ADAPTIVFLOAT: A FLOATING-POINT BASED DATA TYPE FOR RESILIENT DEEP LEARNING INFERENCE

Thierry Tambe 1  En-Yu Yang 1  Zishen Wan 1  Yuntian Deng 1  Vijay Janapa Reddi 1  Alexander Rush 2  David Brooks 1  Gu-Yeon Wei 1

ABSTRACT

Conventional hardware-friendly quantization methods, such as fixed-point or integer, tend to perform poorly at very low word sizes as their shrinking dynamic ranges cannot adequately capture the wide data distributions commonly seen in sequence transduction models. We present AdaptivFloat, a floating-point inspired number representation format for deep learning that dynamically maximizes and optimally clips its available dynamic range, at a layer granularity, in order to create faithful encoding of neural network parameters. AdaptivFloat consistently produces higher inference accuracies compared to block floating-point, uniform, IEEE-like float or posit encodings at very low precision (≤ 8-bit) across a diverse set of state-of-the-art neural network topologies. And notably, AdaptivFloat is seen surpassing baseline FP32 performance by up to +0.3 in BLEU score and -0.75 in word error rate at weight bit widths that are ≤ 8-bit. Experimental results on a deep neural network (DNN) hardware accelerator, exploiting AdaptivFloat logic in its computational datapath, demonstrate per-operation energy and area that is 0.9× and 1.14×, respectively, that of equivalent bit width integer-based accelerator variants.

1 INTRODUCTION

Deep learning approaches have transformed representation learning in a multitude of tasks. Recurrent Neural Networks (RNNs) are now the standard solution for speech recognition, exhibiting remarkably low word error rates (Chiu et al., 2017) while neural machine translation has narrowed the performance gap versus human translators (Wu et al., 2016). Convolutional Neural Networks (CNNs) are now the dominant engine behind image processing and have been pushing the frontiers in many computer vision applications (Krizhevsky et al., 2012; He et al., 2016). Today, deep neural networks (DNNs) are deployed at all computing scales, from resource-constrained IoT edge devices to massive data center farms. In order to exact higher compute density and energy efficiency on these compute platforms, a plethora of reduced precision quantization techniques have been proposed.

In this line of research, a large body of work has focused on fixed-point encodings (Choi et al., 2019; Gupta et al., 2015; Lin et al., 2015; Hwang & Sung, 2014; Courbariaux et al., 2015) or uniform quantization via integer (Migacz, 2017; Jacob et al., 2017). These fixed-point techniques are frequently evaluated on shallow models or on CNNs exhibiting relatively narrow weight distributions. However, as it can be seen from Figure 1, sequence transduction models with layer normalization such as the Transformer (Vaswani et al., 2017) can contain weights more than an order of magnitude larger than those from popular CNN models with batch normalization such as ResNet-50, Inception-v3 or DenseNet-201. The reason for this phenomenon is that batch normalization effectively produces a weight normalization side effect (Salimans & Kingma, 2016) whereas layer normalization adopts invariance properties that do not reparameterize the network (Ba et al., 2016).

Figure 1. Histogram of the weight distribution for (a) ResNet-50, (b) Inception-v3, (c) DenseNet-201 and (d) Transformer whose weight values are more than 10× higher than the maximum weight value from popular CNNs.
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

In the pursuit of wider dynamic range and improved numerical accuracy, there has been surging interest in floating-point based (Drumond et al., 2018; Köster et al., 2017), logarithmic (Johnson, 2018; Miyashita et al., 2016) and posit representations (Gustafson & Yonemoto, 2017), which also form the inspiration of this work.

AdaptivFloat improves on the aforementioned techniques by dynamically maximizing its available dynamic range at a neural network layer granularity. And unlike block floating-point (BFP) approaches with shared exponents that may lead to degraded rendering of smaller magnitude weights, AdaptivFloat achieves higher inference accuracy by remaining committed to the standard floating-point delineation of independent exponent and mantissa bits for each tensor element. However, we break from IEEE 754 standard compliance with a unique clamping strategy for denormal numbers and with a customized proposition for zero assignment, which enables us to engineer leaner hardware.

Rather than proposing binary or ternary quantization techniques evaluated on a small number of carefully selected models, through AdaptivFloat, we aim to inform a generalized floating-point based mathematical blueprint for adaptive and resilient DNN quantization that can be easily applied on neural models of various categories (CNN, RNN or MLP), layer depths and parameter statistics.

By virtue of an algorithm-hardware co-design, we also propose a processing element implementation that exploits the AdaptivFloat arithmetic in its computational datapath in order to yield energy efficiencies that surpass those of integer-based variants. Furthermore, owing to the superior performance of AdaptivFloat at very low word sizes, as it will be shown, higher compute density can be acquired at a lower penalty for computational accuracy compared to block floating-point, integer, or non-adaptive IEEE-like float or posit encodings. Altogether, the AdaptivFloat algorithm-hardware co-design framework offers a compelling alternative to integer or fixed-point solutions.

Finally, we note that the AdaptivFloat encoding scheme is self-supervised as it only relies on unlabeled data distributions in the network.

This paper makes the following contributions:

- We propose and describe AdaptivFloat: a floating-point based data encoding algorithm for deep learning, which maximizes its dynamic range at a neural network layer granularity by dynamically shifting its exponent range and by optimally clipping its representable datapoints.

- We evaluate AdaptivFloat across a diverse set of DNN models and tasks and show that it achieves higher classification and prediction accuracies compared to equivalent bit width uniform, block floating-point and non-adaptive posit and float quantization techniques.

- We propose a hybrid float-integer (HFINT) PE implementation that exploits the AdaptivFloat mechanism and provides a cost-effective compromise between the high accuracy of floating-point computations and the greater hardware density of fixed-point post-processing. Show that the HFINT PE produces higher energy efficiencies compared to conventional monolithic integer-based PEs.

