Efficient inference of Deep Neural Networks (DNNs) is essential to making AI ubiquitous. Two important algorithmic techniques have shown promise for enabling efficient inference - sparsity and binarization. These techniques translate into weight sparsity and weight repetition at the hardware-software level enabling the deployment of DNNs with critically low power and latency requirements. We propose a new method called signed-binary networks to improve efficiency further (by exploiting both weight sparsity and weight repetition together) while maintaining similar accuracy. Our method achieves comparable accuracy on ImageNet and CIFAR10 datasets with binary and can lead to > 69% sparsity. We observe real speedup when deploying these models on general-purpose devices and show that this high percentage of unstructured sparsity can lead to a further reduction in energy consumption on ASICs.

1 INTRODUCTION

There is a lot of interest in making DNN inference more efficient. One promising technique to make DNN inference efficient is the binarization of weights of the DNN. Binarization leads to weight repetition as only two unique values get repeated in the weight tensor. The other promising technique to make DNN inference efficient is by introducing sparsity to weight tensors of the DNN, known as sparse DNNs. Since anything multiplied by zero is zero, weight sparsity leads to ineffectual multiplications. These approaches has been shown to work on general-purpose devices and ASICs.

While there is a rich literature on methods to increase the accuracy of binary models (Liu et al., 2018; Bai, Wang, and Liberty, 2018; Xu et al., 2021), binary networks can not make use of sparsity to improve computational efficiency during DNN inference. This is because weights and/or activations in SOTA binary models are either positive real numbers or negative real numbers. Therefore, DNN inference efficiency is usually achieved either by leveraging binarization or sparsity, but not both. Prior attempts to produce sparse binary networks have suffered a significant accuracy drop when compared to their binary counterparts (Schiavone and Zuluaga, 2020).

In this paper, we demonstrate that the two techniques, namely binarization and sparsity, can be complementary (and therefore are not mutually exclusive). To illustrate this, we propose a new quantization scheme SBWN to create sparse binary weight networks which achieve competitive accuracy on CIFAR10 and ImageNet. Finally, we demonstrate that using SBWN leads to lower runtime when compared to its binary counterpart when leveraging both binarization and sparsity during DNN inference. We also discuss potential theoretical gains in throughput and energy consumption.

Unlike Binary and Ternary Networks, Signed-Binary uses two new quantization functions that can have the values of \{1, 0\} & \{0, -1\}. The value set of the quantization function for a given filter of a CNN is decided randomly before the training starts and remains fixed during training and inference.

We make the following contributions in the paper:

• We propose a new quantization scheme called Signed Binary Weight Networks (SBWN) which is more efficient than binary and ternary weight networks and yet achieves comparable accuracy on object classification tasks. We demonstrate the same by training ResNet models on CIFAR10 and ImageNet datasets.

• We identify a new trade-off between weight repetition and weight sparsity that causes runtime to increase when deploying binary or ternary models. Our method makes the exploitation of weight repetition and weight sparsity complementary which is why it is more efficient. We demonstrate the same by deploying ResNet models on Intel CPUs.

• We discuss potential gains due to sparsity on throughput, energy consumption and accuracy for our method with respect to binary.
Figure 1. Comparison of Binary, Ternary and Signed-Binary (ours). We introduce signed binary weight quantization for improved DNN efficiency through leveraging both weight repetition and weight sparsity.

2 BACKGROUND

Quantization of weights in DNN leads to the same value being repeated again and again in the weight tensor. This phenomenon is known as weight repetition (Hegde et al., 2018; Sze et al., 2020). Since the weights are fixed during DNN inference, this leads to additional opportunities for optimizations. The objective is to improve efficiency during inference with respect to time and energy by exploiting the repetition of weights and reducing memory accesses (Sze et al., 2020).

Using weight repetition for efficiency first originated in the original BNN (Courbariaux et al., 2016) which talked about the idea of filter repetition in BNNs for efficient inference. The authors highlight that the number of unique filters possible in a binary setting is bounded by the filter size. This is explained with an example that a 3x3 2D filter can only have $2^9$ unique filters in a binary network. (Courbariaux et al., 2016) states that there are only 42% of unique filters per layer on average which can lead to reducing the number of XNOR operations by 3x.

