I-ViT: Integer-only Quantization for Efficient Vision Transformer Inference

Zhikai Li^{1,2}, Qingyi Gu^{1*}

¹Institute of Automation, Chinese Academy of Sciences ²School of Artificial Intelligence, University of Chinese Academy of Sciences {lizhikai2020,qingyi.gu}@ia.ac.cn

ABSTRACT

Vision Transformers (ViTs) have achieved state-of-the-art performance on various computer vision applications. These models, however, have considerable storage and computational overheads, making their deployment and efficient inference on edge devices challenging. Quantization is a promising approach to reducing model complexity; unfortunately, existing efforts to quantize ViTs are simulated quantization (aka fake quantization), which remains floating-point arithmetic during inference and thus contributes little to model acceleration. In this paper, we propose I-ViT, an integeronly quantization scheme for ViTs, to enable ViTs to perform the entire computational graph of inference with integer operations and bit-shifting and no floating-point operations. In I-ViT, linear operations (e.g., MatMul and Dense) follow the integer-only pipeline with dyadic arithmetic, and non-linear operations (e.g., Softmax, GELU, and LayerNorm) are approximated by the proposed lightweight integer-only arithmetic methods. In particular, I-ViT applies the proposed Shiftmax and ShiftGELU, which are designed to use integer bit-shifting to approximate the corresponding floating-point operations. We evaluate I-ViT on various benchmark models and the results show that integer-only INT8 quantization achieves comparable (or even higher) accuracy to the full-precision (FP) baseline. Furthermore, we utilize TVM for practical hardware deployment on the GPU's integer arithmetic units, achieving 3.72~4.11× inference speedup compared to the FP model.

1 INTRODUCTION

Vision Transformers (ViTs) have recently achieved great success on a variety of computer vision tasks [2, 6, 8]. Nevertheless, as compared to convolutional neural networks (CNNs), ViTs suffer from higher memory footprints, computational overheads, and power consumption, hindering their deployment and real-time inference on resource-constrained edge devices [15, 17, 19]. Thus, compression approaches for ViTs are being widely researched.

Model quantization, which reduces the representation precision of weight/activation parameters, is an effective and hardware-friendly way to improve model efficiency [7, 13]. However, most previous works focus on simulated quantization (aka fake quantization), *i.e.*, only the inputs/outputs are integer values, and compute-intensive operations are performed with dequantized floating-point values, as shown in Fig. 1(a). This scheme is potentially useful in scenarios with limited data transmission bandwidth, such as recommendation systems, but fails to reduce computational costs and thus has little effect on model acceleration [7, 25].

Therefore, integer-only quantization, which can fully benefit from fast and efficient low-precision integer arithmetic units (e.g.,

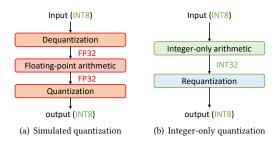


Figure 1: Simulated vs. integer-only quantization. The former needs dequantization and retains floating-point arithmetic, whereas the latter realizes the entire inference with integer-only arithmetic.

GPU's Turing Tensor Cores) as shown in Fig. 1(b), is highly desired in real-time applications [11, 23]. For CNNs, several works have made attempts at integer-only pipelines with dyadic arithmetic for linear (e.g., Dense) or piecewise linear (e.g., ReLU) operations [11, 25]. However, the non-linear operations (e.g., Softmax, GELU, and LayerNorm) in ViTs cannot naively follow the above pipelines, since non-linearity does not satisfy the homogeneity condition for dyadic arithmetic. Another notable challenge is that low-precision nonlinear operations suffer from severe accuracy degradation [17, 19]. To address the above issues, integer polynomial approximations for non-linear operations are proposed [12, 16]; unfortunately, despite an acceptable accuracy, such approaches are inefficient and fail to fully exploit the benefits of hardware logic. Moreover, they are developed for language models, making it infeasible to properly transfer to ViTs due to differences in data distribution. Therefore, how to accurately perform the non-linear operations of ViTs with efficient integer-only arithmetic remains an open issue.

In this paper, we propose I-ViT, which quantizes the entire computational graph with no dequantization, to fill the research gap of integer-only quantization for ViTs. Specifically, linear operations follow the dyadic arithmetic pipeline; and non-linear operations are approximated without accuracy drop by novel light-weight integer-only arithmetic methods, where Shiftmax and ShiftGELU perform most arithmetic with bit-shifting that can be efficiently executed with simple shifters in hardware logic [22], and I-LayerNorm calculates the square root with integer iterations instead.

The main contributions are summarized as follows:

- We propose I-ViT, which fully quantizes the computational graph of ViTs and allows performing the entire inference with integer arithmetic and bit-shifting, without any floating-point operations. To the best of our knowledge, this is the first work on integer-only quantization for ViTs.
- We propose novel light-weight integer approximations for non-linear operations, in particular, Shiftmax and ShiftGELU

^{*}Corresponding author

Preprint, arXiv, 2022.07 Zhikai Li et al.