- We design and characterize an accelerator system targeted for sequence-to-sequence neural networks and show that, when integrated with HFINT PEs, lower overall power consumption compared to an integer-based adaptation is obtained.

The rest of the paper is structured as follows. A summary of prominent number and quantization schemes used in deep learning is narrated in Section 2. We present the intuition and a detailed description of the AdaptivFloat algorithm in Section 3. The efficacy and resiliency of AdaptivFloat is demonstrated in Section 4 across DNN models of varying parameter distributions. Section 5 describes the hardware modeling with energy, area and performance efficiency results reported in Section 6. Section 7 concludes the paper.

2 RELATED WORK

Quantization Techniques. Low-precision DNN training and inference have been researched heavily in recent years with the aim of saving energy and memory costs. A rather significant percentage of prior work in this domain (Wu et al., 2015; Mishra et al., 2017; Park et al., 2017; Zhou et al., 2016; Cai et al., 2017; Zhang et al., 2018; Han et al., 2015) have focused on or evaluated their low precision strategies strictly on CNNs or on models with narrow parameter distributions. Notably, inference performance with modest accuracy degradation has been demonstrated with binary (Courbariaux & Bengio, 2016), ternary (Zhu et al., 2016), and quaternary weight precision (Choi et al., 2019). Often, tricks such as skipping quantization on the sensitive first and last layers are performed in order to escape steeper end-to-end accuracy loss.

Extending these aggressive quantization techniques to RNNs have been reported (Alom et al., 2018), although still with recurrent models exhibiting the same narrow distribution seen in many CNNs. (Park et al., 2018) noticed that large magnitude weights bear a higher impact on model performance and proposed outlier-aware quantization, which requires separate low and high bit-width precision for small and outlier weight values, respectively. However, this technique complicates the hardware implementation by requiring two separate PE datapaths for the small and the outlier weights.
**Hardware-Friendly Encodings.** Linear fixed-point or uniform integer quantization is commonly used for deep learning hardware acceleration (Jouppi et al., 2017; Jacob et al., 2017; Reagen et al., 2016) as it presents an area and energy cost-effective solution compared to floating-point based processors. Moreover, low-precision integer inference has already made its way into commercial systems. NVIDIA’s TensorRT (Migacz, 2017) is a commercial library that determines 8-bit integer quantization parameters offline for GPU inference. Google’s TPU, based on INT8 library, has been deployed in datacenters to perform accelerated inference of DNN applications. While integer quantization has been favorably applied to CNNs, (Bhandare et al., 2019) demonstrated robust INT8 quantization on the Transformer network. In this paper, a broader quantization study on the same network is given with AdaptivFloat showing minor degradation when the weight size is as low as 5-bit.

Aware of the dynamic range limitation of fixed-point encoding, we have seen block floating-point data types, such as Flexpoint (Köster et al., 2017) and inspired variants employed in the Brainwave NPU (Fowers et al., 2018). Block floating-point’s appeal stems from its potential to achieve floating-point-like dynamic range with hardware cost and implementation comparable to fixed-point. However, by collapsing the exponent value of each tensor element to that of the element with the highest magnitude, elements with smaller magnitudes will be more prone to data loss. Logarithmic approaches (Vogel et al., 2018; Lee et al., 2017) replacing fixed-point multipliers with shifters have demonstrated smaller power consumption and higher throughput compared to linear-based architectures.

**Number Formats with Higher Dynamic Range.** For DNN computation workloads with very large operands, 16-bit number formats such as INT16 and FP16 have been adopted. And several commercial hardware accelerators such as the 2nd generation TPU and Intel FPGAs have opted to use the Bfloat16 data type as it preserves the dynamic range of 32-bit float by retaining its eight exponent bits, but incurs reduced precision with 7 fractional bits.

Additionally, there has been increasing interest in using the posit data type in deep learning due to its ability to exact higher accuracy and larger dynamic range compared to floats (Gustafson & Yonemoto, 2017). In particular, posit’s tapered precision can represent small values, where the majority of DNN parameters tend to fall, more accurately than floating-point numbers. However, although posit offers a wider reach compared to floats, its accuracy on larger numbers, for a given bit width, may be lower than floats. Furthermore, due to the dynamic nature of its regime bits, hardware implementation of a posit-based datapath exhibits worse energy-delay product compared to fixed-point and floating-point implementations (Carmichael et al., 2018).

![Figure 2. Illustration of the 0 value representation in AdaptivFloat](image)

We include the posit numerical format in our experimental DNN performance evaluation and comparison with the AdaptivFloat data type.

### 3 Methodology

In this section, we provide greater details on AdaptivFloat, the floating-point based number encoding format for adaptive and resilient DNN quantization. We describe the inner workings behind the adjustment of the available dynamic range of representable values in order to best fit the weights of the neural network layers.

#### 3.1 The AdaptivFloat Format

The AdaptivFloat number representation scheme generally follows the IEEE 754 Standard floating-point format that includes a sign bit, exponent bit, and mantissa bit fields. In order to efficiently encode in hardware all the representable datapoints, we avoid the computation of denormal values in the AdaptivFloat number system.

The main problem arising as a result of not using denormals in floating-point is the lack of representation for the “zero” point, which is essential to neural network computations. We solve this constraint by sacrificing the positive and negative minimum values to allocate the slot for “zero” as shown in Figure 2.

