BMXNet: An Open-Source Binary Neural Network Implementation Based on MXNet

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ABSTRACT

Binary Neural Networks (BNNs) can drastically reduce memory size and accesses by applying bit-wise operations instead of standard arithmetic operations. Therefore it could significantly improve the efficiency and lower the energy consumption at runtime, which enables the application of state-of-the-art deep learning models on low power devices. BMXNet is an open-source BNN library based on MXNet, which supports both XNOR-Networks and Quantized Neural Networks. The developed BNN layers can be seamlessly applied with other standard library components and work in both GPU and CPU mode. BMXNet is maintained and developed by the multimedia research group at Hasso Plattner Institute and released under Apache license. Extensive experiments validate the efficiency and effectiveness of our implementation. The BMXNet library, several sample projects, and a collection of pre-trained binary deep models are available for download at https://github.com/hpi-xnor

CCS CONCEPTS

•**Software and its engineering** → **Software libraries and repositories;** •**Computer systems organization** → **Neural networks;** •**Computing methodologies** → **Computer vision;**

KEYWORDS

Open Source, Computer Vision, Binary Neural Networks, Machine Learning

1 INTRODUCTION

In recent years, deep learning technologies achieved excellent performance and many breakthroughs in both academia and industry. However the state-of-the-art deep models are computational expensive and consume large storage space. Deep learning is also strongly demanded by numerous applications from areas such as mobile platforms, wearable devices, autonomous robots and IoT devices. How to efficiently apply deep models on such low power

devices becomes a challenging research problem. The recently introduced Binary Neural Networks (BNNs) could be one of the possible solutions for this problem.

Several approaches [4, 7, 14, 15] introduce the usage of BNNs. These BNNs have the capability of decreasing the memory consumption and computational complexity of the neural network. This is achieved by on the one hand storing the weights, that are typically stored as 32 bit floating point values, as binary values, by binarizing the floating point values with the *sign function*, to be of either $\{0, 1\}$ or $\{-1, 1\}$, and storing several of them in a single 32 bit float or integer. Computational complexity, on the other hand, is reduced by using xnor and popcount for performing matrix multiplications used in convolutional and fully connected layers. Most of the publicly available implementations of BNN do not store the weights in their binarized form [4, 7, 14, 15], nor use xnor and popcount [7, 15] while performing the matrix multiplications in convolutional and fully connected layers.

The deep learning library Tensorflow [8] tries to decrease the memory consumption and computational complexity of deep neural networks, by quantizing the 32 bit floating point weights and inputs into 8 bit integers. Together with the minimum and maximum value of the weight/input matrix, 4× less memory usage and also decreased computational complexity is achieved, as all operations only need to be performed on 8 bit values rather than 32 bit values.

BMXNet stores the weights of convolutional and fully connected layers in their binarized format, which enables us to store 32/64 weights in a single 32/64 bit float/integer and use 32× less memory. During training and inference we binarize the input to each binary convolution and fully connected layer in the same way as the weights get binarized, and perform matrix multiplication using bit-wise operations (xnor and popcount). Our implementation is also prepared to use networks that store weights and use inputs with arbitrary bit widths as proposed by Zhou et al. [15].

The deep learning library MXNet [3] serves as a base for our code. MXNet is a high performance and modular deep learning library, that is written in C++. MXNet provides Bindings for other popular programming languages like Python, R, Scala and Go, and is used by a wide range of researchers and companies.

2 FRAMEWORK

BMXNet provides activation, convolution and fully connected layers that support quantization and binarization of input data and weights. These layers are designed as drop-in replacements for the corresponding MXNet variants and are called QActivation,

Haojin Yang, Martin Fritzsche, Christian Bartz, Christoph Meinel

`QConvolution` and `QFullyConnected`. They provide an additional parameter, `act_bit`, which controls the bit width the layers calculate with.

A Python example usage of our framework in comparison to MXNet is shown in Listing 1 and 2. We do not use binary layers for the first and last layer in the network, as we have confirmed the experiments of [14] showing that this greatly decreases accuracy. The standard block structure of a BNN in BMXNet is conducted as: *QActivation-QConv/QFC-BatchNorm-Pooling* as shown in Listing 2.

