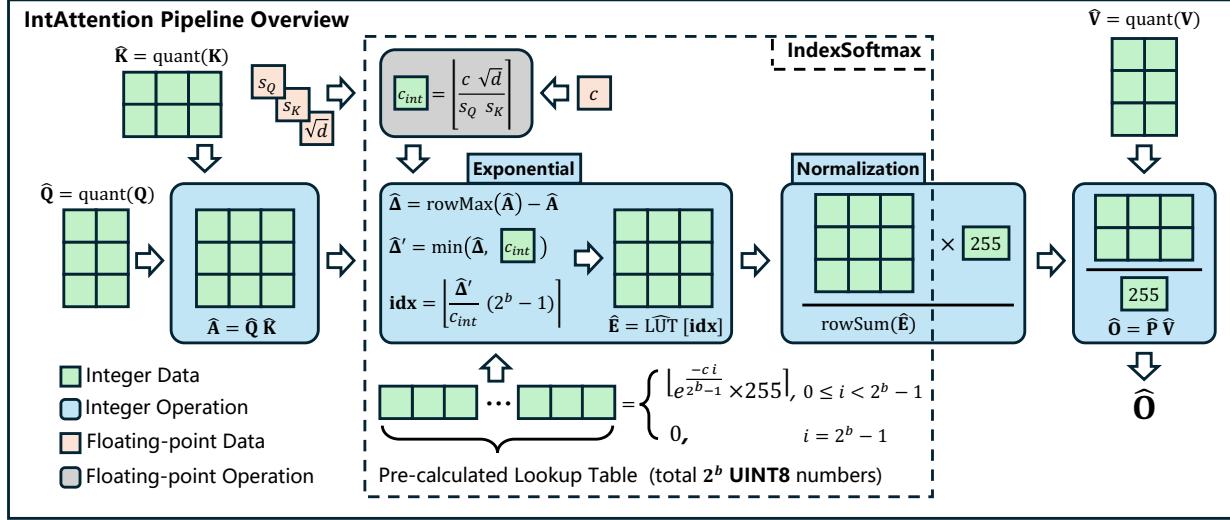


Figure 3. Overview of the proposed IntAttention pipeline.

determines dynamic optimal clipping ranges to quantize attention scores to as low as 3 bits (Shkolnik et al., 2024). TurboAttention uses a small LUT for the integer part of the exponent and a 3rd-order polynomial for the fractional part, plus sparsification of negligible exponentials (Kang et al., 2025). These techniques eliminate heavy floating-point exponent operations and can be applied directly in attention inference, but the normalization step (sum and divide) typically remains in high-precision arithmetic, so the dataflow remains mixed-precision and still burdens edge CPUs.

**Integer-only softmax in Transformer quantization.** Fully integer softmax schemes are integrated into integer-quantized Transformer pipelines. I-BERT uses low-order integer polynomials and iterative integer refinements to approximate softmax (Kim et al., 2021). I-ViT introduces *Shiftmax*, expressing the exponential via bit shifts and additions (Li & Gu, 2023). I-LLM proposes *DI-ClippedSoftmax*, performing clipping and scaling entirely in integer form (Hu et al., 2024). Although these methods deliver a true integer dataflow, they usually depend on quantization-aware training or calibration to recover accuracy, and add runtime overhead for scale/clip estimation factors that limit their seamless deployment on edge devices.

In summary, hardware co-design approaches deliver very high efficiency but depend on specialized logic and retraining, which limits portability. Input-aware quantization and LUT-based methods are more deployable, but they typically leave the normalization step in floating-point or high-precision calculation, so the dataflow is still mixed-precision. Integer-only softmax methods promise a fully integer path, but they require model adaptation through fine-tuning or reconstruction. None of these families removes the full dequantize  $\rightarrow$  softmax  $\rightarrow$  requantize loop in a way that is both strictly integer and truly plug-and-play.

## 2.4 Motivation and Design Goals

The breakdown in subsection 2.2 shows that once the matrix multiplications in attention are quantized and accelerated, the dominant latency on edge processors comes from the remaining dequantize  $\rightarrow$  softmax  $\rightarrow$  requantize path. Prior work alleviates parts of this path, but always at the cost of at least one key property: it either assumes custom hardware, falls back to floating point in the normalization step, or requires model retraining. As a result, the practical end-to-end gain for real deployment remains limited.