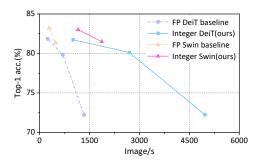


Figure 2: Accuracy-speed curves of I-ViT and the FP baseline on DeiT [21] and Swin [18]. Accuracy is evaluated on ImageNet dataset, and speed is obtained from the latency on an RTX 2080Ti GPU (batch=8). As we can see, I-ViT provides significant accelerations (3.72~4.11×) while achieving similar (or even higher) accuracy.

use integer bit-shifting to accomplish most arithmetic, which fully benefit from the efficient hardware logic.

I-ViT is evaluated on various models for the large-scale classification task, achieving compression with similar (or even higher) accuracy. Moreover, we deploy I-ViT on an RTX 2080Ti GPU using TVM¹ [4], which accelerates the integeronly inference of ViTs with Turing Tensor Cores, achieving a 3.72~4.11× speedup over the FP model (as shown in Fig. 2).

2 RELATED WORKS

2.1 Vision Transformers

Thanks to the global receptive fields captured by the attention mechanism, ViTs have shown superior performance on various computer vision tasks [8, 9, 24]. ViT [6] is the first effort to apply transformer-based models to vision applications and achieves high accuracy than CNNs on the classification task. DeiT [21] introduces an efficient teacher-student strategy via adding a distillation token, reducing the time and data cost in the training phase. Swin [18] presents shifted window attentions at various scales, which boosts the performance of ViTs. Furthermore, ViTs have also been applied to more complexed vision applications, such as object detection [2, 27] and semantic segmentation [3].

Despite the promising performance, ViTs' complicated architectures with large memory footprints and computational overheads is intolerable in real-world applications [15, 19], especially in time/resource-constrained scenarios. Thus, the compression approaches for ViTs are necessary for practical deployments.

2.2 Model Quantization

Model quantization, which converts the floating-point parameters to low-precision values, is a prevalent solution to compressing models in a hardware-friendly manner [13]. Most previous works are designed to quantize CNNs [7], and recently, several quantization methods oriented to ViTs' unique structures are proposed. Ranking loss [19] is presented to maintain the correct relative order of the quantized attention map. PSAQ-ViT [15] pushes the quantization of ViTs to data-free scenarios based on patch similarity. To realize the full quantization of ViTs, FQ-ViT [17] introduces quantization

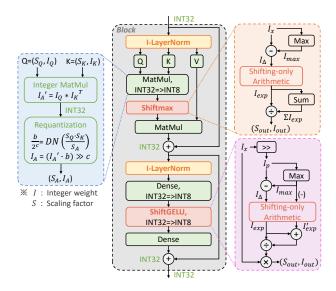


Figure 3: Overview of the proposed I-ViT. The entire computational graph is performed with integer-only arithmetic, where linear Mat-Mul and Dense operations follow the dyadic arithmetic pipeline and the proposed Shiftmax, ShiftGELU, and I-LayerNorm accomplish the non-linear operations. Except for the labeled INT32, the remaining data streams are all INT8 precision.

strategies for LayerNorm and Softmax. However, all the above approaches are simulated quantization, which requires the quantized parameters to be dequantized back again and then perform floating-point operations. This scheme fails to use efficient low-precision arithmetic and thus has little contribution to model acceleration.

Integer-only quantization, which eliminates dequantization and enables the entire inference to be performed with integer-only arithmetic, can potentially address the above challenges. Dyadic arithmetic is proposed to perform the integer-only pipeline for CNNs [11, 25], however, it is designed for linear and piecewise linear operations based on the homogeneity condition, and thus is not applicable to non-linear operations in ViTs. Several studies focus on integer polynomial approximations [12, 16], yet they are inefficient and are developed for language models and not for ViTs. In addition, various approximation methods that hold floating-point arithmetic are presented [20, 26]; while they lower certain computational costs, they cannot meet the demands of integer arithmetic. As a result, integer-only quantization for ViTs remains a research gap.

3 METHODOLOGY

3.1 Overview

The overview of the proposed integer-only quantization scheme for ViTs is illustrated as Fig. 3. The main body of ViTs is a stack of blocks, and each block is divided into a multi-head self-attention (MSA) module and a multi-layer perceptron (MLP) module. The MSA's attentional map is calculated as follows:

$$Attn(Q, K, V) = Softmax \left(\frac{Q \cdot K^{T}}{\sqrt{d}}\right) V$$
 (1)

where d is the size of hidden features. And the MLP module consists of two dense layers and a GELU activation function.

¹https://github.com/apache/tvm

In this work, we are interested in quantizing the entire computational graph of ViTs. To facilitate TVM implementation, we apply the simplest symmetric uniform quantization strategy as follows:

$$I = \left\lfloor \frac{\operatorname{clip}(R, -m, m)}{S} \right\rfloor, \text{ where } S = \frac{2m}{2^k - 1}$$
 (2)

where R and I denote the floating-point values and the quantized integer values, respectively, S is the scaling factor of quantization, m is the clipping value determined by the naive min-max method, k is the quantization bit-precision, and $\lfloor \cdot \rfloor$ is the round operator.