Moreover, at very low bit compression, customization based on the value range of a neural network layer can greatly reduce the quantization error with little overhead on the shared extra parameters. Thus, similar to integer quantization that uses a quantization scale (or step), we introduce a bias value, $cexpbias$, to dynamically shift the range of exponent values at a layer granularity. The calculation of $cexpbias$ is described in Section 3.2. A benefit of using $cexpbias$ is the simplicity of the hardware logic required to perform the adaptive operation compared to the multiplying quantization scale used in integer quantization. This contrast is discussed in detail.
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

Algorithm 1: AdaptivFloat Bit Vector to Value

Input: bit vector \( x \), number of bits \( n \), number of exponent bits \( e \) and \( \exp_{bias} \)

// Get Mantissa bits
\( m := n - e - 1 \)

// Extract sign, exponent, mantissa
\( \text{sign} := 1 \) if \( x[n-1] = 0 \), otherwise \(-1\)
\( \exp := x[n-2 : m] + \exp_{bias} \)
\( \text{mant} := 1 + x[m-1 : 0] / 2^m \)

// Map to 0 if exp, mant bits are zeros
if \( x[n-2 : 0] = 0 \) then
\( \text{val} := 0 \)
else
\( \text{val} := \text{sign} \times 2^{\exp} \times \text{mant} \)
end if
return \( \text{val} \)

Algorithm 2: AdaptivFloat Quantization

Input: Matrix \( W_{fp} \), number of bits \( n \) and number of exponent bits \( e \)

// Get Mantissa bits
\( m := n - e - 1 \)

// Obtain sign and abs matrices
\( W_{sign} := sign(W_{fp}) \)
\( W_{abs} := abs(W_{fp}) \)

// Determine \( \exp_{bias} \) and range
Find normalized \( \exp_{max} \) for \( \max(W_{abs}) \) such that
\( 2^\exp_{max} \leq \max(W_{abs}) < 2^{\exp_{max}+1} \)
\( \exp_{bias} := \exp_{max} - (2^e - 1) \)
\( \text{value}_{min} := 2^{\exp_{bias}} \times (1 + 2^{-m}) \)
\( \text{value}_{max} := 2^{\exp_{max}} \times (2 - 2^{-m}) \)

// Handle unrepresentable values
Round \( \text{value} < \text{value}_{min} \) in \( W_{abs} \) to 0 or \( \text{value}_{min} \)
Clamp \( \text{value} > \text{value}_{max} \) in \( W_{abs} \) to \( \text{value}_{max} \)

// Quantize \( W_{fp} \)
Find normalized \( W_{exp} \) and \( W_{mant} \) such that
\( W_{abs} = 2^{W_{exp}} \times W_{mant} \), and \( 1 \leq W_{mant} < 2 \)
\( W_q := \text{quantize and round} \ W_{mant} \text{ by scale} = 2^{-m} \)

// Reconstruct output matrix
\( W_{\text{adptiv}} := W_{sign} \times 2^{W_{exp}} \times W_q \)
return \( W_{\text{adptiv}} \)

in Section 5.

Algorithm 1 shows how a bit vector, with a \( \exp_{bias} \) generated per layer, is converted to its decimal representation. If both exponent bits and mantissa bits are zeros, the bit vector should be interpreted as zero. Otherwise, the bit vector is converted by the following equation:

\[
\text{sign} \times 2^{\text{exponent value}} \times \text{mantissa value}
\]

where the exponent value is the addition of exponent bits and \( \exp_{bias} \), and the mantissa value is calculated by appending an implied “one” as the MSB and follow the same format as standard floating point.

3.2 Quantization

Having defined the AdaptivFloat data format, the quantization problem is simply mapping a full precision value to the nearest representable datapoint. For this purpose, we need to determine the optimal AdaptivFloat \( \exp_{bias} \) which will maximize the available dynamic range of the encoding format in order to provide the most accurate rendering of a particular matrix (or NN layer). This is analogous to determining the quantization scale for integer quantizations, but \( \exp_{bias} \) is a small, typically negative, integer value rather than the high-precision floating-point scaling factor needed in integer quantization (Migacz, 2017).

Algorithm 2 describes how to find the most suitable \( \exp_{bias} \) in order to encode, as faithfully as possible, the AdaptivFloat-quantized weight matrix. We first compute the sign matrix, \( W_{sign} \), and the matrix of absolute values, \( W_{abs} \), from the full precision weight matrix \( W_{fp} \). Then, the algorithm finds the maximum absolute value from \( W_{abs} \) to determine the \( \exp_{bias} \) corresponding to a suitable range of representable datapoints for the weight matrix to quantize.

Before doing quantization on \( W_{abs} \), we first round the values smaller than the AdaptivFloat minimum representable value to zero or \( \text{value}_{min} \) at a halfway threshold. Then, we clamp values larger than the max value, \( \text{value}_{max} \), to \( \text{value}_{max} \). The quantization involves rewriting \( W_{abs} \) into normalized exponent and mantissa form with an exponent matrix \( W_{exp} \) and a mantissa matrix \( W_{mant} \). The mantissa matrix is quantized by the quantization scale calculated by the number of mantissa bits. \( W_q \) indicates the quantized mantissa matrix. Finally, the AdaptivFloat-quantized matrix is reconstructed by multiplication of \( W_{sign} \), \( 2^{W_{exp}} \), and \( W_q \).

We use the notation \( \text{AdaptivFloat} < n, e > \) to indicate a \( n \)-bit AdaptivFloat number with \( e \) exponent bits. Figure 3 provides an illustration showing how the \( \exp_{bias} \) is chosen to best fit the range of values in a weight matrix and the resulting quantized datapoints adhering to the \( \text{AdaptivFloat} < 4, 2 > \) format. The bit vectors containing the AdaptivFloat quantized values can be packed and stored in hardware memory resources.