Our objective is to remove this bottleneck in a way that is directly usable in existing quantized attention pipelines. This leads to four design goals:

1. **Integer execution.** All stages of attention, including the analogue of exponentiation and the row-wise normalization, must run in integer arithmetic. This allows the computation to fully exploit the efficient integer units that are already available on edge hardware, instead of invoking slower floating-point paths.
2. **Plug-in deployment.** The method must serve as a drop-in replacement for standard attention in pre-trained models. It should not require quantization-aware training, fine-tuning, or structural changes. This makes it directly adoptable in large existing models and gives it immediate deployment value.
3. **Portable efficiency.** The implementation must rely only on common integer primitives such as add, multiply, shift, and indexed lookup, and must parallelize cleanly on SIMD-style cores (for example ARM NEON). It should not introduce extra global passes for per-input statistics. This keeps the method practical on a wide range of commodity devices.

4. **Fidelity under acceleration.** The operator must deliver a clear latency and energy advantage over floating-point softmax, while maintaining accuracy close to the original FP16 attention. In other words, efficiency gains cannot come at the expense of unacceptable degradation.

### 3 INTATTENTION

**IntAttention** transforms the conventional quantized attention block into a true integer-domain pipeline, removing the dequantize  $\rightarrow$  softmax  $\rightarrow$  requantize detour that dominates latency on edge processors. By preserving a contiguous integer path from the  $\mathbf{QK}^\top$  logits to the  $\mathbf{PV}$  multiplication, **IntAttention** executes entirely on commodity integer units, requires no model retraining, and can be used as a drop-in replacement in existing quantized attention inference.

At the kernel of **IntAttention** is *IndexSoftmax*, whose core operation is integer clipping followed by lookup-table based exponent approximation. The resulting UINT8 attention map  $\hat{\mathbf{P}}$  feeds directly into the integer  $\mathbf{PV}$  kernel, so no floating-point computation appears on the runtime path.

Implementation of *IndexSoftmax* relies on three tightly coupled mechanisms: integer-domain clipping, LUT exponentials, and integer scale normalization, which are designed and tuned together rather than as independent modules. This coupling minimizes extra passes or global statistics, preserves parallelism on SIMD-style integer units, and yields substantial reductions in latency and energy while maintaining accuracy close to the baseline.

An overview of the proposed *IntAttention* pipeline is illustrated in Figure 3. The following subsections detail each mechanism and the integration choices that enable efficient, portable integer attention.

#### 3.1 IndexSoftmax

**Integer-Domain Clipping via Sparsity-Aware Pruning**  
The exponential in Softmax exhibits an inherent *sparsity*: as inputs decrease,  $\exp(\cdot)$  rapidly approaches zero. In practice shown in Figure 4, a small subset of high valued logits dominates the normalization term, while the majority contribute negligibly. Evaluating exponentials for these near-zero terms wastes arithmetic and increases memory traffic, especially on edge devices. To exploit this, we introduce an **integer-domain clipping** mechanism that removes low-importance logits before the exponential approximation. Unlike floating-point sparse/efficient attention variants, our method stays entirely in the integer domain and avoids type conversions.

Formally, given integer logits  $\hat{\mathbf{A}} \in \mathbb{Z}^{L \times L}$ , we apply row-

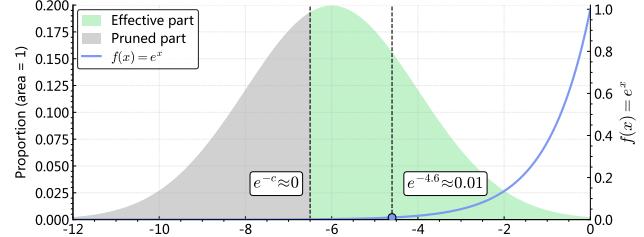


Figure 4. Illustration of the exponential activation in Softmax. Most logits lie in the near-zero region, where  $e^x$  contributes negligibly to the normalization. Only a small subset of higher logits significantly affects the output distribution.

wise max-subtraction for stability:

$$\hat{\Delta} = \text{rowmax}(\hat{\mathbf{A}}) - \hat{\mathbf{A}}, \quad (7)$$

which yields nonnegative distances from the dominant value in each row. We then use a quantization aligned clipping threshold  $c_{\text{int}}$ , derived from the clipping threshold  $c$  via the quantization scale factor in Equation 4:

$$c_{\text{int}} = \text{round}\left(\frac{c}{\alpha}\right) = \text{round}\left(\frac{c\sqrt{d}}{s_Q s_K}\right). \quad (8)$$

Clipping is performed elementwise:

$$\hat{\Delta}' = \min(\hat{\Delta}, c_{\text{int}}), \quad (9)$$

so entries whose contributions to  $\exp(-\alpha \hat{\Delta})$  are negligible are saturated at  $c_{\text{int}}$ .