With the quantized integer values, to avoid dequantization and achieve integer-only inference, we apply the dyadic arithmetic pipeline for linear operations, as detailed in Section 3.2. Since the above pipeline is based on the homogeneity condition (e.g., MatMul($S_Q \cdot I_Q$, $S_K \cdot I_K$)== $S_Q \cdot S_K \cdot \text{MatMul}(I_Q, I_K)$), it is not applicable to non-linearity (e.g., Softmax($S_A \cdot I_A$) $\neq S_A \cdot \text{Softmax}(I_A)$). Thus, nonlinear operations require accurate and efficient approximations by integer-only arithmetic. To this end, Shiftmax and ShiftGELU are proposed, which utilize efficient shifters in hardware logic to accomplish most arithmetic, and I-LayerNorm calculates the square root of the variance in an integer iterative manner. The above schemes are described in detail in Sections 3.3-3.5, respectively.

3.2 Dyadic Arithmetic for Linear Operations

The dyadic arithmetic pipeline, which uses integer bit-shifting to efficiently realize floating-point operations of scaling factors, allows linear operations to be performed with integer-only arithmetic. Although it is designed for CNNs[11, 25], it can also be followed for linear operations in ViTs, including Conv in the embedding layer, and MatMul and Dense in the transformer layer, and to our knowledge, we are the first to apply it to ViTs.

Taking MatMul as an instance, when the inputs are $Q=(S_Q,I_Q)$ and $K=(S_K,I_K)$, the output is calculated as follows:

$$A' = S_A' \cdot I_A' = S_Q \cdot S_K \cdot \left(I_Q * I_K^T \right) \tag{3}$$

where $I_A{}' = I_Q * I_K{}^T$ performs integer-only arithmetic. Following the principle of practical hardware implementation (e.g., DP4A), when the inputs I_Q and I_K are INT8 types, the output $I_A{}'$ is INT32 type. Thus, we need to requantize $I_A{}'$ to INT8 type as the input for the next layer, which is calculated as follows:

$$I_A = \left| \frac{S_A' \cdot I_A'}{S_A} \right| = \left| \frac{S_Q \cdot S_K}{S_A} \cdot \left(I_Q * I_K^T \right) \right| \tag{4}$$

where S_A is the pre-calculated scaling factor of the output activation. Although the scaling factors remain floating-point values, their multiplication and division operations in Eq. 4 can be avoided by converting the rescaling to a dyadic number (DN) as follows:

$$DN\left(\frac{S_Q \cdot S_K}{S_A}\right) = \frac{b}{2^c} \tag{5}$$

where b and c are both positive integer values. In this case, the rescaling can be efficiently accomplished by integer multiplication and bit-shifting. To summarize, the integer-only arithmetic pipeline of MatMul can be denoted as follows:

$$I_A = \left(b \cdot \left(I_Q * I_K^T\right)\right) >> c \tag{6}$$

where >> indicates right bit-shifting.

Algorithm 1: Integer-only Softmax: Shiftmax

Input: $(I_{in}, S_{in}, k_{out})$: (integer input, input scaling factor, output bit-precision) Output: (I_{out}, S_{out}) : (integer output, output scaling factor) **Function** ShiftExp(*I*, *S*): $I_p \leftarrow I + (I >> 1) - (I >> 4);$ $\triangleright I \cdot \log_2 e$ $I_0 \leftarrow \lfloor 1/S \rceil$; $q \leftarrow \lfloor I_p/(-I_0) \rfloor;$ $r \leftarrow -(I_p - q \cdot (-I_0));$ $I_b \leftarrow ((-r) >> 1) + I_0;$ ▶ Integer part ▶ Decimal part ▶ Eq. 11 $I_{exp} \leftarrow I_b << (N-q);$ $S_{exp} \leftarrow S/(2^N);$ return $(I_{exp}, S_{exp});$ ▶ Eq. 10 **End Function** Function Shiftmax(I_{in} , S_{in} , k_{out}): $I_{\Delta} \leftarrow I_{in} - \max(I_{in});$ ▶ Eq. 8 $(I_{exp}, S_{exp}) \leftarrow \mathsf{ShiftExp}(I_{\Delta}, S_{in});$ $(I_{out}, S_{out}) \leftarrow IntDiv(I_{exp}, \sum I_{exp}, k_{out});$

3.3 Integer-only Softmax: Shiftmax

End Function

Softmax in ViTs translates the attention scores into probabilities, which acts on the hidden features and is calculated as follows:

return $(I_{out}, S_{out}); \rightarrow I_{out} \cdot S_{out} \approx \text{Softmax}(I_{in} \cdot S_{in})$

Softmax
$$(x_i) = \frac{e^{x_i}}{\sum_j^d e^{x_j}} = \frac{e^{S_{x_i} \cdot I_{x_i}}}{\sum_j^d e^{S_{x_j} \cdot I_{x_j}}}, \text{ where } i = 1, 2, \dots, d \quad (7)$$

