A Convolutional Neural Network Framework support on CPU and GPU

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***Abstract*—Today, artificial intelligence(AI) has become an irresistible historical trend. Many AI-assisted learning frameworks have also emerged, such as Tensorflow, Keras, Pytorch, and Caffe. These tools greatly simplify the cost of AI learning and research. However, while they bring convenience, people's understanding of some underlying knowledge of artificial intelligence is very insufficient. Therefore, this paper will build a convolutional neural network framework support on CPU and GPU without the aid of any machine learning framework. And I use the framework to build convolutional neural network to solve MNIST and CIFAR-10. After about mintues of training on CPU, 98% and 50% accuracy were achieved on MNIST and CIFAR test set respectively. After about one minute of training on GPU, 98% and 70% accuracy were achieved on MNIST and CIFAR test set respectively.**

I. Introduction

In recent years, the development of artificial intelligence in the field of science and technology is also obvious to all. From the controversy caused by the development of driverless cars to AlphaGo's victory [3] over the top Go player, artificial intelligence has attracted enough attention. Machine learning, a branch of artificial intelligence, has attracted wide attention, and deep learning, a branch of machine learning, has become a research hotspot in recent years.

Artificial intelligence has had its decline. But after a brief dip, there was a boom. So what exactly does AI rely on to turn things around? That's rapid iterations of hardware and software. Of course, the most important thing is its excellent problem solving ability. But imagine that without the computing power of current hardware and the iterative updates in software, there would be no AI today.

The software accelerator of AI is numerous learning frameworks, like TensorFlow [1], Pytorch [10], Keras [6], Caffe [5] and so on. They can help us build neural networks like building blocks, and can realize forward propagation, automatic differentiation and back propagation. In addition, they also do a lot of automatic processing of the details of neural network construction and training, such as what activation function should be applied, how to initialize the parameters, how to dynamically set the learning rate, what update algorithm is applied to the gradient of back propagation and so on. Although this brings great convenience to the study and research of neural network, it also makes people lack of understanding of the underlying knowledge of neural network.

This paper makes the following contributions:

- I (use C++ language) build and train a convolutional neural network[1] to recognize handwritten digits without calling any machine learning library functions. About 98% accuracy was achieved in the test set (10,000 test images in MNIST) after a training round of about 7 minutes (60,000 training images in MNIST).
- I (use C++ language) build a convolutional neural network framework[2] support on CPU. And I use the framework to solve MNIST and CIFAR-10. 98% and 50% accuracy were achieved on MNIST and CIFAR test set respectively.
- I (use C++ language) build a convolution neural network framework[3] support on GPU. I implement the forward and backward process of each layer by calling CUDNN or launch kernels which I wrote. And I use the framwork to solve MNIST and CIFAR-10. 98% and 70% accuracy were achieved on MNIST and CIFAR test set respecively. I believe with fine-tuning the result will be better.
- The variation rule of data dimension in forward propagation is explained in detail.The method of calculating and updating the gradient of each layer in back propagation is introduced in detail. Some other details of neural network training, such as parameter initialization and learning rate selection, are also introduced.

The rest of the paper is organized as follows: Section II introduces the background and history about AI and its accelerators. Section III elaborates the process of building and training Convolutional Neural Network. Section IV introduces the convolutional network framework support on CPU. Section V gives a introduction about framework support on GPU. Section VI compares the convolutional neural network constructed in this paper with Pytorch.

II. Background

A. History of artificial intelligence

Artificial intelligence has been formally proposed since the 1950s and 1960s. In 1950, a senior student named Marvin Minsky and his classmate Dunn Edmond built the world's first neural network computer, and this computer also showed the beginning of computing. Coincidentally, in 1950, Alan Turing also came up with a remarkable idea called the Turing Test [2],

[1]This work was publicly at https://github.com/gty111/ConvNN/tree/main
[2]This work was publicly at https://github.com/gty111/ConvNN/tree/cpu
[3]This work was publicly at https://github.com/gty111/ConvNN/tree/cudnn

Fig. 1. GTX580

in which he assumed that a computer would be an intelligent machine if it could converse with a human being without being identified as a machine. During the course of the year Alan had boldly predicted the feasibility of intelligent machines. In 1956, at a conference, the term artificial intelligence was formally introduced by computer expert John McCarthy. Later, this behavior was considered to be the official birth of artificial intelligence.