To match LUT-based exponentiation, we adopt the sign convention  $\mathbf{m} - \mathbf{A}$  (rather than  $\mathbf{A} - \mathbf{m}$  in Equation 6), ensuring all arguments to  $\exp(-x)$  are nonnegative and lie within  $[0, c]$ . Combined with clipping, this confines the exponential evaluation to a compact, table-friendly domain.

Overall, integer-domain clipping provides two benefits: (i) it removes redundant work on near-zero contributions, reducing arithmetic and bandwidth, and (ii) it establishes a quantization consistent, bounded range for integer-domain exponentiation. These properties lay the groundwork for an efficient, fully integer Softmax pipeline that is both sparsity-aware and deployment friendly on low-power accelerators.

**Efficient Exponential Approximation Using Lookup Tables**  
Evaluating  $\exp(\cdot)$  is costly in quantized inference. Classical implementations use iterative or polynomial schemes (e.g., Padé or Taylor series) that require multiple floating-point operations. On GPUs this cost can be amortized by massive parallelism, but on edge devices, where bandwidth and instruction latency dominate,  $\exp(\cdot)$  often becomes the bottleneck once the matrix multiplications are quantized. The result is a fast integer  $\mathbf{QK}^\top$  followed by a floating-point Softmax that breaks the integer dataflow and limits further speedup.

We address this by replacing the exponential stage with a *table-driven* surrogate. After integer-domain clipping defined in Equation 9, all inputs to  $\exp(-x)$  lie in a finite interval  $[0, c]$ . Over this range the function is bounded, so a fixed resolution discretization provides an effective and simple approximation. We therefore precompute a *fixed* lookup table with  $2^b$  entries,

$$\text{LUT}[i] = \begin{cases} \exp\left(-\frac{ci}{2^b - 1}\right), & 0 \leq i < 2^b - 1, \\ 0, & i = 2^b - 1. \end{cases} \quad (10)$$

and map clipped integer distances to indices by a linear rescaling,

$$\text{idx} = \left\lfloor \frac{\hat{\Delta}'}{c_{\text{int}}} (2^b - 1) \right\rfloor, \quad (11)$$

The exponential surrogate is then obtained by a gather:

$$\hat{\mathbf{E}} = \text{LUT}[\text{idx}] \approx \exp(-\alpha \hat{\Delta}'), \quad (12)$$

Among LUT-only methods, the closest is EXAQ, which uses a *dynamic* clipping rule based on per-tensor standard deviation statistics together with ultra-low LUT resolutions ( $b \in \{2, 3\}$ ) (Shkolnik et al., 2024). This adds global reductions and control overhead that are expensive on edge devices. In contrast, we adopt *fixed* hyperparameters ( $c, b$ ) selected offline. Empirically shown in Figure 9, performance is insensitive to  $c$  within a practical range, and modestly increasing  $b$  to a moderate table size has a negligible runtime impact while clearly improving approximation accuracy. As long as the table remains moderate, lookup latency is effectively constant, so pursuing extremely small tables offers little real benefit but degrades fidelity. A moderate, fixed-resolution LUT achieves a stronger balance between accuracy and efficiency for integer attention on edge hardware.

### 3.2 LUT Rebuild and Integer Scale Normalization

Quantization of the probability matrix  $\mathbf{P}$  has a crucial impact on the final attention output. While prior methods often scale probabilities by  $\times 127$  and store them in signed INT8, we adopt an unsigned UINT8 formulation scaled by  $\times 255$ , which fully utilizes the available range and improves numerical smoothness during normalization. This design allows the softmax path to remain entirely in the integer domain, with both the lookup table and output probabilities quantized to UINT8. Because the precision of  $\mathbf{P}$  is inherently limited by its 8-bit representation, Using excessively precise floating-point lookup tables brings little benefit. Therefore,

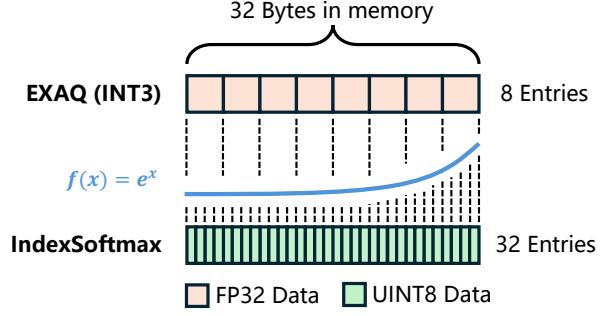


Figure 5. IndexSoftmax achieves 4x higher LUT resolution under the same memory budget, enabling higher-fidelity exponential approximation without dynamic clipping or global statistics, which are costly on edge devices.

our exponential lookup table is also quantized to UINT8, so that each entry is compact yet expressive enough to represent the clipped exponential curve.