Due to the non-linearity, Softmax cannot follow the dyadic arithmetic pipeline discussed above, and the exponential arithmetic in Eq. 7 is typically unsupported by integer-only logic [20]. To address the above issues, we propose the approximation method Shiftmax, which can utilize simple hardware logic to achieve accurate and efficient integer-only arithmetic of Softmax. First, to smooth the data distribution and prevent overflow, we restrict the range of the exponential arithmetic as follows:

$$Softmax(x_i) = \frac{e^{S_{\Delta_i} \cdot I_{\Delta_i}}}{\sum_{i}^{d} e^{S_{\Delta_j} \cdot I_{\Delta_j}}} = \frac{e^{S_{x_i} \cdot (I_{x_i} - I_{max})}}{\sum_{i}^{d} e^{S_{x_j} \cdot (I_{x_j} - I_{max})}}$$
(8)

where $I_{max} = \max\{I_{x_1}, I_{x_2}, \cdots, I_{x_d}\}$. Here, $I_{\Delta_i} = I_{x_i} - I_{max}$ is a non-positive value and $S_{\Delta_i} = S_{x_i}$, and we simplify them as I_{Δ} and S_{Δ} in the following part for easier expression.

Then, we are motivated to convert the base from e to 2 to fully utilize the efficient shifters. Instead of a brute-force conversion, we perform an equivalent transformation using the base changing formula of the exponential function. Importantly, since $\log_2 e$ can be approximated by binary as $(1.0111)_b$, the floating-point multiplication with it can be achieved by integer shifting as follows:

$$e^{S_{\Delta} \cdot I_{\Delta}} = 2^{S_{\Delta} \cdot (I_{\Delta} \cdot \log_2 e)} \approx 2^{S_{\Delta} \cdot (I_{\Delta} + (I_{\Delta} > 1) - (I_{\Delta} > 2)))}$$
(9)

The power term is denoted as $S_{\Delta} \cdot I_p$, which is not ensured as an integer and cannot be directly used for shifting. Thus, we decompose it into an integer part and a decimal part as follows:

$$2^{S_{\Delta} \cdot I_p} = 2^{(-q) + S_{\Delta} \cdot (-r)} = 2^{S_{\Delta} \cdot (-r)} >> q \tag{10}$$

 $^{^2\}mathrm{To}$ avoid too small values after right shifting, we first have a $N\text{-}\mathrm{bit}$ left shifting.

Preprint, arXiv, 2022.07 Zhikai Li et al.

where $S_{\Delta} \cdot (-r) \in (-1, 0]$ is the decimal part, and q and r are both positive integer values. For low-cost computation, we approximate $2^{S_{\Delta} \cdot (-r)}$ in range (-1, 0] by the linear function as follows:

$$2^{S_{\Delta} \cdot (-r)} \approx [S_{\Delta} \cdot (-r)]/2 + 1$$

$$= S_{\Delta} \cdot [((-r) >> 1) + I_0], \quad \text{where } I_0 = \lfloor 1/S_{\Delta} \rceil$$
(11)

The above completes the approximation of the numerator in Eq. 8, *i.e.*, $S_{\Delta} \cdot I_{exp} \approx e^{S_{\Delta} \cdot I_{\Delta}}$, where S_{Δ} can be removed via fraction reduction since the scaling factor of the denominator obtained by summing is also S_{Δ} . This turns Eq. 8 into an integer division, which is calculated with the specified output bit-precision k_{out} as follows:

$$I_{out_i} = \frac{S_{\Delta} \cdot I_{exp_i}}{S_{\Delta} \cdot \sum_{j}^{d} I_{exp_j}} = \text{IntDiv}(I_{exp_i}, \sum_{j}^{d} I_{exp_j}, k_{out})$$

$$= \left(\left\lfloor \frac{2^M}{\sum_{j}^{d} I_{exp_j}} \right\rfloor \cdot I_{exp_i} \right) >> (M - (k_{out} - 1))$$

$$S_{out} = 1/2^{k_{out} - 1}$$
(12)

where M is a sufficiently large integer, and $S_{out_i} \cdot I_{out_i}^{3}$ can approximate the result of Softmax(x_i).

The integer-only flow of Shiftmax is summarized in Algorithm 1. Instead of complex second-order polynomial approximations [12], Shiftmax performs all arithmetic with bit-shifting, except for one integer subtraction, summation, and division, which significantly improves computational efficiency. In addition, only Eqs. 9 and 11 are mathematically approximated, while all others are equivalent transformations, which ensures the accuracy of Shiftmax.

3.4 Integer-only GELU: ShiftGELU

GELU is the non-linear activation function in ViTs, which, from the study [10], can be approximated by a sigmoid function as follows:

GELU(x) =
$$x \cdot \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-t^2/2} dt$$

$$\approx x \cdot \sigma(1.702x) = S_x \cdot I_x \cdot \sigma(S_x \cdot 1.702I_x)$$
(13)

Thus, the challenge becomes the realization of the sigmoid function's integer-only arithmetic. First, 1.702 can be approximated by binary as $(1.1011)_b$, thus $1.702I_x$ can be achieved by integer shifting, i.e. $I_p = I_x + (I_x >> 1) + (I_x >> 3) + (I_x >> 4)$. Then, we equivalently transform the sigmoid function as follows:

$$\sigma(S_X \cdot I_p) = \frac{1}{1 + e^{-S_X \cdot I_p}} = \frac{e^{S_X \cdot I_p}}{e^{S_X \cdot I_p} + 1}$$

$$= \frac{e^{S_X \cdot (I_p - I_{max})}}{e^{e^{S_X \cdot (I_p - I_{max})}} + e^{S_X \cdot (-I_{max})}}$$
(14)

where the numerator is in exact correspondence with the numerator of Eq. 8, thus the two implementations are identical. After that, the integer approximation of GELU is done by following the integer division in Eq. 12 and then multiplying it with $S_X \cdot I_X$.