UCNN (Hegde et al., 2018) was the first work that demonstrated efficiency by using weight repetition on ASICs. This reduces memory accesses and decreases the number of arithmetic operations required during DNN inference. Sum-Merge (Prabhakar and Kuhar et al., 2021) extends the idea of UCNN even further by using both weight repetition and weight sparsity for efficient DNN inference.

3 MOTIVATION AND LIMITATIONS OF PRIOR WORK

The motivation of this paper is to combine Binary DNNs with Sparse DNNs. Since ternary has also been referred to as sparse binary (Zhu et al., 2016), we analyze why ternary networks are sub-optimal sparse binary networks. Authors of Ternary Weight Networks (TWN) (Li, Zhang, and Liu, 2016) argued that when compared to its binary counterpart, the number of arithmetic operations in TWNs would be unchanged as arithmetic operations corresponding to zero-valued weights can be skipped during DNN inference. They claim that switching from binary to ternary leads to an increase in the expressivity as the 3x3 2D filter can have $3^9$ unique filters instead of $2^9$. However, this increase in expressivity is also a drawback of ternary networks. This is because ternarization makes it exponentially hard to extract efficiency using filter repetition. Switching from binary to signed-binary on the contrary results in the same number of unique 3x3 filters. This is because a filter in \{1,0\} bucket will be a two’s complement of a filter in \{0,-1\} bucket. In addition, as signed-binary 3x3 filters will be sparse, it will lead to more efficient DNN inference when compared to Binary.

Unlike ternary which requires atleast two bits to represent one weight in a DNN, weights of binary and signed-binary can be represented using one bit only. Time taken for DNN inference when using 1-bit, 2-bit, and FP weights has been evaluated in (Cowan et al., 2020). They demonstrate that switching from one bit to two bits results in a 2x increase in runtime on ARM CPUs. Hence, signed-binary would be more efficient for DNN inference when compared to Ternary when using implementation like (Cowan et al., 2020) for general-purpose devices. To conclude, switching from a binary network to ternary network results in the introduction of sparsity at the expense of weight repetition which is not a limitation for our method.

4 SIGNED BINARY WEIGHT NETWORKS

Unlike Binary and Ternary, we use two quantization functions instead of one that take full-precision latent weight as input and gives the quantized weight as the output to quantize a convolutional layer. The value sets of the two quantization functions are \{1,0\} and \{0,-1\}.

Let the convolutional filter have a $R \times S$ kernel size and $C$ input channels. The quantization function takes latent full-precision weights $W$ as input and outputs the quantized weight $W^{\text{quant}}$. The quantized weight $W^{\text{quant}}$ would be the product of the sign-factor $\beta$ and the BitMap $U$.

$$Q : W \rightarrow W^{\text{quant}}$$

$$W^{\text{quant}} = \beta U$$

$$\forall W \in \mathbb{R}^{R \times S \times C}, \beta \in \{+1, -1\}, U \in \{0, 1\}^{R \times S \times C}$$
or \( \{0, -1\}^{R \times S \times C} \). The values of the quantization function for a given filter of a CNN are decided randomly before the training starts and never change.

**How is signed-binary implemented for efficient training?** Bucketing. Each filter will have a different quantization function for a convolutional layer \( i \) having \( K \) filters. Since every filter of a convolutional layer is independent of every other filter, we can sort these filters into two buckets based on the values of the quantization function for each filter. In other words, we quantize the full-precision latent weights of a convolutional layer from \( \mathbb{R}^{R \times S \times C \times K} \) to \( \{0, 1\}^{R \times S \times C \times K} \) and \( \{0, -1\}^{R \times S \times C \times K \times (1-P)} \) where \( P \) is the percentage of filters whose quantization functions have the values \( \{0,1\} \).

**What are the two quantization functions?** If a filter \( i \) is assigned to \( \{0, 1\} \) bucket, the sign-factor \( \beta_i \) is equal to 1. Following (Zhu et al., 2016), we use the threshold value of \( \Delta = 0.05 \times \max(|W|) \) for the quantization function. Similarly, if a filter \( i \) is assigned to \( \{0, 1\} \) bucket, the sign-factor \( \beta_i \) is equal to -1 and the threshold value of \( \Delta = 0.05 \times \max(|W|) \) is used for the quantization function. We find assigning both quantization function with equal probability gives high accuracy (see appendix).