Over the clipped interval  $[0, c]$ , the floating-point table is linearly mapped to integers table:

$$\hat{\mathbf{LUT}} = \left\lfloor 255 \times \text{LUT} \right\rfloor, \quad (13)$$

so that very small values are preserved with fine integer granularity. Given the clipped index vector  $\text{idx}$ , we gather a rowwise surrogate

$$\hat{\mathbf{E}} = \hat{\mathbf{LUT}}[\text{idx}], \quad (14)$$

accumulate its row sum with a widened integer accumulator and produce 8-bit probabilities by fixed-point scaling:

$$\hat{\mathbf{P}} = \left\lfloor \frac{255 \cdot \hat{\mathbf{E}}}{\text{rowSum}(\hat{\mathbf{E}})} \right\rfloor. \quad (15)$$

All steps are fully integer-friendly: a single LUT gather, one 32-bit accumulation, and an elementwise scale. By performing normalization in the integer domain, we avoid any floating-point operations in the runtime path. As shown in Figure 5, compared with EXAQ, which encodes only 8 exponential values using INT3 LUT resolution under a 32-byte budget, our *IndexSoftmax* stores 32 entries within the same memory footprint, achieving 4x higher resolution and substantially improving LUT-based approximation fidelity without requiring dynamic clipping or global statistics, which are costly on edge processors.

### 3.3 Quantization Scope and Compatibility

Our default configuration uses per-tensor symmetric quantization for the surrounding multiplications  $\mathbf{QK}^\top$  and  $\mathbf{PV}$ , which provides a balance between accuracy and implementation simplicity. The proposed **IndexSoftmax** is, however,

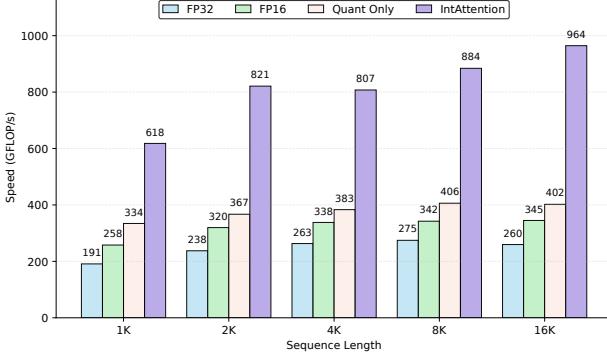


Figure 6. Speed comparison among different attention implementations on **RK3588S2** across varying sequence lengths with  $\text{headdim} = 128$ .

compatible with finer-grained schemes such as per-channel or per-block quantization. In these cases, clipping becomes group-specific while the subsequent lookup and normalization remain unchanged.

Let the quantization be defined over groups  $g = 1, \dots, G$  (channels or blocks). Denote the scales by  $s_Q^{(g)}$  and  $s_K^{(g)}$ , and define

$$\alpha^{(g)} = \frac{s_Q^{(g)} s_K^{(g)}}{\sqrt{d}}, \quad c_{\text{int}}^{(g)} = \left\lfloor \frac{c}{\alpha^{(g)}} \right\rfloor. \quad (16)$$

Clipping in subsection 3.1 is then applied group-wise using  $c_{\text{int}}^{(g)}$ :

$$\hat{\Delta}'^{(g)} = \min(\hat{\Delta}^{(g)}, c_{\text{int}}^{(g)}). \quad (17)$$

The index mapping and lookup table follow the same formulas with  $c_{\text{int}}^{(g)}$ , while the LUT itself can be shared across groups since the continuous bound  $c$  and resolution  $b$  are fixed:

$$\text{idx} = \left\lceil \hat{\Delta}'^{(g)} \frac{2^b - 1}{c_{\text{int}}^{(g)}} \right\rceil, \quad \hat{\mathbf{E}} = \text{LUT}[\text{idx}]. \quad (18)$$

Row-wise normalization in Equation 15 proceeds identically after concatenating or summing contributions within each row. Thus, moving from per-tensor to per-channel or per-block quantization increases only the bookkeeping of scales and the computation of group-specific  $c_{\text{int}}^{(g)}$ , while preserving the integer-only dataflow, the LUT resolution, and the overall pipeline structure.