Algorithm 2 shows the integer-only flow of ShiftGELU. Except for a few fundamental arithmetic operations, ShiftGELU utilizes shifters in hardware logic to perform all other arithmetic and thus enables the efficient inference of ViTs. Furthermore, compared to the second-order polynomial method that only approximates for

Algorithm 2: Integer-only GELU: ShiftGELU

```
Input: (I_{in}, S_{in}, k_{out}): (integer input, input scaling factor, output bit-precision)

Output: (I_{out}, S_{out}): (integer output, output scaling factor)

Function ShiftGELU(I_{in}, S_{in}, k_{out}):

 | I_p \leftarrow I_{in} + (I_{in} >> 1) + (I_{in} >> 3) + (I_{in} >> 4); \triangleright 1.702I 
 | I_{\Delta} \leftarrow I_p - \max(I_p); 
 | (I_{exp}, S_{exp}) \leftarrow \text{ShiftExp}(I_{\Delta}, S_{in}); 
 | (I'_{exp}, S'_{exp}) \leftarrow \text{ShiftExp}(-\max(I_p), S_{in}); 
 | (I_{div}, S_{div}) \leftarrow \text{IntDiv}(I_{exp}, I_{exp} + I'_{exp}, k_{out}); 
 | (I_{out}, S_{out}) \leftarrow (I_{in} \cdot I_{div}, S_{in} \cdot S_{div}); 
 | \text{return} (I_{out}, S_{out}); \qquad \triangleright I_{out} \cdot S_{out} \approx \text{GELU}(I_{in} \cdot S_{in}) 
End Function
```

a specific interval [12], the approximation of ShiftGELU works on the entire domain of definition, which can potentially provide higher accuracy and robustness.

3.5 Integer-only LayerNorm: I-LayerNorm

LayerNorm in ViTs normalizes the input in the hidden feature dimension as follows:

$$LayerNorm(x) = \frac{x - Mean(x)}{\sqrt{Var(x)}} \cdot \gamma + \beta$$
 (15)

In contrast to BatchNorm that holds fixed parameters from training and can be folded during inference, LayerNorm needs to dynamically compute statistics (*i.e.*, mean and standard deviation) in the inference phase. The integer arithmetic units allow straightforward calculation of the mean and variance of the data, yet they fail to support the square root arithmetic for obtaining the standard deviation [16]. Thus, we employ the light-weight integer iterative approach [5] as follows:

$$I_{i+1} = (I_i + \lfloor \operatorname{Var}(I_x)/I_i \rfloor)/2 = (I_i + \lfloor \operatorname{Var}(x)/I_i \rfloor) >> 1$$
 (16)

where I_i is the result of the i-th iteration, and I_0 is initialized as $2^{\lfloor \operatorname{bit}(\operatorname{Var}(I_X))/2 \rfloor}$. The naive stopping criterion for the iterations is $I_{i+1} \geq I_i$, which unfortunately cannot guarantee a constant latency. We experimentally find that 10 iterations can achieve most convergence, thus we modify the stopping criterion to the iteration counts to facilitate hardware implementation.

4 EXPERIMENTS

We evaluate I-ViT in both accuracy on the large-scale classification task and latency on the practical hardware to fully demonstrate the superiority, as detailed in Sections 4.1 and 4.2, respectively.

4.1 Accuracy Evaluation

Implementation Details: I-ViT is evaluated on various popular models, including ViT [6], DeiT [21], and Swin [18] on ImageNet (ILSVRC-2012) [14] dataset for the large-scale image classification task. The pre-trained models are all obtained from timm⁴ library. First, we use Eq. 2 to quantize the weights of the pre-trained FP model for the initialization of I-ViT. Then, we perform quantization-aware fine-tuning using naive STE [1] to recover the accuracy.

 $^{^3}S_{out}$ is the scaling factor for the k_{out} -bit symmetric quantization with m=1.

 $^{^4} https://github.com/rwightman/pytorch-image-models \\$

Table 1: Accuracy results of I-ViT evaluated on various models on ImageNet dataset. Compared to the FP baseline, I-ViT, which quantizes the entire computational graph and enables integer-only inference, can achieve similar or even higher accuracy.