3.3 Shifting the AdaptivFloat Range

The main characteristic of the AdaptivFloat quantization is using the \( \exp_{bias} \) to shift the range of quantized datapoints.
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

\[ W_{FP}: \text{full precision weight matrix} \]

Find \( e^{\text{bias}} \) to fit max absolute value of \( W_{FP} \) and get representable datapoints

\[ \text{exp range: } [-8,-1] \]
\[ \text{exp bias: } -8 \]

\[ \text{exp range: } [-9,-2] \]
\[ \text{exp bias: } -9 \]

\[ \text{exp range: } [-10,-3] \]
\[ \text{exp bias: } -10 \]

\[ \text{exp range: } [-7,0] \]
\[ \text{exp bias: } -7 \]

\[ \text{exp range: } [-6,1] \]
\[ \text{exp bias: } -6 \]

\[ \text{exp range: } [-5,2] \]
\[ \text{exp bias: } -5 \]

Figure 4. Illustration of \( \text{AdaptivFloat} < 4, 2 > \) quantization from a full precision weight matrix

\[ \text{exp bias} = -2 \]
\[ \text{abs(min)} = 0.375 \]
\[ \text{abs(max)} = 3 \]

\( e^{\text{bias}} \) found to fit max absolute value of \( W_{FP} \) and get representable datapoints

Get quantized \( W_{\text{adaptiv}} \) by rounding to nearest datapoints

4 EXPERIMENTAL RESULTS

For bit compression evaluation, we select three popular DNN models of distinct neural types and applications, and exhibiting relatively narrow to wide spread in their weight distributions. The models considered, as shown in Table 1, are: (1) Transformer (Vaswani et al., 2017), which made a very consequential impact in the field of machine translation and question answering; (2) a 4-layer LSTM encoder, 1-layer LSTM decoder, attention-based sequence-to-sequence (seq2seq) network (Chorowski et al., 2015) commonly used in speech recognition; and (3) ResNet-50, a well-known image classification CNN (He et al., 2016). The Transformer and the LSTM-based Seq2Seq networks are trained on the OpenNMT platform (Klein et al., 2017) using the WMT’17 English-to-German and LibriSpeech datasets, respectively. And, the Pytorch toolkit (Pytorch) is used to train ResNet-50 using the ImageNet dataset.

We compare the efficacy of AdaptivFloat along with numerical data types frequently employed for deep learning acceleration, namely block floating-point (BFP), IEEE-like
We begin by quantifying the quantization error of the num-
ber formats with respect to baseline FP32 precision. The
quantization for the first and last layers.

Finally, we note that the following results are generated by
quantizing all of the layers in the DNN models in order
to capture the whole-length performance of these five nu-
merical data types unlike several works (Choi et al., 2019;
Zhou et al., 2016; Mishra et al., 2017) that intentionally skip
quantization for the first and last layers.

### 4.1 Root Mean Squared Error

We begin by quantifying the quantization error of the num-
ber formats with respect to baseline FP32 precision. The
boxplots depicted in Figure 5 show the distribution of the
root mean squared (RMS) quantization error emanating
from the data types and computed across all layers of the
three models under evaluation. AdaptiveFloat consistently
produces lower average quantization error compared to uni-
form, BFP, posit, or IEEE-like float encoding. Furthermore,
among the self-adaptive data types, AdaptiveFloat exhibits
the tightest error spread for all bit widths of the Transformer
and seq2seq networks, while BFP’s error spread is thinnest
for the 6-bit and 8-bit versions of the ResNet-50 model –
although with a higher mean compared to AdaptiveFloat.
This suggests that BFP would fare best in networks with
slimmer weight distribution such as ResNet-50. Among the
non-adaptive data types, we see that posit generally yields
both a lower average RMS quantization error and a narrower
interquartile error range compared to Float. These results
provide important insights to quantized DNN performance
as we dive into the bare inference accuracy results in the
next subsection.

### 4.2 Inference Performance Analysis

Tables 2, 3, and 4 show the resiliency of the data types
under study as they are put to the test under varying weight
bit compression on the Transformer, sequence-to-sequence,
and ResNet-50 models, respectively. The inference results
are tabulated after post-training quantization (PTQ) and af-
fter quantization-aware re-training (QAR) from the plateaued
FP32 baseline. The training setup and the hyper-parameter
recipe are kept the same for all five data types under evalua-
tion in order to impose a fair comparison.

The key observation we can distill is that AdaptiveFloat
demonstrates much greater resiliency at very low precision
(≤ 6-bit) compared to the other four data formats. For in-
stance, at 4-bit encoding, AdaptiveFloat can still yield, after
retraining, a decent BLEU score of 25.5 on the Transformer
model while the impact from the other four number for-
mats is catastrophic due to insufficient dynamic range or
decimal accuracy. We can make similar observations on
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

![Figure 5](image)

**Figure 5.** Root mean square of the quantization error w.r.t. FP32 at 4-bit, 6-bit and 8-bit weight precision across the layers of the Transformer, Seq2Seq and ResNet-50 models. AdaptivFloat produces the lowest mean error compared to the other number systems.