## 5 Accuracy

**Evaluating Signed-Binary against Binary and Ternary Quantization** We compare the ability of signed-binary to perform object classification tasks against binary and ternary by training ResNets on CIFAR10 under idential settings. For the most direct comparison of quantization schemes, we focus our evaluation on the basic form of each model. All strategies to further improve learning (Zhu et al., 2016; Liu et al., 2020; Bai, Wang, and Liberty, 2018) may be applied on top of the base model for any of these quantization schemes. Quantized weights can only belong to the set \( \{0, -1, 1\} \). Please see appendix for more details and hyperparameters. We find in Table 1 that when trained from scratch, signed-binary and binary achieve similar accuracy on CIFAR10 object classification task.

**Evaluation on ImageNet** We evaluate if it is possible to perform object classification tasks at scale by training signed-binary ResNet18 from scratch. Baseline ResNet18 trained using vanilla SBWN gives us 61.94% top-1 validation accuracy on ImageNet. Adding simple techniques like distillation (Hinton et al., 2015) increases the top-1 accuracy to 64.6%. We find that SBWN is able to perform complex tasks comparably when compared to its binary counterpart without any architectural modifications, scaling factors, or jointly optimizing for information loss and quantization error (Qin et al., 2020b) built for binary networks.

### Table 1. Quantization scheme ablation across architecture: Binary, Ternary, and Signed-Binary ResNets are trained on CIFAR10 under identical settings. We observe that Binary and Signed-Binary achieve similar top-1 validation accuracy even though signed-binary has sparse weight tensors.

| Architecture | B | SB (ours) | T | FP |
|--------------|---|-----------|---|----|
| ResNet20     | 90.20 | 90.05 | 90.86 | 91.99 |
| ResNet32     | 91.51 | 91.55 | 92.03 | 92.90 |
| ResNet44     | 91.93 | 91.98 | 92.40 | 93.30 |
| ResNet56     | 92.42 | 92.52 | 92.90 | 93.63 |
| ResNet110    | 92.64 | 92.68 | 93.33 | 93.83 |

**Table 2. Evaluation on ImageNet using ResNet18**: We train Signed-Binary ResNet18 from scratch on ImageNet to achieve competitive accuracy when compared to Binary and Ternary Weight Networks. Legend: \( SB = \text{Signed-Binary} \), \( B = \text{Binary} \), \( T = \text{Ternary} \), and \( BW = \text{Bit-Width of Weights} \). †: architecture modifications, including more skip connections and distillation to improve performance. * performs joint optimization for information retention which can be extended to any low-bit quantization.

| Method                  | BW | Top-1 Acc |
|-------------------------|----|-----------|
| SBWN (ours)             | SB | 64.62     |
| BWN (Rastegari et al., 2016) | B  | 60.8      |
| TWN (Li, Zhang, and Liu, 2016) | T  | 61.8      |
| ABC-Net (Lin, Zhao, and Pan, 2017) | B  | 62.8      |
| BWNH (Hu, Wang, and Cheng, 2018) | B  | 64.3      |
| DSQ (Gong et al., 2019)  | B  | 63.7      |
| LS† (Pouransari, Tu, and Tuzel, 2020) | B  | 66.1      |
| IR-Net* (Qin et al., 2020b) | B  | 66.5      |

| Full Precision          | 32 | 69.6      |

## 6 Efficiency

### 6.1 Deploying on Intel CPU

We demonstrate that signed-binary is more efficient than binary and ternary networks when leveraging both weight sparsity and weight repetition during DNN inference. We deploy quantized ResNet-18 models on Intel CPUs by using (Prabhakar and Kuhar et al., 2021) and measure the actual time taken during inference. All DNN inference experiments are subject to identical test environments and methodology. Please see appendix for more details. We use SumMerge for DNN inference in two configurations (1) with sparsity support turned OFF and (2) with sparsity support turned ON. We observe that signed-binary would be the most efficient compared to binary and ternary. Signed-binary is 1.26x faster than binary and 1.75x faster than ternary when sparsity support is turned on.
Signed Binary Weight Networks

Figure 2. Speedup over Binary Quantized ResNet18 on Intel CPU: Signed-Binary is designed for efficiency while binary and ternary make suboptimal use of weight repetition and/or weight sparsity. We find that signed-binary performs best for every convolutional layer across all quantization schemes when software leverages both weight repetition and weight sparsity.