Model	Method	Bit-prec.	Intonly	Top-1 Acc.(%)	Diff.(%)
ViT-S	Baseline	FP32	×	81.39	-
	I-ViT(ours)	INT8	✓	81.27	-0.12
ViT-B	Baseline	FP32	×	84.53	-
	I-ViT(ours)	INT8	\checkmark	84.76	+0.23
DeiT-T	Baseline	FP32	×	72.21	-
	I-ViT(ours)	INT8	\checkmark	72.24	+0.03
DeiT-S	Baseline	FP32	×	79.85	-
	I-ViT(ours)	INT8	\checkmark	80.12	+0.27
DeiT-B	Baseline	FP32	×	81.85	-
	I-ViT(ours)	INT8	✓	81.74	-0.11
Swin-T	Baseline	FP32	×	81.35	-
	I-ViT(ours)	INT8	\checkmark	81.50	+0.15
Swin-S	Baseline	FP32	×	83.20	-
	I-ViT(ours)	INT8	✓	83.01	-0.19

Table 2: Ablation studies of the accuracy of Shiftmax and ShiftGELU. Replacing (→) these two modules with second-order polynomial approximations [12] leads to poor performance, where polynomial GELU causes more severe accuracy degradation. Note that while maintaining high accuracy, shifting-oriented arithmetic of Shiftmax and ShiftGELU is more hardware-friendly and efficient.

Model	Method	Shifting-oriented	Top-1 Acc (%)	Diff (%)
	Wichiod	oming oriented	10p 171cc.(70)	DIII.(70)
DeiT-S	I-ViT(ours)	✓	80.12	-
	Shiftmax \rightarrow Poly.	×	80.02	-0.10
	ShiftGELU \rightarrow Poly.	×	79.24	-0.88
	Shiftmax, ShiftGELU Poly.	×	79.11	-1.01
Swin-S	I-ViT(ours)	✓	83.01	-
	$Shiftmax \rightarrow Poly.$	×	82.79	-0.22
	ShiftGELU \rightarrow Poly.	×	82.10	-0.91
	${\tt Shiftmax,ShiftGELU} \to {\tt Poly}.$	×	81.86	-1.15

The above implementations are done on PyTorch, and the model inference details (*e.g.*, bit-shifting) follow the TVM implementation to ensure consistent accuracy with the TVM deployment.

Table 1 reports the accuracy results of I-ViT and the FP baseline on various benchmark models. Although I-ViT reduces the bit-precision of the parameters and enables integer-only inference, it maintains comparable accuracy, even slightly more than the FP baseline, which adequately demonstrates the effectiveness and robustness of the proposed approximation schemes for the floating-point non-linear operations Softmax, GELU, and LayerNorm.

We also perform ablation studies for comparison with the second-order polynomial approximations designed for language models, as shown in Table 2. Due to the differences in data distribution of ViTs and language models, replacing Shiftmax and ShiftGELU with the polynomial approximations results in severe accuracy degradation, and in particular, polynomial GELU that only approximates for the specific interval is not applicable to ViTs. It is also worth mentioning that the proposed schemes are shifting-oriented arithmetic and can thus benefit more from the efficient hardware logic.

Table 3: Latency results of I-ViT evaluated on an RTX 2080Ti GPU (batch=8), which is compared with the FP baseline and simulated quantization. We also report the memory footprint (Size) and computational cost (BitOps, i.e., Bit-Operations). Compared to the FP baseline, simulated quantization only provides about 1.8× speedup, while I-ViT can achieve a significant 3.72~4.11× speedup. Note that unlike other methods that use GPU's floating-point cores, I-ViT utilizes Turing Tensor Cores that support integer-only arithmetic.

Model	Method	Intonly	Size(MB)	BitOps(G)	Latency(ms)	Speedup
DeiT-T	Baseline	×	20	1280	5.99	×1.00
	Simulated	×	5	1280	3.46	$\times 1.73$
	I-ViT(ours)	✓	5	80	1.61	$\times 3.72$
DeiT-S	Baseline	×	88	4710	11.5	×1.00
	Simulated	×	22	4710	6.42	×1.79
	I-ViT(ours)	\checkmark	22	294	2.97	×3.87
DeiT-B	Baseline	×	344	17920	32.6	×1.00
	Simulated	×	86	17920	17.1	×1.91
	I-ViT(ours)	✓	86	1120	7.93	×4.11
Swin-T	Baseline	×	116	4608	16.8	×1.00
	Simulated	×	29	4608	9.23	×1.82
	I-ViT(ours)	✓	29	288	4.29	×3.92
Swin-S	Baseline	×	200	8909	27.8	×1.00
	Simulated	×	50	8909	14.8	×1.88
	I-ViT(ours)	✓	50	557	6.92	$\times 4.02$

Table 4: Ablation studies of the latency of Shiftmax and ShiftGELU on an RTX 2080Ti GPU (batch=8). Replacing (\rightarrow) these two modules with original floating-point arithmetic leads to longer latency and a failure to be deployed on integer-only hardware.

Model	Method	Intonly	Latency(ms)	Diff.(ms)
DeiT-S	I-ViT(ours)	✓	2.97	-
	$Shiftmax \rightarrow Float$	×	3.38	+0.41
	$ShiftGELU \rightarrow Float$	×	3.69	+0.72
	$\texttt{Shiftmax}, \texttt{ShiftGELU} \rightarrow \texttt{Float}$	×	4.05	+1.08
Swin-S	I-ViT(ours)	✓	6.92	-
	Shiftmax → Float	×	7.77	+0.85
	$ShiftGELU \rightarrow Float$	×	8.20	+1.28
	$\texttt{Shiftmax}, \texttt{ShiftGELU} \rightarrow \texttt{Float}$	×	9.07	+2.15

4.2 Latency Evaluation

Implementation Details: We deploy I-ViT on an RTX 2080Ti GPU using TVM to measure the real hardware latency. Since ViT [6] and DeiT [21] have the same model structure, we only evaluate DeiT [21] and Swin [18]. First, we use TVM to build and compile the same model as PyTorch, followed by the auto-tuning to optimize the computational schedule, and then we perform the end-to-end latency tests. Note that although the GPU is not an integer-only hardware, depending on the DP4A instructions, I-ViT can perform efficient integer-only inference on its Turing Tensor Cores.