During this period of ten years, computers were widely used in mathematics and natural languages, mainly solving algebra and geometry problems. This situation has made many scholars see the machine to artificial intelligence development confidence. Even more, several scholars at the time believed that within twenty years machines would be able to do everything humans could. In the 1970s, artificial intelligence entered its first trough, because researchers' estimation of the difficulty of the project was wrong in the research on artificial intelligence, which not only led to the failure of the cooperation plan, but also cast a shadow on the development of artificial intelligence. At the same time, the public opinion is also slowly pressure, which is the loss of most research funds. At that time, artificial intelligence faced three technical dilemmas: First, the performance of the computer could not meet the requirements, which would cause many early programs could not be used in the field of artificial intelligence; Second, the problem is relatively complex, the early artificial intelligence is aimed at specific problems, because the specific problems are usually few and the complexity is very low, but as long as the difficulty of the problem increases, the program will be overwhelmed; Third, the amount of data was not enough. In those days, there were no large enough databases to support deep learning of programs, which would make it impossible for machines to read enough data to be intelligent.

In 2006, neural network expert Hinton proposed neural network deep learning algorithm [9], which greatly improved the capability of neural network and challenged the support vector machine. At the same time, it opened the wave of deep learning in academia and industry.

B. The rise of the GPU

Nvidia was founded in 1993. At first, GPUs were mainly used for graphics display adapters. However, with the development of artificial intelligence, Nvidia released the first computational graphics card, the GTX580 which AlexNet [8] is trained on. AlexNet is a great success in artifical intelligence. This success came from the efficient use of GPUs, ReLUs, a new regularization technique called dropout, and techniques to generate more training examples by deforming the existing ones. This success has brought about a revolution in computer vision; ConvNets are now the dominant approach for almost all recognition and detection tasks and approach human performance on some tasks.

The emergence of computable GPUs have led to a boom in machine learning. The booming development of machine learning feeds back into the GPU field. So machine learning and GPU are mutually reinforcing. And Nvidia's great strategic vision is doomed to its success. Today GPU is not only brilliant in the field of artificial intelligence, but also indispensable for people's entertainment life. It's even more important than CPU, and Nvidia's market cap proves it.

C. The current development of artificial intelligence

I'm sure you've all heard of some of the current AI hits, such as NovelAI and chatGPT.

1) NovelAI: The NovelAI uses Diffusion Anime image generation. Stable Diffusion works by generating an image based on your text prompt, starting with only noise, and gradually enhancing the image until there is no noise left at all. The AI connects your text to images, generating a new composition every single time you prompt it.

2) chatGPT: ChatGPT is a model which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to InstructGPT, which is trained to follow an instruction in a prompt and provide a detailed response. They trained this model using Reinforcement Learning from Human Feedback (RLHF), using the same methods as InstructGPT, but with slight differences in the data collection setup. They trained an initial model using supervised fine-tuning: human AI trainers provided conversations in which they played both sides—the user and an AI assistant. They gave the trainers access to model-written suggestions to help them compose their responses. ChatGPT is fine-tuned from a model in the GPT-3.5 series, which finished training in early 2022.

D. CUDNN

CUDNN stands for the NVIDIA CUDA® Deep Neural Network library. It is a GPU-accelerated library of primitives for deep neural networks. CUDNN provides highly tuned implementations for standard routines such as forward and backward convolution, pooling, normalization, and activation layers. The software stack with cuDNN is shown at Fig.2. As Fig.3 shows, many AI framework relys on cuDNN to accelerate on GPU. In this paper, I also use CUDNN to accelerate training on GPU.

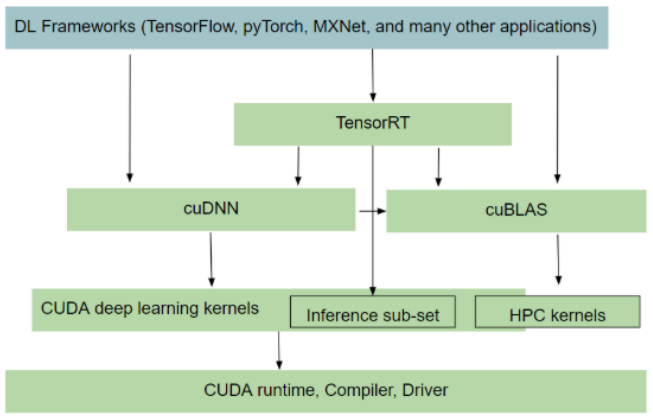

DL Frameworks (TensorFlow, pyTorch, MXNet, and many other applications)
TensorRT
cuDNN
cuBLAS
CUDA deep learning kernels
Inference sub-set
HPC kernels
CUDA runtime, Compiler, Driver