Explanation (1) When sparsity support is turned off: In this scenario, the software is only relying on repeating values within the weight tensor for speedup. Because binary and signed-binary have two unique values per convolutional filter, they take similar time for DNN inference. Ternary is much slower as it has three unique values per convolution filter which makes extracting efficiency by using weight repetition exponentially harder.

(2) When sparsity support is turned on: In this scenario, the software not only cares about the repeating values in the weight tensor but also skips computations on zero weights to improve the runtime. Here we observe that ternary is slower than binary because the reduction in work due to sparsity is not able to compensate for the exponential decrease in weight repetition. Our method, on the other hand, does not suffer from this problem and is able to exploit weight repetition and weight sparsity to the fullest and is most efficient.

6.2 Sparsity and Further Analysis on ASICs
We find that ResNet-18 with 64.6% top-1 on ImageNet has 69% sparsity while ResNet20 with 90.05% accuracy on CIFAR10 has 60% sparsity. Theoretically, the throughput can be increased by ~3x for ResNet18 when switching from binary to signed-binary due to reported sparsity. This is because ideally when we eliminate ineffectual computations resulting from zero weights, we can eliminate the time that was associated with them to increase throughput (Emer et al., 2021). However, since the addition of support for unstructured sparsity is an emerging technology, the speedup we observe on real hardware is in the range 1.26x-1.75x.

To estimate energy reduction due to the unstructured sparsity of DNNs, we use the cycle-level microarchitectural simulator (Muñoz-Matrínez et al., 2021) of sparsity support-ASIC (Qin et al. 2020). We take the publicly released code and use it under default configuration (details in the appendix). We observe that increasing the unstructured weight sparsity from 0% to 69% leads to a ~2x reduction in energy during DNN inference. Thus, switching from binary to signed-binary would lead to significant improvements in power consumption on ASICs.

6.3 Signed-Binary vs Binary with comparable non-zero parameters
Since Signed-Binary ResNet trained on CIFAR10 has slightly greater than 50% sparsity, reducing the total number of parameters of the binary ResNet by half, results in a binary model with comparable non-zero weights. This is done by reducing depth and by reducing width of the binary ResNet. We train all models under identical conditions (setup details in the appendix). We find that Signed-Binary ResNet performs better by 1.5% on CIFAR10 when both have comparable non-zero parameters (please see table-1 in appendix). Thus, signed-binary leads to a higher accuracy than binary when both methods have comparable number of effectual operations.

7 LIMITATIONS AND DISCUSSION
We hope our work will be useful in scenarios where the time and energy required for inference are of great significance. The scope of this work is limited to weight quantization and weight sparsity. In the future, we would like to extend this work to Signed-Binary Neural Networks and address the challenge of combining sparsity in weights and activations with binarization and also create a software system to demonstrate actual speedup.

8 CONCLUSION
This paper introduces a new weight quantization scheme called Signed-Binary. Results on ImageNet and CIFAR10 illustrate that signed-binary method achieves comparable accuracy to binary. Signed-Binary enables modern hardware-software to increase inference efficiency by better exploiting weight repetition and weight sparsity. We demonstrate signed-binary is more efficient than binary and ternary by performing ablations study on weight sparsity and weight repetition while deploying these models on Intel CPUs. Finally, we discuss gains with respect to efficiency and find that switching from binary to signed-binary with respect to throughput and energy consumption on ASICs.

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A APPENDIX

A.1 Signed-Binary vs Binary with comparable non-zero parameters

Signed-Binary ResNet trained on CIFAR10 has slightly greater than 50% sparsity. If we reduce the total number of parameters of the binary ResNet by half, the resulting model would have a comparable number of non-zero weights to signed-binary ResNet. This is done by reducing depth (see Table 3) and width (see Table 4). We train these models under identical conditions (setup details in the section below). To clarify, rows 1 & 2 of Table 4 & 3 have the same number of total parameters, while rows 1 & row 3 have a comparable number of non-zero parameters. Thus, signed-binary leads to a higher accuracy than binary when both methods have a comparable number of effectual operations.