## 4 EXPERIMENTS

**Main results.** The speed of **IntAttention** is up to **3.7x** faster than FP16 and **2.0x** faster than Quantized-Only pipelines on Armv8 CPUs. Furthermore, it achieves an average **61% energy reduction** while maintaining **accuracy comparable to baseline** across both language and vision models.

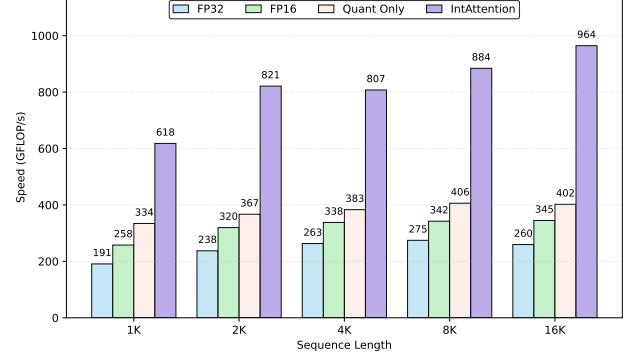


Figure 7. Speed comparison among different attention implementations on **Apple M2** across varying sequence lengths with  $\text{headdim} = 128$ .

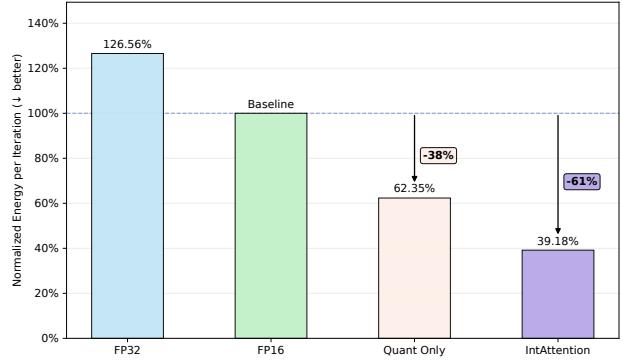


Figure 8. Normalized energy consumption per iteration across different precision settings, using FP16 as the baseline for comparison.

### 4.1 Experimental Setup

**Models.** We evaluate **IntAttention** across both language and vision models to verify its generality. For language, we adopt LLaMA-3.2-1B (Dubey et al., 2024), OPT-1.3B (Zhang et al., 2022), and Qwen3-1.7B (Yang et al., 2025). For vision, we include DeiT-B-224 (Touvron et al., 2021a), ViT-L-P16-384 (Dosovitskiy et al., 2021), and CaiT-L-M48-448 (Touvron et al., 2021b). All models are configured under identical settings to ensure a fair comparison among different pipelines.

**Datasets.** To provide broad coverage of modeling capabilities, language models are tested on WikiText (Merity et al., 2017) and six comprehension or commonsense benchmarks: HellaSwag (Zellers et al., 2019), LAMBADA (Paperno et al., 2016), PIQA (Bisk et al., 2020), WinoGrande (Sakaguchi et al., 2021), ARC-Challenge, and ARC-Easy (Clark et al., 2018). Vision models are evaluated on ImageNet-1K (Deng et al., 2009) using the standard validation split.

Table 1. End-to-end language task performance of **IntAttention** compared with baselines across multiple benchmarks.

Model	Method	WikiText ↓	HellaSwag	Lambada	PIQA	WinoG	ARC-C	ARC-E	Avg. ↑
LLaMA -3.2-1B	FP16	12.663	63.65%	62.95%	74.59%	60.69%	36.18%	60.48%	59.76%
	Quant Only	13.701	63.39%	62.62%	74.32%	60.62%	35.84%	<b>60.56%</b>	59.56%
	<b>IntAttention</b>	<b>13.070</b>	<b>63.50%</b>	<b>63.61%</b>	<b>74.92%</b>	<b>61.01%</b>	<b>36.43%</b>	60.48%	<b>59.92%</b>
OPT -1.3B	FP16	16.413	53.73%	57.85%	72.41%	59.43%	29.61%	50.97%	54.00%
	Quant Only	18.323	<b>54.11%</b>	58.00%	<b>72.31%</b>	58.64%	<b>29.69%</b>	<b>50.97%</b>	53.95%
	<b>IntAttention</b>	<b>16.802</b>	53.65%	<b>58.78%</b>	72.25%	<b>59.35%</b>	29.18%	50.80%	<b>54.00%</b>
Qwen3 -1.7B	FP16	23.013	60.43%	50.73%	72.25%	61.09%	42.83%	69.61%	59.49%
	Quant Only	32.945	<b>58.95%</b>	46.24%	<b>68.17%</b>	<b>58.72%</b>	<b>37.28%</b>	61.32%	<b>55.12%</b>
	<b>IntAttention</b>	<b>27.751</b>	58.44%	<b>46.94%</b>	67.30%	58.56%	37.03%	<b>61.87%</b>	55.02%

Table 2. End-to-end vision task performance of **IntAttention** compared with baselines across multiple benchmarks.