Listing 1: LeNet

```
def get_lenet():
 data = mx.symbol.Variable('data')
 # first conv layer
 conv1 = mx.sym.Convolution(...)
 tanh1 = mx.sym.Activation(...)
 pool1 = mx.sym.Pooling(...)
 bn1 = mx.sym.BatchNorm(...)
 # second conv layer
 conv2 = mx.sym.Convolution(...)
 bn2 = mx.sym.BatchNorm(...)
 tanh2 = mx.sym.Activation(...)
 pool2 = mx.sym.Pooling(...)
 # first fullc layer
 flatten = mx.sym.Flatten(...)
 fc1 = mx.symbol.FullyConnected(..)
 bn3 = mx.sym.BatchNorm(...)
 tanh3 = mx.sym.Activation(...)
 # second fullc
 fc2 = mx.sym.FullyConnected(...)
 # softmax loss
 lenet = mx.sym.SoftmaxOutput(...)
 return lenet
```

Listing 2: Binary LeNet

```
def get_binary_lenet():
 data = mx.symbol.Variable('data')
 # first conv layer
 conv1 = mx.sym.Convolution(...)
 tanh1 = mx.sym.Activation(...)
 pool1 = mx.sym.Pooling(...)
 bn1 = mx.sym.BatchNorm(...)
 # second conv layer
 ba1 = mx.sym.QActivation(...)
 conv2 = mx.sym.QConvolution(...)
 bn2 = mx.sym.BatchNorm(...)
 pool2 = mx.sym.Pooling(...)
 # first fullc layer
 flatten = mx.sym.Flatten(...)
 ba2 = mx.sym.QActivation(..)
 fc1 = mx.symbol.QFullyConnected(..)
 bn3 = mx.sym.BatchNorm(...)
 tanh3 = mx.sym.Activation(...)
 # second fullc
 fc2 = mx.sym.FullyConnected(...)
 # softmax loss
 lenet = mx.sym.SoftmaxOutput(...)
 return lenet
```

2.1 Quantization

The quantization on bit widths ranging from 2 to 31 bit is available for experiments with training and prediction, using low precision weights and inputs. The quantized data is still stored in the default 32 bit float values and the standard MXNet dot product operations are applied.

We quantize the weights following the linear quantization as shown by [15]. Equation 1 will quantize a real number *input* in the range $[0, 1]$ to a number in the same range representable with a bit width of $\boldsymbol{k}$ bit.

$$quantize(input, k) = \frac{round((2^k - 1) * input)}{2^k - 1} \quad (1)$$

2.2 Binarization

The extreme case of quantizing to 1 bit wide values is the binarization. Working with binarized weights and input data allows for highly performant matrix multiplications by utilizing the CPU instructions xnor and popcount.

2.2.1 Dot Product with xnor *and* popcount. Fully connected and convolutional layers heavily rely on dot products of matrices, which in turn require massive floating point operations. Most modern CPUs are optimized for these types of operations. But especially for real time applications on embedded or less powerful devices (cell phones, IoT devices) there are optimizations that improve performance, reduce memory and I/O footprint, and lower power consumption [2].

To calculate the dot product of two binary matrices $A \circ B$, no multiplication operation is required. The element-wise multiplication and summation of each row of A with each column of B can be approximated by first combining them with the xnor operation and then counting the number of bits set to 1 in the result which is the population count [14].

Listing 3: Baseline xnor GEMM Kernel

```
void xnor_gemm_baseline_no_omp(int M, int N, int K,
                               BINARY_WORD *A, int lda,
                               BINARY_WORD *B, int ldb,
                               float *C, int ldc){
  for (int m = 0; m < M; ++m) {
    for (int k = 0; k < K; k++) {
      BINARY_WORD A_PART = A[m*lda+k];
      for (int n = 0; n < N; ++n) {
        C[m*ldc+n] += __builtin_popcountl(~(A_PART ∧ B[k*ldb+n]));
      }
    }
  }
}
```

We can approximate the multiplication and addition of two times 64 matrix elements in just a few processor instructions on x64 CPUs and two times 32 elements on x86 and ARMv7 processors. This is enabled by hardware support for the xnor and popcount operations. They translate directly into a single assembly command. The population count instruction is available on x86 and x64 CPUs supporting SSE4.2, while on ARM architecture it is included in the NEON instruction set.

An unoptimized GEMM (General Matrix Multiplication) implementation utilizing these instructions is shown in Listing 3. The compiler intrinsic `__builtin_popcount` is supported by both gcc and clang compilers and translates into the machine instruction on supported hardware. `BINARY_WORD` is the packed data type storing 32 (x86 and ARMv7) or 64 (x64) matrix elements, each represented by a single bit.

We have implemented several optimized versions of the xnor GEMM kernel. We leverage processor cache hierarchies by blocking and packing the data, use unrolling techniques and OpenMP for parallelization.