The latency results of I-ViT on an RTX 2080Ti GPU are shown in Table 3, and it is compared with the FP baseline and simulated INT8 quantization. Note that although they all run on the same device, I-ViT utilizes the integer arithmetic units of Turing Tensor Cores, whereas the others utilize the floating-point arithmetic units. For simulated quantization, the weights expressed in INT8 reduce memory by 4×; nevertheless, the computations are performed in dequantized FP32 precision, which cannot reduce the

Preprint, arXiv, 2022.07 Zhikai Li et al.

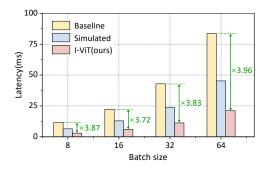


Figure 4: Latency results of DeiT-S [21] evaluated on an RTX 2080Ti GPU with various batch sizes. I-ViT maintains a constant acceleration effect for the same model architecture at various batch sizes.

computational costs. Thanks to the low-precision data transmission between operations, it provides about 1.8× speedup. In contrast, for I-ViT without dequantization, the weights and computations are entirely in INT8 precision, which can reduce the computational costs by $16\times$ and thus enables a significant $3.72\sim4.11\times$ speedup. Moreover, from the results, I-ViT is more effective in accelerating more computationally-intensive models.

The ablation studies of the latency of Shiftmax and ShiftGELU are conducted, as shown in Table 4. Replacing them with original floating-point arithmetic, which cannot be deployed on integer-only hardware, produces longer latency. For instance, the replacement increases the latency of DeiT-S by 1.08ms (1.36×) compared to I-ViT. We also evaluate the latency of DeiT-S with various batch sizes, as shown in Fig. 4. It can be seen that I-ViT is robust to the batch size and can maintain a constant acceleration effect.

It should be highlighted that despite the significant speedup on the RTX 2080Ti GPU that provides an evident strength of I-ViT, both the software support of TVM and the hardware support of Turing Tensor Cores are not optimal, for instance, there is no full parallelism after increasing the batch size in Fig. 4. Therefore, it is believed that deploying I-ViT on dedicated hardware (*e.g.*, FPGAs) will further enhance the acceleration potential.

5 CONCLUSIONS

In this paper, we propose I-ViT, which is the first integer-only quantization scheme for ViTs to the best of our knowledge. I-ViT quantizes the entire computational graph to enable the integer-only inference, where linear operations follow the dyadic arithmetic pipeline; and non-linear operations are performed by the proposed novel light-weight integer-only approximation methods. In particular, Shiftmax and ShiftGELU perform most arithmetic with bit-shifting, which can fully benefit from the efficient hardware logic. Compared to the FP baseline, I-ViT achieves similar (or even higher) accuracy on various benchmarks. In addition, we utilize TVM to deploy I-ViT on an RTX 2080Ti GPU, whose Turing Tensor Cores can accelerates the integer-only inference of ViTs, achieving a 3.72~4.11× speedup over the FP model.

In the future, we will consider deploying I-ViT on dedicated integer-only hardware (*e.g.*, FPGAs) to obtain better acceleration performance. Furthermore, we also plan to extend I-ViT to more complex vision tasks (*e.g.*, object detection).