![Distribution of Quantized Weights in signed-binary ResNet18 trained on ImageNet with Distillation](image)

**Figure 3. Distribution of Quantized Weights in signed-binary ResNet18 trained on ImageNet with Distillation**: While the weight distribution of signed-binary convolutional layers looks similar to ternary, the positive and negative weights are present in different filters.

A.2 Weight Distribution of Signed-Binary Networks

We would like to see the distribution of weights of Signed-Binary ResNet18 trained on ImageNet dataset using Distillation. We take all quantized layers of ResNet18 and plot the distribution of quantized weights per convolutional layer in Figure 3. We find that the model is highly sparse with the majority of weights pruned.

Table 3. Reducing the number of parameters by reducing depth: We observe that the accuracy of binary is 1.3% lower than signed-binary with comparable non-zero weights.

| Quant | # Parameters | Depth | Acc  |
|-------|--------------|-------|------|
| SB    | 0.46M        | 32    | 91.55% |
| B     | 0.46M        | 32    | 91.22% |
| B     | 0.27M        | 20    | 90.16% |

Table 4. Reducing the number of parameters by reducing width: We observe that the accuracy of binary is 1.7% lower than signed-binary with comparable non-zero weights.

| Quant | # Parameters | Width | Acc  |
|-------|--------------|-------|------|
| SB    | 0.27M        | 1×    | 90.05% |
| B     | 0.27M        | 1×    | 90.20% |
| B     | 0.14M        | [0.7×] | 88.5% |

A.3 Experiment Setups

**CIFAR10 Experiment** The data loader pipeline consists of simple augmentations - padding by 4 pixels on each size, random crop to 32 × 32, Random Horizontal Flip with probability 0.5, and normalization. We train from scratch for 350 epochs and use the Adam Optimizer. We start with an initial learning rate of 0.01 and reduce it by a factor of 10 at epochs 150, 200, and 320. For apples-to-apples comparison with binary and ternary, we do a sweep over batch sizes {16, 32, 64, 128, 256} (ablation in appendix) and activation functions (ReLU, PReLU, TanH) and report the best top-1 validation accuracy. For ablations on (1) value assignment percentage and (2) comparison with binary networks with comparable effectual operations, we select the batch size to be 32 and activation function to be PReLU.

**ImageNet Experiment** We train ResNet-18 using SBWN on ImageNet. We use standard practices to train binary networks, like (1) normalizing the input using batch-norm before convolution instead of after convolution (Rastegari et al., 2016) and (2) the first and the last layers are not quantized (Zhu et al., 2016). We use a first-order polynomial learning-rate annealing schedule with Adam optimizer and PReLU (He et al., 2015). We use an FFCV data loader (Leclerc et al., 2022) with simple augmentations - Random Resize Crop to 224 × 224, Random Horizontal Flipping, and Color Jitter with (brightness, contrast, saturation, hue) set as (0.4, 0.4, 0.4, 0). We decrease the learning rate from $2.0 \times e^{-4}$ to $2.0 \times e^{-8}$ while training for 320...
epochs and do not use weight decay, and an effective batch size of 256 is used to train the model.

**Deploying on CPUs** We use SumMerge (Prabhakar and Kuhar et al., 2021) for this task. We run all experiments on Intel Xeon Gold 6226 CPU. In order to make our test environment as close as possible to the test environment of the authors of (Prabhakar and Kuhar et al., 2021), we disable simultaneous multi-threading, and enable 2MB huge pages and disable dynamic frequency scaling as well. The test methodology is exactly the same as used by the authors of (Prabhakar and Kuhar et al., 2021), i.e., each experiment is run 50 times when the machine is unloaded and the values for run with the lowest execution time are reported. All arithmetic operations are in floating-point. All DNN inference experiments are subject to identical test environments and methodology.