| Table 5. Impact of both weight and activation quantization on the BLEU score of the Transformer model. Baseline FP32 performance is 27.4 |
|---------------------------------------------------------------|
| **BIT WIDTH** | **FLOAT** | **BFP** | **UNIFORM** | **POSIT** | **ADAPTIVFLOAT** |
|----------------|-----------|--------|-------------|-----------|------------------|
| W8/A8          | 27.4      | 27.4   | 10.1        | 26.9      | 27.5             |
| W6/A6          | 25.9      | 0.0    | 5.7         | 25.7      | 27.1             |
| W4/A4          | 0.0       | 0.0    | 0.0         | 0.0       | 0.3              |

| Table 6. Impact of both weight and activation quantization on the WER of the Seq2Seq model. Baseline FP32 performance is 13.34 |
|---------------------------------------------------------------|
| **BIT WIDTH** | **FLOAT** | **BFP** | **UNIFORM** | **POSIT** | **ADAPTIVFLOAT** |
|----------------|-----------|--------|-------------|-----------|------------------|
| W8/A8          | 12.77     | 12.86  | 12.86       | 12.96     | 12.59            |
| W6/A6          | 14.58     | 14.68  | 14.04       | 14.50     | 12.79            |
| W4/A4          | INF       | 78.68  | 48.86       | INF       | 21.94            |

| Table 7. Impact of both weight and activation quantization on the Top-1 accuracy of the ResNet-50 model. Baseline FP32 performance is 76.2 |
|---------------------------------------------------------------|
| **BIT WIDTH** | **FLOAT** | **BFP** | **UNIFORM** | **POSIT** | **ADAPTIVFLOAT** |
|----------------|-----------|--------|-------------|-----------|------------------|
| W8/A8          | 75.7      | 75.7   | 75.9        | 75.8      | 76.0             |
| W6/A6          | 73.5      | 73.4   | 74.1        | 73.6      | 75.0             |
| W4/A4          | 63.3      | 63.0   | 64.3        | 63.0      | 72.4             |

The seq2seq and ResNet-50 models as AdaptivFloat show modest retrained performance degradation at 4-bit and 5-bit weight precision. Notably, only a 1.2 Top-1 accuracy drop is seen with a weight width of 4-bit. When the weights of the seq2seq model are quantized to 4-bit, the non-adaptive data types (float and Posit) are essentially unable to provide expressible transcription. This suggests that, for resilient performance at very low word size, it is critical to have a quantization scheme that can adjust its available dynamic range to represent the network’s weights as faithfully as possible. AdaptivFloat’s observed robustness at very low precision enables higher compute density into reconfigurable architectures at a low penalty for computational accuracy.

Adding noise to weights when computing the parameter gradients has been shown to exact a regularization effect that can improve generalization performance (Noh et al., 2017). This effect can be seen in all data types but is particularly pronounced in AdaptivFloat with performance exceeding FP32 by up to +0.3 in BLEU score, -0.75 in word error rate and +0.1 in Top-1 accuracy.

**4.3 Effect of both Weight and Activation Quantization**

Tables 5, 6, and 7 report the inference performance from reducing the word size of both weights and activations on the Transformer, Seq2Seq, and ResNet-50 models, respectively. W/n/A/n signifies a quantization of n-bit weight and n-bit activation.

We observe that AdaptivFloat’s 8-bit performance is as good as, if not better than, the baseline FP32 result on all three DNN models while the degradation at 6-bit is still modest. Interestingly, in the case of the seq2seq model, the 6-bit AdaptivFloat weight and activation quantization generates...
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

Figure 6. Conventional n-bit Integer-based PE.

Figure 7. n-bit Hybrid Float-Integer PE.

regularization effective enough to exceed the FP32 baseline. At 4-bit weight and activation precision, the performance degradation of AdaptivFloat is steeper on the sequence models than on ResNet-50 as many of the activations from the attention mechanisms fall outside of the available dynamic range of the number format.

5 PE ARCHITECTURE

AdaptivFloat’s superior bit compression ability paves the way to efficient bit packing into resource-constrained accelerators. In this section, we describe the design of a hybrid Float-Integer (HFINT) PE that exploits the AdaptivFloat logic in its computational datapath and provides an efficient compromise between the high accuracy of floating-point computations and the greater hardware density of fixed-point post-processing. We contrast the proposed PE architecture against that of a conventional integer (INT) PE.

5.1 Conventional Integer PE

The micro-architecture of a n-bit integer-based PE is shown in Figure 6. It contains fixed-point vector MAC units receiving n-bit integer weight and activation vectors. The MAC partial sums are stored in $2^n + \log_2(H)$-bit registers in order to accumulate up to $H$ values without overflow. A high-precision scaling factor is typically used to dequantize the computation with high accuracy (Migacz, 2017). Using a $S$-bit scaling factor requires the scaled results to be stored in registers of width $2^n + \log_2(H) + S$, which later are bit-shifted right by the fractional value of the scaling. Then, the data is clipped and truncated back to $n$ bits before being modulated by the neural network activation function. An 8-bit integer-based PE architecture will be referred later in the document as INT8/24/40 to designate a datapath with 8-bit MAC operands, accumulated into 24-bit (to add up to 256 values without overflow) and then scaled to 40-bit using a 16-bit scaling factor.

5.2 Hybrid Float-Integer PE

Figure 7 illustrates the micro-architecture of a n-bit Hybrid Float-Integer (HFINT) PE. The vector MACs units perform floating-point multiplications between a n-bit float weight vector and a n-bit float activation vector — and accumulate the result as integer. The weights and activations stored on-chip are quantized according to the AdaptivFloat algorithm described in Algorithm 2 in Section 3. The extracted AdaptivFloat $exp_{bias}$ for weight and activation tensors are saved in allocated 4-bit registers and are used to shift the exponent range of the accumulated partial sums. We note that while the AdaptivFloat $exp_{bias}$ for the static weights are extracted post-training, the $exp_{bias}$ for the dynamic activations are informed from statistics during offline batch inference on the test dataset. The accumulation precision needs to be $2^n + \log_2(H) + 2^n + \log_2(H) + S$-bit. At the end of the PE datapath, the integer activations are converted back to the AdaptivFloat format. The 8-bit HFINT
William Shakespeare was an English poet, widely regarded as the greatest writer in the English language.

PE architecture will be referred to as HFINT8/30 to indicate an 8-bit MAC datapath with 30-bit accumulation.