2.2.2 Training. We carefully designed the binarized layers (utilizing xnor and population count operations) to exactly match the output of the built-in layers of MXNet (computing with BLAS dot product operations) when limiting those to the discrete values -1 and +1. This enables massively parallel training with GPU support by utilizing CuDNN on high performance clusters. The trained model can then be used on less powerful devices where the forward pass for prediction will calculate the dot product with the xnor and popcount operations instead of multiplication and addition.

The possible values after performing an xnor and popcount matrix multiplication $\underset{(m \times n)}{A} \circ \underset{(n \times k)}{B}$ are in the range $[0, +n]$ with the step size 1, whereas a normal dot product of matrices limited to discrete values -1 and +1 will be in the range $[-n, +n]$ with the step size 2. To enable GPU supported training we modify the training process. After calculation of the dot product we map the result back to the range $[0, +n]$ to match the xnor dot product, as in Equation 2.

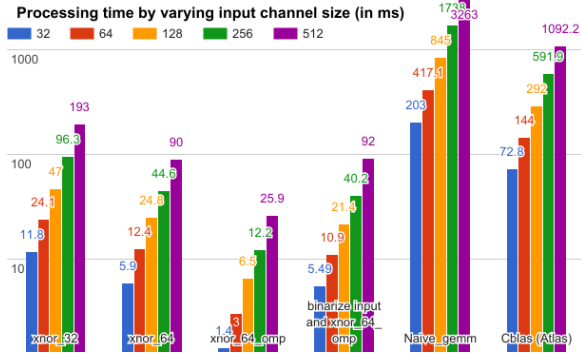$$output_{xnor\_dot} = \frac{output_{dot} + n}{2} \quad (2)$$

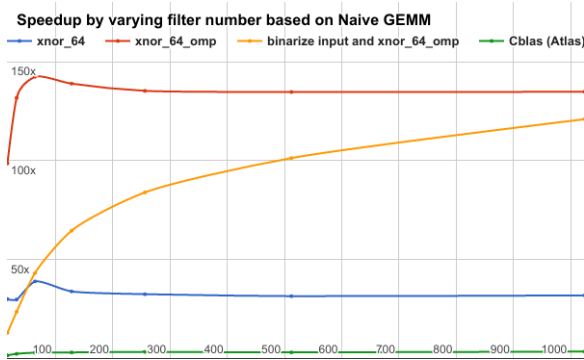**Figure 1: Processing time comparison of GEMM methods**

**Figure 2: Speedup comparison based on naive gemm method
by varying filter number of the convolution layer. The input
channel size is fixed to 256 while the kernel size and batch
size are set to 5×5 and 200 respectively.**

2.2.3   Model Converter. After training a network with BMXNet,
the weights are stored in 32 bit float variables. This is also the case
for networks trained with a bit width of 1 bit. We provide a model
converter[1] that reads in a binary trained model file and packs the
weights of `QConvolution` and `QFullyConnected` layers. After this
conversion only 1 bit of storage and runtime memory is used per
weight. A ResNet-18 network with full precision weights has a size
of 44.7*MB*. The conversion with our model converter achieves 29×
compression resulting in a file size of 1.5*MB* (cf. Table 1).

3   EVALUATION

In this section we report the evaluation results of both efficiency
analysis and classification accuracy over MNIST [13], CIFAR-10 [11]
and ImageNet [5] datasets using BMXNet.

3.1   Efficiency Analysis

All the experiments in this section have been performed on Ubuntu
16.04/64-bit platform with Intel $2.50GHz \times 4$ CPU with *popcnt* in-
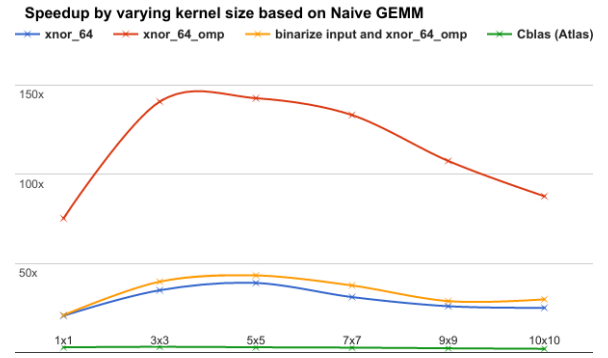struction (SSE4.2) and 8G RAM.