**ASIC** We use STONNE (Muñoz-Matrínez et al., 2021), a cycle-level microarchitectural simulator for DNN Inference Accelerator SIGMA (Qin et al., 2020a) for this experiment. We use the docker image released by the authors of (Muñoz-Matrínez et al., 2021). We use the standard configuration of SIGMA with 256 multiplier switches, 256 read ports in SDMemory and 256 write ports in SDMemory. The reduction networks is set to ASNETWORK and the memory controller is set to SIGMA\_SPARSE\_GEMM. We use SimulatedConv2d function in the PyTorch frontend version of STONNE. For a given convolutional layer, we run STONNE twice, once with 0% sparsity and once with 69% sparsity. We calculate the reduction in energy consumption by dividing the energy of the dense convolutional layer by the energy of the sparse convolutional layer. Since the precision (or bit-width) of the weights is a parameter of SIGMA, the reduction in energy due to sparsity when compared to dense model is not a function of the precision (or bit-width) of the weights of the DNN.

### A.4 Additional Ablations

#### A.4.1 Signed-Binary Quantization Functions

We perform ablation on value assignment percentage in Table 5. We find that randomly assigning the value set to the quantization function of a filter leads to the highest validation accuracy for the CIFAR10 dataset. We see an improvement of 1.2% and 6% top-1 accuracy with respect to the naive \{1, 0\} quantization function used in the literature. In addition, we also ablate on (1) non-linearity, (2) threshold used in signed-binary quantization functions, and (3) batch size by training ResNet20 on the CIFAR10 dataset. Please take a look at Table 6 for ablation on delta (the setup and other ablations are reported in the section below). We observe that PReLU works best for our method, and our method is not sensitive to the choice of threshold \(\Delta\).

| Delta \((\Delta)\) | Accuracy |
|-------------------|----------|
| 0.01 * \text{max}(|W|) | 90.09    |
| 0.05 * \text{max}(|W|) | 90.05    |
| 0.1 * \text{max}(|W|)  | 89.95    |

#### A.4.2 Batch sizes and non-linearity

We perform ablation on (1) batch sizes, (2) non-linearity on CIFAR10 dataset and report the numbers in Table 7 and 7 respectively. The setup is the same as mentioned above. We observe that for our method, there is a drop in accuracy with higher batch size and PReLU (Maas, Hannun, and Ng, 2013) works best.

| ResNet20 CIFAR10 | Val Acc (top-1) |
|------------------|-----------------|
| % \{0,1\} filters | % \{0,-1\} filters |
| 0                | 1               | 88.84  |
| 0.25             | 0.75            | 89.32  |
| 0.5              | 0.5             | 90.05  |
| 0.75             | 0.25            | 89.30  |
| 1                | 0               | 89.07  |

| ResNet18 ImageNet | Val Acc (top-1) |
|-------------------|-----------------|
| % \{0,1\} filters | % \{0,-1\} filters |
| 1                 | 0               | 55.23  |
| 0.5               | 0.5             | 61.94  |
| 0.25              | 0.75            | 62.29  |
| 0.75              | 0.25            | 62.04  |
Table 7. Ablation Studies: (a) **Batch Size**: The setup is identical across batch sizes and the non-linearity used is PReLU. We observe a decrease in accuracy when a high batch size of 256 is used. (b) **Non-Linearity**: The setup is identical across non-linearity and the batch size used is 32. We observe that PReLU works best for our method.

| Batch Size | Top1 Acc | Non-Linearity | Top1 Acc |
|------------|----------|---------------|----------|
| 16         | 89.44    | ReLU          | 88.64    |
| 32         | 90.05    | PReLU         | 90.05    |
| 128        | 89.59    | TanH          | 88.75    |
| 256        | 88.51    | LReLU         | 89.22    |

### A.5 Datasets

Licenses of ImageNet and CIFAR10 datasets used in this paper are listed in Table 1. Every accuracy reported in this paper is on validation set of the dataset.

Table 8. **Dataset with Licenses**: License and source of the datasets used.

| Dataset    | License     | Source       |
|------------|-------------|--------------|
| ImageNet   | Non-Commercial | ILSVRC2012  |
| CIFAR10    | N/A         | CIFAR        |

ImageNet and CIFAR10 are standard publicly used datasets. Since they do not own their images, therefore they do not have a release license. Actual images may have their own copyrights but ImageNet provides stipulations for using their dataset (for non-commercial use). We do not recommend using the resulting signed-binary models trained on these datasets for any commercial use.