A key contrast to note between the INT PE and the HFINT PE, apart from the differing data types employed in the vector MAC units, is the INT PE requires a post-accumulation multiplier in order to perform the adaptive operation of the quantization. This in turn increases the required post-accumulation precision by $S$-bit before truncation. In the next section, we provide energy, performance, and area comparisons between the two PE topologies.

6 Hardware Evaluation

6.1 Algorithm-Hardware Co-design Methodology

We developed a design and verification flow, as illustrated in Figure 8, which closes the loop between software modeling and backend hardware implementation. The AdaptivFloat and integer quantizations are performed in the Pytorch deep learning framework during and post training. The extracted AdaptivFloat $\exp \times \text{bias}$ for weights and activations and the scaling factor from the integer quantization are sent to the C++ simulator, along with the quantized weights.

In order to evaluate the hardware on a realistic DNN workload, we designed an accelerator system, depicted in Figure 9, targeted for RNN and FC sequence-to-sequence networks where we have seen wider parameter distributions compared to convolution networks. The accelerator is evaluated with four PEs that are integrated as either INT or HFINT. Each PE contains an input/bias buffer with sizes ranging from 1KB to 4KB and a weight buffer whose size ranges from 256KB to 1MB depending on the vector size and operand bit width. A global buffer (GB) unit with 1MB of storage collects the computed activations from the individual PEs via the arbitrated crossbar channel and then broadcasts them back to the four PEs, in order to process the next time step or the next layer.

In this experimental setup, we note here that the HFINT PE uses MAC operands with 3 exponent bits which was found to yield the best inference accuracy across the ResNet-50, Seq2Seq, and Transformer networks.

The INT and HFINT accelerators were both designed in SystemC with synthesizable and bit-accurate components from the MatchLib (Khailany et al., 2018) and HLSLibs (HLSLibs) libraries. Verilog RTL was autogener- ated by the Catapult high-level synthesis (HLS) tool with HLS constraints uniformly set with the goal to achieve maximum throughput on the pipelined designs.

For fair power, performance and area (PPA) comparisons, the two designs employ the same evaluation methodology. Energy and performance results are reported on the post-HLS Verilog netlists by the Catapult tool at 1GHz clock frequency using a commercial 16nm FinFET standard cell library. The simulated workload consists of 100 LSTM time steps with 256 hidden units operating in a weight stationary
6.2 Energy, Performance and Area Analyses

We first look at PPA efficiencies in the PE, which is the computational workhorse of the accelerator. Moreover, we evaluate the effect of increasing throughput via the inner MAC vector size which is also equal to the number of parallel lanes (i.e., vector MAC units).

Figure 10 shows that the HFINT PEs achieve smaller per-operation energy than the INT PEs at either 4-bit or 8-bit MAC operands and across vector sizes. Larger vector size and operand bit width benefits more the HFINT PE than the INT PE in terms of energy efficiency. Precisely, from 4-bit operands and vector size of 4 – to 8-bit operands and vector size of 16, the per-operation energy of the HFINT PE is $0.97 \times$ to $0.90 \times$ that of the INT PE. The smaller per-operation energy of the HFINT PE stems from the fact that its vector MACs contain smaller mantissa multipliers and exponent adders that consume less overall power than full bitwidth multipliers as used in vector MACs of the INT PEs.

Increasing the vector size is found to improve overall energy efficiency due to higher spatial reuse of the accumulated partial sums. On the other hand, the INT PEs exhibit $1.04 \times$ to $1.21 \times$ higher performance per unit area compared to the HFINT PEs due to the more compact and homogeneous logic in the vector MACs.

Table 8 reports the power, area, and compute time of an 8-bit INT and 8-bit HFINT accelerator system with 4 PEs and a global buffer. The PEs here have a MAC vector size of 16 in both systems. The HFINT accelerator reports $0.92 \times$ the power and $1.14 \times$ the area of the integer-based adaptation, confirming the efficiency trends reported in Figure 10. Note that both accelerators have the same compute time because the HLS tool generated the same aggregate pipelining result for both designs.

7 Conclusion

Fixed-point quantization schemes can be inadequate for networks possessing relatively wide parameter distributions commonly seen in deep sequence transduction models such as the Transformer. This paper presents AdaptivFloat, a resilient floating-point based encoding solution that dynamically maximizes and optimally clips its available dynamic range, at a layer granularity, in order to create accurate encodings of neural network parameters from narrow to wide distribution spread. AdaptivFloat demonstrates marked robustness at very low precision ($\leq 6$-bit) on the Transformer, LSTM-based seq2seq, and ResNet-50 networks. This paves the way to higher compute density into reconfigurable architectures – at a much lower penalty for computational accuracy compared to leading encoding types such as block floating-point, uniform, or non-adaptive float or posin number formats. We also illustrate the algorithm-hardware co-design of AdaptivFloat, which allows the extracted $exp_{bias}$ of weights and activations to be stored on allocated registers on-chip in order to perform the adaptive operation of the quantization. The proposed processing elements and accelerators that leverage this mechanism demonstrate per-operation energy that is $0.90 \times$ to $0.97 \times$ that of integer-based adaptations at varying vector sizes and MAC operand bit widths. Altogether, the AdaptivFloat algorithm-hardware co-design framework offers a compelling alternative to integer or fixed-point solutions.

8 Acknowledgments

This work was supported by the Application Driving Architectures (ADA) Research Center, a JUMP Center co-sponsored by SRC and DARPA.

References

Alom, M. Z., Moody, A. T., Maruyama, N., Essen, B. C. V., and Taha, T. M. Effective quantization approaches for recurrent neural networks. 2018. URL http://arxiv.org/abs/1802.02615.
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

Bu, L. J., Kiros, J. R., and Hinton, G. E. Layer normalization. 2016. URL http://arxiv.org/abs/1607.06450.