REFERENCES

- BENGIO, Y., LÉONARD, N., AND COURVILLE, A. Estimating or propagating gradients through stochastic neurons for conditional computation. arXiv preprint arXiv:1308.3432 (2013).
- [2] CARION, N., MASSA, F., SYNNAEVE, G., USUNIER, N., KIRILLOV, A., AND ZAGORUYKO, S. End-to-end object detection with transformers. In European conference on computer vision (2020), Springer, Cham, pp. 213–229.
- [3] CHEN, H., WANG, Y., GUO, T., XU, C., DENG, Y., LIU, Z., MA, S., XU, C., XU, C., AND GAO, W. Pre-trained image processing transformer. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (2021), pp. 12299–12310.
- [4] CHEN, T., MOREAU, T., JIANG, Z., ZHENG, L., YAN, E., SHEN, H., COWAN, M., WANG, L., HU, Y., CEZE, L., ET AL. {TVM}: An automated {End-to-End} optimizing compiler for deep learning. In 13th USENIX Symposium on Operating Systems Design and Implementation (OSDI 18) (2018), pp. 578–594.
- [5] CRANDALL, R., AND POMERANCE, C. Prime numbers. Springer, 2001.
- [6] DOSOVITSKIY, A., BEYER, L., KOLESNIKOV, A., WEISSENBORN, D., ZHAI, X., UN-TERTHINER, T., DEHGHANI, M., MINDERER, M., HEIGOLD, G., GELLY, S., ET AL. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929 (2020).
- [7] GHOLAMI, A., KIM, S., DONG, Z., YAO, Z., MAHONEY, M. W., AND KEUTZER, K. A survey of quantization methods for efficient neural network inference. arXiv preprint arXiv:2103.13630 (2021).
- [8] HAN, K., WANG, Y., CHEN, H., CHEN, X., GUO, J., LIU, Z., TANG, Y., XIAO, A., XU, C., XU, Y., ET AL. A survey on visual transformer. arXiv e-prints (2020), arXiv-2012.
- [9] HAN, K., XIAO, A., WU, E., GUO, J., XU, C., AND WANG, Y. Transformer in transformer. Advances in Neural Information Processing Systems 34 (2021).
- [10] HENDRYCKS, D., AND GIMPEL, K. Gaussian error linear units (gelus). arXiv preprint arXiv:1606.08415 (2016).
- [11] JACOB, B., KLIGYS, S., CHEN, B., ZHU, M., TANG, M., HOWARD, A., ADAM, H., AND KALENICHENKO, D. Quantization and training of neural networks for efficient integer-arithmetic-only inference. In *Proceedings of the IEEE conference on com*puter vision and pattern recognition (2018), pp. 2704–2713.
- [12] Kim, S., Gholami, A., Yao, Z., Mahoney, M. W., and Keutzer, K. I-bert: Integeronly bert quantization. In *International conference on machine learning* (2021), PMLR, pp. 5506–5518.
- [13] KRISHNAMOORTHI, R. Quantizing deep convolutional networks for efficient inference: A whitepaper. arXiv preprint arXiv:1806.08342 (2018).
- [14] KRIZHEVSKY, A., SUTSKEVER, I., AND HINTON, G. E. Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems 25 (2012).
- [15] LI, Z., MA, L., CHEN, M., XIAO, J., AND GU, Q. Patch similarity aware data-free quantization for vision transformers. arXiv preprint arXiv:2203.02250 (2022).
- [16] LIN, Y., LI, Y., LIU, T., XIAO, T., LIU, T., AND ZHU, J. Towards fully 8-bit integer inference for the transformer model. arXiv preprint arXiv:2009.08034 (2020).
- [17] LIN, Y., ZHANG, T., SUN, P., LI, Z., AND ZHOU, S. Fq-vit: Fully quantized vision transformer without retraining. arXiv preprint arXiv:2111.13824 (2021).
- [18] LIU, Z., LIN, Y., CAO, Y., HU, H., WEI, Y., ZHANG, Z., LIN, S., AND GUO, B. Swin transformer: Hierarchical vision transformer using shifted windows. In Proceedings of the IEEE/CVF International Conference on Computer Vision (2021), pp. 10012–10022.
- [19] LIU, Z., WANG, Y., HAN, K., ZHANG, W., MA, S., AND GAO, W. Post-training quantization for vision transformer. Advances in Neural Information Processing Systems 34 (2021).
- [20] STEVENS, J. R., VENKATESAN, R., DAI, S., KHAILANY, B., AND RAGHUNATHAN, A. Softermax: Hardware/software co-design of an efficient softmax for transformers. In 2021 58th ACM/IEEE Design Automation Conference (DAC) (2021), pp. 469-474.
- [21] TOUVRON, H., CORD, M., DOUZE, M., MASSA, F., SABLAYROLLES, A., AND JÉGOU, H. Training data-efficient image transformers & distillation through attention. In International Conference on Machine Learning (2021), PMLR, pp. 10347–10357.
- [22] WANG, H., LI, Z., GU, J., DING, Y., PAN, D. Z., AND HAN, S. On-chip qnn: To-wards efficient on-chip training of quantum neural networks. arXiv preprint arXiv:2202.13239 (2022).
- [23] Wu, H., Judd, P., Zhang, X., Isaev, M., and Micikevicius, P. Integer quantization for deep learning inference: Principles and empirical evaluation. arXiv preprint arXiv:2004.09602 (2020).
- [24] Wu, K., Peng, H., Chen, M., Fu, J., and Chao, H. Rethinking and improving relative position encoding for vision transformer. In Proceedings of the IEEE/CVF International Conference on Computer Vision (2021), pp. 10033–10041.
- [25] YAO, Z., DONG, Z., ZHENG, Z., GHOLAMI, A., YU, J., TAN, E., WANG, L., HUANG, Q., WANG, Y., MAHONEY, M., ET AL. Hawq-v3: Dyadic neural network quantization. In International Conference on Machine Learning (2021), PMLR, pp. 11875–11886.
- [26] ZHU, D., LU, S., WANG, M., LIN, J., AND WANG, Z. Efficient precision-adjustable architecture for softmax function in deep learning. IEEE Transactions on Circuits and Systems II: Express Briefs 67, 12 (2020), 3382–3386.
- [27] ZHU, X., SU, W., LU, L., LI, B., WANG, X., AND DAI, J. Deformable detr: Deformable transformers for end-to-end object detection. arXiv preprint arXiv:2010.04159 (2020).