Method	DeiT-B-224		ViT-L-P16-384		CaiT-L-M48-448		Avg.↑	
	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
FP16	81.802	95.598	85.628	97.782	86.090	97.588	84.507	96.989
Quant-Only	<b>81.896</b>	<b>95.708</b>	83.844	97.150	85.742	97.530	83.707	96.796
<b>IntAttention</b>	81.826	95.62	<b>85.224</b>	<b>97.668</b>	<b>86.100</b>	<b>97.640</b>	<b>84.383</b>	<b>96.976</b>

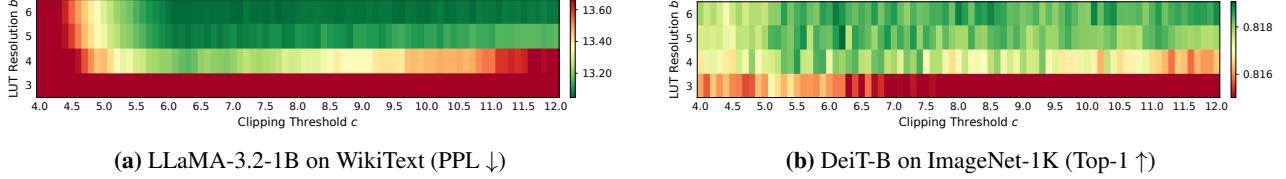
**Metrics.** For language tasks, we report perplexity on WikiText and accuracy on the remaining datasets using the open source *lm-evaluation-harness* (Gao et al., 2024), followed by the arithmetic average of the accuracy scores. For vision tasks, we report Top-1 and Top-5 accuracy on ImageNet and their average. For efficiency evaluation, we further record throughput in GFLOP/s, energy consumption per iteration, and attention breakdown latency. These metrics jointly reflect both model quality and system efficiency, allowing a comprehensive comparison between floating-point and integer pipelines in terms of trade-off between accuracy and performance.

**Hardware and settings.** Performance measurements are conducted on two ARMv8-based platforms, each using 8 threads. The first is an embedded development board powered by a Rockchip RK3588S2 processor, which provides NEON and dot-product instruction support. The second is a laptop equipped with an Apple M2 chip, supporting NEON, dot-product, and I8MM instructions. Both systems run Arm Compute Library (ACL) version 52.4.0. Unless otherwise specified, the sequence length  $L$  takes values from 1K, 2K, 4K, 8K, 16K with a typical head dimension of  $d = 128$ . We compare four pipelines: FP32, FP16, INT8 quant-only, and *IntAttention*, with FP16 serving as the baseline for normalization.

## 4.2 Efficiency

**Speed.** We first measure attention throughput in GFLOP/s across sequence lengths for all four pipelines described above. As shown in Figure 6 and Figure 7, *IntAttention* achieves the best performance on both platforms. On RK3588S2, the speedup over FP16 lies between 2.1x and 3.7x, and over the Quantized-Only pipeline between 1.6x and 2.0x. On Apple M2, the gains over FP16 fall between 2.4x and 2.8x, and over Quantized Only between 1.9x and 2.4x. The exact factor varies modestly with microkernel efficiency and memory traffic. These results indicate that maintaining an integer dataflow with *IndexSoftmax* removes the Softmax bottleneck studied in Table 4.4 and yields consistent end-to-end speedups on both platforms.

**Energy consumption.** We next examine energy efficiency, since edge deployment is typically power-limited. On RK3588S2, energy per attention iteration (joules) is normalized to the FP16 baseline (Figure 8). *IntAttention* uses only 39.18% of FP16 energy, a 61% reduction, and is 37% lower than the Quantized Only pipeline. The savings come from an integer dataflow that removes dequantization, reduces memory traffic, and replaces exponentials with a compact lookup table, which translates to consistent energy benefits across all tested sequence lengths.



**Figure 9. Hyperparameter sensitivity of IntAttention** over LUT resolution  $b$  and clipping threshold  $c$ . Red indicates noticeable degradation ( $> 1$  PPL or  $> 0.3\%$  Top-1), while green denotes high-fidelity regions.