Bhandare, A., Sripathi, V., Karkada, D., Menon, V., Choi, S., Datta, K., and Saletore, V. Efficient 8-bit quantization of transformer neural machine language translation model. 2019. URL http://arxiv.org/abs/1906.00532.

Cai, Z., He, X., Sun, J., and Vasconcelos, N. Deep learning with low precision by half-wave gaussian quantization. 2017. URL http://arxiv.org/abs/1702.00953.

Carmichael, Z., Langroudi, S. H. F., Khazanov, C., Lillie, J., Gustafson, J. L., and Kudithipudi, D. Deep positron: A deep neural network using the posit number system. 2018. URL http://arxiv.org/abs/1812.01762.

Chiu, C., Sainath, T. N., Wu, Y., Prabhavalkar, R., Nguyen, P., Chen, Z., Kannan, A., Weiss, R. J., Rao, K., Gohina, K., Jaitly, N., Li, B., Chorowski, J., and Bacchiani, M. State-of-the-art speech recognition with sequence-to-sequence models. 2017. URL http://arxiv.org/abs/1712.01769.

Choi, J., Venkataramani, S., Srinivasan, V., Gopalakrishnan, K., Wang, Z., and Chuang, P. Accurate and efficient 2-bit quantized neural networks. 2019.

Chorowski, J., Bahdanau, D., Serdyuk, D., Cho, K., and Bengio, Y. Attention-based models for speech recognition. In Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montréal, Québec, Canada, pp. 577–585, 2015.

Courbariaux, M. and Bengio, Y. Binarynet: Training deep neural networks with weights and activations constrained to +1 or -1. 2016. URL http://arxiv.org/abs/1602.02830.

Courbariaux, M., Bengio, Y., and David, J. Binaryconnect: Training deep neural networks with binary weights during propagations. 2015. URL http://arxiv.org/abs/1511.00363.

Drumond, M., Lin, T., Jaggi, M., and Falsafi, B. End-to-end DNN training with block floating point arithmetic. 2018. URL http://arxiv.org/abs/1804.01526.

Fowers, J., Ovtcharov, K., Papamichael, M., Massengill, T., Liu, M., Lo, D., Alkalay, S., Haselman, M., Adams, L., Ghandi, M., et al. A configurable cloud-scale dnn processor for real-time ai. In Proceedings of the 45th Annual International Symposium on Computer Architecture. pages 1-14. IEEE Press, 2018.

Gupta, S., Agrawal, A., Gopalakrishnan, K., and Narayanan, P. Deep learning with limited numerical precision. 2015. URL http://arxiv.org/abs/1502.02551.

Gustafson and Yonemoto. Beating floating point at its own game: Posit arithmetic. June 2017. ISSN 2409-6008. doi: 10.14529/jsfi170206. URL https://doi.org/10.14529/jsfi170206.

Han, S., Mao, H., and Dally, W. J. Deep compression: Compressing deep neural network with pruning, trained quantization and huffman coding. 2015.

He, K., Zhang, X., Ren, S., and Sun, J. Deep residual learning for image recognition. In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778, June 2016. doi: 10.1109/CVPR.2016.90.

HLSLibs. Open-source high-level synthesis ip libraries. Technical report. URL https://github.com/hlslibs.

Hwang, K. and Sung, W. Fixed-point feedforward deep neural network design using weights +1, 0, and 1. In 2014 IEEE Workshop on Signal Processing Systems (SiPS), pp. 1–6, Oct 2014. doi: 10.1109/SiPS.2014.6968082.

Jacob, B., Kligys, S., Chen, B., Zhu, M., Tang, M., Howard, A. G., Adam, H., and Kalenichenko, D. Quantization and training of neural networks for efficient integer-arithmetic-only inference. 2017. URL http://arxiv.org/abs/1712.05877.

Johnston, J. Rethinking floating point for deep learning. 2018. URL http://arxiv.org/abs/1811.01721.

Jouppi, N. P., Young, C., Patil, N., Patterson, D., Agrawal, G., Bajwa, R., Bates, S., Bhatia, S., Boden, N., Borchers, A., Boyle, R., Cantin, P., Chao, C., Clark, C., Coriell, J., Daley, M., Dau, M., Dean, J., Gelb, B., Ghemmaghami, T. V., Gottipati, R., Gulland, W., Hagemann, R., Ho, C. R., Hogberg, D., Hu, J., Hundt, R., Hurt, D., Ibarz, J., Jaffey, A., Jaworski, A., Kaplan, A., Khaitan, H., Killebrew, D., Koch, A., Kumar, N., Lacy, S., Laudon, J., Law, J., Le, D., Leary, C., Liu, Z., Lucke, K., Lundin, A., MacKean, G., Maggiore, A., Mahony, M., Miller, K., Nagarajan, R., Narayanaswami, R., Ni, R., Nix, K., Norrie, T., Omernick, M., Penukonda, N., Phelps, A., Ross, J., Ross, M., Salek, A., Samadiani, E., Severn, C., Sizikov, G., Snelham, M., Souter, J., Steinberg, D., Swing, A., Tan, M., Thorson, G., Tian, B., Toma, H., Tuttle, E., Vasudevan, V., Walter, R., Wang, W., Wilcox, E., and Yoon, D. H. In-datacenter performance analysis of a tensor processing unit. In 2017 ACM/IEEE 44th Annual International Symposium on Computer Architecture (ISCA), pp. 1–12, June 2017. doi: 10.1145/3079856.3080246.
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

Khailany, B., Khmer, E., Venkatesan, R., Clemons, J., Emer, J. S., Fojtik, M., Klinefelter, A., Pellauer, M., Pinckney, N., Shao, Y. S., Srinath, S., Torng, C., Xi, S. L., Zhang, Y., and Zimmer, B. A modular digital vlsi flow for high-productivity soc design. In Proceedings of the 55th Annual Design Automation Conference, DAC ’18, pp. 72:1–72:6, New York, NY, USA, 2018. ACM. ISBN 978-1-4503-5700-5. doi: 10.1145/3195970.3199846. URL http://doi.acm.org/10.1145/3195970.3199846.