**Figure 3: Speedup comparison based on naive gemm method
by varying kernel size of the convolution layer. The input
channel size, batch size and filter number are set to 256, 200
and 64 respectively.**

In the current deep neural network implementations, most of
the fully connected and convolution layers are implemented us-
ing GEMM. According to the evaluation result from [9], over 90%
of the processing time of the Caffe-AlexNet [10] model is spent
on such layers. We thus conducted experiments to measure the
efficiency of different GEMM methods. The measurements were
performed within a convolution layer, where we fixed the parame-
ters as follows: filter number=64, kernel size=5×5, batch size=200,
and the matrix sizes M, N, K are 64, 12800, $kernel_w \times kernel_h \times$
$inputChannelSize$, respectively. Figure 1 shows the evaluation re-
sults. The colored columns denote the processing time in millisec-
onds across varying input channel size; xnor_32 and xnor_64 de-
note the xnor_gemm operator in 32 bit and 64 bit; xnor_64_omp
denotes the 64 bit xnor_gemm accelerated by using the OpenMP[2]
parallel programming library; `binarize input and xnor_64_omp`
further accumulated the processing time of input data binariza-
tion. From the results we can determine that xnor_64_omp achieved
about 50× and 125× acceleration in comparison to Cblas(Atlas[3])
and naive gemm kernel, respectively. By accumulating the bina-
rization time of input data we still achieved about 13× acceleration
compared with Cblas method.

Figures 2 and 3 illustrate the speedup achieved by varying filter
number and kernel size based on the naive gemm method.

3.2   Classification Accuracy

We further conduted experiments with our BNNs on the MNIST,
CIFAR-10 and ImageNet datasets. The experiments were performed
on a work station which has an Intel(R) Core(TM) i7-6900K CPU,
64 GB RAM and 4 TITAN X (Pascal) GPUs.

By following the same strategy as applied in [7, 14, 15] we al-
ways avoid binarization at the first convolution layer and the last
fully connected layer. Table 1 depicts the classification test ac-
curacy of our binary, as well as full precision models trained on
MNIST and CIFAR-10. The table shows that the size of binary
models is significantly reduced, while the accuracy is still competi-
tive. Table 2 demonstrates the validation accuracy of our binary,

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[1]https://github.com/hpi-xnor/BMXNet/tree/master/smd_hpi/tools/model-converter

[2]http://www.openmp.org/

[3]http://math-atlas.sourceforge.net/

	Architecture	Test Accuracy (Binary/Full Precision)	Model Size (Binary/Full Precision)
MNIST	Lenet	0.97/0.99	206kB/4.6MB
CIFAR-10	ResNet-18	0.86/0.90	1.5MB/44.7MB

Table 1: Classification test accuracy of binary and full precision models trained on MNIST and CIFAR-10 dataset. No pre-training or data augmentation was used.

Full Precision Stage	Val-acc-top-1	Val-acc-top-5	Model Size
none	0.42	0.66	3.6MB
1st	0.48	0.73	4.1MB
2nd	0.44	0.69	5.6MB
3rd	0.49	0.73	11.3MB
4th	0.47	0.71	36MB
1st, 2nd	0.49	0.73	6.2MB
All	0.61	0.84	47MB

Table 2: Classification test accuracy of binary, partially binarized and full precision models trained on ImageNet. ResNet-18 architecture was used in the experiment.

partially-binarized and full precision models trained on ImageNet. The ResNet implementation in MXNet consists of 4 ResUnit stages, we thus also report the results of a partially-binarized model with specific full precision stages. The partially-binarized model with the first full precision stage shows a great accuracy improvement with very minor model size increase, compared to the fully binarized model.

4 EXAMPLE APPLICATIONS

4.1 Python Scripts

The BMXNet repository [1] contains python scripts that can train and validate binarized neural networks. The script `smd_hpi/examples/binary_mnist/mnist_cnn.py` will train a binary LeNet [12] with the MNIST [13] data set. To train a network with the CIFAR-10 [11] or ImageNet [5] data set there is a python script based on the ResNet-18 [6] architecture. Find it at `smd_hpi/examples/binary-imagenet1k/train_cifar10/train_[dataset].py`. For further information and example invocation see the corresponding `README.md`

4.2 Mobile Applications

4.2.1 Image Classification. The Android application `android -image-classification` and iOS application `ios-image-classification` can classify the live camera feed based on a binarized ResNet-18 model trained on the ImageNet dataset.

4.2.2 Handwritten Digit Detection. The iOS application `ios-mnist` can classify handwritten numbers based on a binarized LeNet model trained on the MNIST dataset.

5 CONCLUSION

We introduced BMXNet, an open-source binary neural network implementation in C/C++ based on MXNet. The evaluation results show up to 29× model size saving and much more efficient xnor

GEMM computation. In order to demonstrate the applicability we developed sample applications for image classification on Android as well as iOS using a binarized ResNet-18 model. Source code, documentation, pre-trained models and sample projects are published on GitHub [1].

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