**Table 3.** Ablation study on different softmax implementations. Comparison between IndexSoftmax and EXAQ variants (INT2/INT3) across **language benchmarks**.

Model	Method	WikiText $\downarrow$	HellaSwag	Lambada	PIQA	Winog	ARC-C	ARC-E	Avg. $\uparrow$
LLaMA -3.2-1B	FP16	12.663	63.65%	62.95%	74.59%	60.69%	36.18%	60.48%	59.76%
	EXAQ (INT2)	17.753	57.56%	50.48%	70.73%	56.99%	33.28%	56.19%	54.21%
	EXAQ (INT3)	13.757	62.72%	60.72%	72.96%	58.01%	36.01%	59.55%	58.33%
	IndexSoftmax	<b>12.784</b>	<b>63.44%</b>	<b>63.38%</b>	<b>74.16%</b>	<b>60.46%</b>	<b>36.43%</b>	<b>60.65%</b>	<b>59.75%</b>
OPT -1.3B	FP16	16.413	53.73%	57.85%	72.41%	59.43%	29.61%	50.97%	54.00%
	EXAQ (INT2)	38.782	52.58%	<b>58.76%</b>	72.25%	58.33%	28.16%	50.59%	53.50%
	EXAQ (INT3)	17.248	53.36%	58.28%	71.93%	<b>59.43%</b>	<b>30.38%</b>	50.51%	53.98%
	IndexSoftmax	<b>16.424</b>	<b>53.79%</b>	58.53%	<b>72.20%</b>	<b>59.43%</b>	29.44%	<b>51.01%</b>	<b>54.06%</b>
Qwen3 -1.7B	FP16	23.013	60.43%	50.73%	72.25%	61.09%	42.83%	69.61%	59.49%
	EXAQ (INT2)	34.431	58.11%	45.37%	68.17%	59.35%	39.42%	63.05%	55.58%
	EXAQ (INT3)	29.006	59.98%	49.45%	70.78%	<b>61.79%</b>	41.47%	67.76%	58.77%
	IndexSoftmax	<b>22.356</b>	<b>60.41%</b>	<b>51.66%</b>	<b>72.25%</b>	61.09%	<b>42.24%</b>	<b>69.07%</b>	<b>59.45%</b>

**Table 4.** Ablation study on different softmax implementations. Comparison between IndexSoftmax and EXAQ variants (INT2/INT3) across **vision benchmarks**.

Method	DeiT-B-224		ViT-L-P16-384		CaiT-L-M48-448		Avg. $\uparrow$	
	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5	Top-1	Top-5
FP16	81.802	95.598	85.628	97.782	86.090	97.588	84.507	96.989
EXAQ INT2	81.554	95.482	85.222	97.668	85.866	97.554	84.214	96.901
EXAQ INT3	81.768	95.584	85.428	97.722	85.998	<b>97.596</b>	84.398	96.962
IndexSoftmax	<b>81.804</b>	<b>95.590</b>	<b>85.616</b>	<b>97.774</b>	<b>86.114</b>	97.582	<b>84.511</b>	<b>96.982</b>

### 4.3 Accuracy

We now evaluate the accuracy impact of running attention entirely within the integer domain. We integrate *IndexSoftmax* with quantized  $QK^\top$  and a UINT8 probability matrix in the **PV** stage to form *IntAttention*. As shown in [Table 1](#), this end-to-end pipeline improves over the Quantized Only baseline on most models and tasks and, on LLaMA and OPT, matches or slightly exceeds the baseline. Qwen3 remains

more sensitive to attention quantization, yet *IntAttention* narrows the gap and yields a clear perplexity gain on WikiText. On ImageNet, as shown in [Table 2](#), *IntAttention* is slightly below Quantized-Only for DeiT-B while remaining above the baseline, and it shows consistent gains for ViT-L and CaiT. These results indicate that an all integer attention with UINT8 **P** effectively preserves attention mass through **PV** and maintains the fidelity of probability aggregation.

#### 4.4 Ablation Study

**Hyperparameter Sensitivity** *IntAttention* exposes only two hyperparameters: the clipping threshold  $c$  and LUT resolution  $b$  (see Equation 8, Equation 10), and both are empirically robust. A joint sweep on LLaMA-3.2-1B/WikiText and DeiT-B/ImageNet-1K shows a broad stability plateau for  $b \geq 4$  and  $c \in [5.5, 7.7]$  (Figure 9). Colors near the red boundary indicate insufficient LUTs or overly clipping. Intermediate tones remain acceptable, while the deep green region yields near optimal accuracy. A consistent ridge around  $c \approx 6.6$  emerges across modalities, balancing fidelity with the sparsity implied by truncated exponentials. We therefore fix and recommend to use  $(b, c) = (5, 6.6)$ , where  $b = 5$  corresponds to a  $2^5 = 32$  entries INT8 LUT ( $\approx 32$  B) for all experiments with negligible memory and no measurable runtime overhead.