Klein, G., Kim, Y., Deng, Y., Senellart, J., and Rush, A. M. Opennmt: Open-source toolkit for neural machine translation. 2017. URL http://arxiv.org/abs/1701.02810.

Köster, U., Webb, T., Wang, X., Nassar, M., Bansal, A. K., Constable, W., Elibol, O., Hall, S., Hornof, L., Khosrowshahi, A., Kloss, C., Pai, R. J., and Rao, N. Flexpoint: An adaptive numerical format for efficient training of deep neural networks. 2017. URL http://arxiv.org/abs/1711.02213.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. Imagenet classification with deep convolutional neural networks. In Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1, NIPS’12, pp. 1097–1105, USA, 2012. Curran Associates Inc. URL http://dl.acm.org/citation.cfm?id=2999134.2999257.

Lee, E. H., Miyashita, D., Chai, E., Murmann, B., and Wong, S. S. Lognet: Energy-efficient neural networks using logarithmic computation. In 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 5900–5904, March 2017. doi: 10.1109/ICASSP.2017.7953288.

Lin, D. D., Talathi, S. S., and Annapureddy, V. S. Fixed point quantization of deep convolutional networks. 2015. URL http://arxiv.org/abs/1511.06393.

Migacz, S. 8-bit inference with tensorrt. In NVIDIA GPU Technology Conference, 2017. URL http://on-demand.gputechconf.com/gtc/2017/presentation/s7310-8-bit-inference-with-tensorrt.pdf.

Mishra, A. K., Nurvitadhi, E., Cook, J. J., and Marr, D. WRPN: wide reduced-precision networks. 2017. URL http://arxiv.org/abs/1709.01134.

Miyashita, D., Lee, E. H., and Murmann, B. Convolutional neural networks using logarithmic data representation. 2016. URL http://arxiv.org/abs/1603.01025.

Noh, H., You, T., Mun, J., and Han, B. Regularizing deep neural networks by noise: Its interpretation and optimization. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA, pp. 5109–5118, 2017.

Park, E., Ahn, J., and Yoo, S. Weighted-entropy-based quantization for deep neural networks. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 7197–7205, July 2017. doi: 10.1109/CVPR.2017.761.

Park, E., Kim, D., and Yoo, S. Energy-efficient neural network accelerator based on outlier-aware low-precision computation. In 2018 ACM/IEEE 45th Annual International Symposium on Computer Architecture (ISCA), pp. 688–698, June 2018. doi: 10.1109/ISCA.2018.00063.

Pytorch. Imagenet training in pytorch. Technical report. URL https://github.com/pytorch/examples/tree/master/imagenet.

Reagen, B., Whatmough, P., Adolf, R., Rama, S., Lee, H., Lee, S. K., Hernandez-Lobato, J. M., Wei, G., and Brooks, D. Minerva: Enabling low-power, highly-accurate deep neural network accelerators. In 2016 ACM/IEEE 43rd Annual International Symposium on Computer Architecture (ISCA), pp. 267–278, June 2016. doi: 10.1109/ISCA.2016.32.

Salimans, T. and Kingma, D. P. Weight normalization: A simple reparameterization to accelerate training of deep neural networks. In Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain, pp. 901, 2016. URL http://papers.nips.cc/paper/6114-weight-normalization-a-simple-reparameterization.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. Attention is all you need. 2017. URL http://arxiv.org/abs/1706.03762.

Vogel, S., Liang, M., Guntoro, A., Stechele, W., and Ascheid, G. Efficient hardware acceleration of cnns using logarithmic data representation with arbitrary logbase. In Proceedings of the International Conference on Computer-Aided Design, ICCAD ’18, pp. 9:1–9:8, New York, NY, USA, 2018. ACM. ISBN 978-1-4503-5950-4. doi: 10.1145/3240765.3240803. URL http://doi.acm.org/10.1145/3240765.3240803.

Wu, J., Leng, C., Wang, Y., Hu, Q., and Cheng, J. Quantized convolutional neural networks for mobile devices. 2015. URL http://arxiv.org/abs/1512.06473.
AdaptivFloat: A Floating-point based Data Type for Resilient Deep Learning Inference

Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., Klingner, J., Shah, A., Johnson, M., Liu, X., Kaiser, L., Gouws, S., Kato, Y., Kudo, T., Kazawa, H., Stevens, K., Kurian, G., Patil, N., Wang, W., Young, C., Smith, J., Riesa, J., Rudnick, A., Vinyals, O., Corrado, G., Hughes, M., and Dean, J. Google’s neural machine translation system: Bridging the gap between human and machine translation. 2016. URL http://arxiv.org/abs/1609.08144.

Zhang, D., Yang, J., Ye, D., and Hua, G. Lq-nets: Learned quantization for highly accurate and compact deep neural networks. 2018. URL http://arxiv.org/abs/1807.10029.

Zhou, S., Ni, Z., Zhou, X., Wen, H., Wu, Y., and Zou, Y. Dorefa-net: Training low bitwidth convolutional neural networks with low bitwidth gradients. 2016. URL http://arxiv.org/abs/1606.06160.

Zhu, C., Han, S., Mao, H., and Dally, W. J. Trained ternary quantization. 2016. URL http://arxiv.org/abs/1612.01064.