**IndexSoftmax Component.** We also isolate the core probability module to confirm that the improvement is not an artifact of model-specific tuning by replacing only the Softmax operator while keeping all other components unchanged. Across language and vision models shown in Table 3 and Table 4, *IndexSoftmax* preserves baseline accuracy with negligible loss and, on average, surpasses EXAQ (INT3) by about 1.4% under the same memory budget. A single fixed configuration is used for all models and datasets. The effect comes from employing a higher LUT resolution at a fixed clipping threshold, which enlarges the effective approximation domain, maintains the shape and ordering of attention distributions, and stabilizes normalization. As a result, *IndexSoftmax* provides a simple and accurate integer-domain replacement that does not require additional tuning.

**P Matrix Quantization.** We ablate the quantization scheme for the attention probability matrix  $\mathbf{P}$ , which is constrained to the range  $[0, 1]$ . As shown in Table 5, quantizing  $\mathbf{P}$  with a signed INT8 format causes unnecessary dynamic range waste and distorts small probability values, leading to a lower cosine similarity and higher relative L1 error. In contrast, the unsigned UINT8 quantization fully allocates the representable range to  $[0, 1]$ , yielding a substantially higher similarity and lower RMSE. This demonstrates that aligning the quantization domain with the inherent distribution of  $\mathbf{P}$ , a strictly positive and normalized probability matrix, is essential for maintaining attention fidelity and ensuring numerical stability in quantized attention.

**Latency breakdown.** As shown in Figure 2, in a conventional INT8 attention pipeline the portion outside GEMM, namely Softmax together with quantization and dequantization, becomes the dominant cost and contributes about 58% to 65% of total latency across sequence lengths. Replacing this stage with *IndexSoftmax* and keeping the path entirely

Table 5. Accuracy comparison of two quantization formats for the attention probability matrix  $\mathbf{P}$ , evaluated against the FP16 baseline.

Format	CosSim $\uparrow$	Relative L1 $\downarrow$	RMSE $\downarrow$
INT8	0.996612	0.07739742	0.0023912
UINT8	<b>0.999081</b>	<b>0.04097954</b>	<b>0.0012436</b>

in the integer domain reduces this overhead to about 14% to 22% and removes dequantization. As a result, the bottleneck shifts back to the  $\mathbf{QK}$  and  $\mathbf{PV}$  matrix multiplications, which now account for the clear majority of time. This ablation clarifies the throughput gains: *IntAttention* removes the quantization induced hotspot and restores a compute profile in which further optimization should focus on GEMM kernels.

#### 4.5 Discussion

**Accuracy perspective.** *IntAttention* maintains strong accuracy, and the remaining gaps mainly from quantizing  $\mathbf{Q}$ ,  $\mathbf{K}$ , and  $\mathbf{V}$  rather than the Softmax itself. Prior work such as *SageAttention* series reduces this loss with input smoothing and finer per-block quantization scales, improving the dynamic range seen by the attention maps (Zhang et al., 2025a;b;c). Our method is orthogonal: it keeps the entire attention path in the integer domain and stabilizes probability normalization. Combining smoothing and per-block scaling with the integer dataflow of *IntAttention* is expected to further improve accuracy with little additional cost.

**Efficiency perspective.** The latency analysis shows that removing dequantization and replacing Softmax with *IndexSoftmax* shifts the bottleneck back to the  $\mathbf{QK}$  and  $\mathbf{PV}$  matrix multiplications. This makes the optimization target clear. Future speedups should focus on stronger GEMM kernels and low-bit implementations when hardware support becomes available.

## 5 CONCLUSION

This paper presents **IntAttention**, a fully integer and plug-and-play attention pipeline that eliminates the costly dequantize  $\rightarrow$  softmax  $\rightarrow$  requantize path in quantized attention. By introducing **IndexSoftmax**, a LUT-based integer replacement for softmax with integer normalization, IntAttention executes end-to-end attention entirely within the integer domain. Experiments on Armv8 edge processors show up to **3.7x** latency reduction and **61%** lower energy consumption while maintaining accuracy comparable to baseline. These results demonstrate that integer-native attention, not only integer matmuls, is key to unlocking efficient and deployable Transformer inference on edge hardware.

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