Fig. 2. Software stack with cuDNN

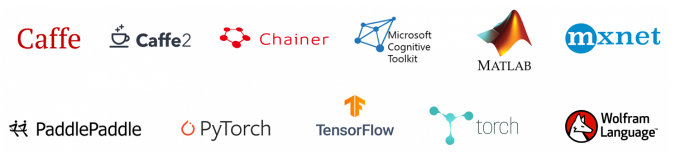


Fig. 3. Framework relied on cuDNN

III. The Detail of Building and Training Convolutional Neural Network

I use MNIST (Fig.4) data set to be fed to the network. The overview of network's structure is shown in Fig.5. The meaning of symbol is shown in Tab.IV.

A. MNIST

MNIST data set comes from the American National Institute of Standards and Technology (NIST), which is a smaller version of NIST. The training set is composed of handwritten numbers from 250 different people. Fifty percent were high school students, 50 percent were from the Census Bureau staff, and the test set was a similar percentage of handwritten numerical data.

All the integers in the files are stored in the MSB first (high endian) format used by most non-Intel processors. Users of Intel processors and other low-endian machines must flip the bytes of the header.There are 4 files in MNIST which shown in Tab.I. Label file format is shown in Tab.II. The labels values are 0 to 9. Image file format is shown in Tab.III. Pixels are organized row-wise. Pixel values are 0 to 255. 0 means background (white), 255 means foreground (black).

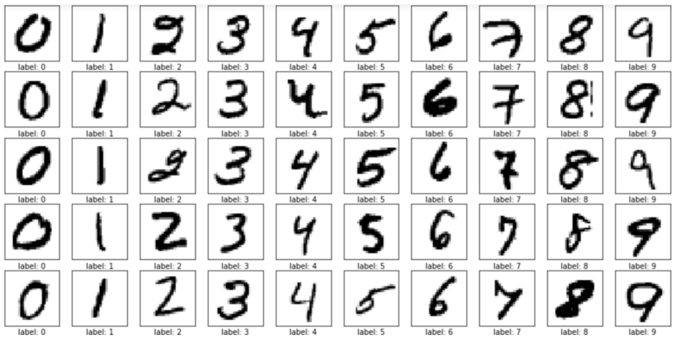


Fig. 4. Part of MNIST

TABLE I
MNIST Files

File name	description
train-images-idx3-ubyte	training set images
train-labels-idx1-ubyte	training set labels
t10k-images-idx3-ubyte	test set images
t10k-labels-idx1-ubyte	test set labels

TABLE II
MNIST TRAINING SET LABEL FILE (train-labels-idx1-ubyte)

offset	type	value	description
0000	32 bit integer	0x800000801(2049)	magic number (MSB first)
0004	32 bit integer	60000	number of items
0008	unsigned byte	??	label
0009	unsigned byte	??	label
......			
xxxx	unsigned byte	??	label

TABLE III
MNIST TRAINING SET IMAGE FILE (train-images-idx3-ubyte)

offset	type	value	description
0000	32 bit integer	0x800000803(2051)	magic number (MSB first)
0004	32 bit integer	60000	number of images
0008	32 bit integer	28	number of rows
0012	32 bit integer	28	number of columns
0016	unsigned byte	??	pixel
0017	unsigned byte	??	pixel
......			
xxxx	unsigned byte	??	pixel

TABLE IV
Symbol Table

NAME	description
fcw	weight of full connection layer
fcb	bias of full connection layer
convw	weight of convolution layer
convb	bias of convolution layer

B. CIFAR-10

CIFAR-10 [7] is a color image data set that is closer to universal objects. CIFAR-10 is a small data set collated by Hinton students Alex Krizhevsky and Ilya Sutskever for the identification of pervasive objects. A total of 10 categories of RGB color pictures are included: airplane, automobile, bird, cat, deer, dog, frog, horse, ship and truck. The size of each picture is 3x32×32, and there are 6,000 images for each category. There are a total of 50,000 training pictures and 10,000 test pictures in the data set. Compared with the grayscale image of MNIST, CIFAR-10 is a 3-channel color RGB image, and it is a real object in the real world. It is not only noisy, but also has different proportions and features of objects.

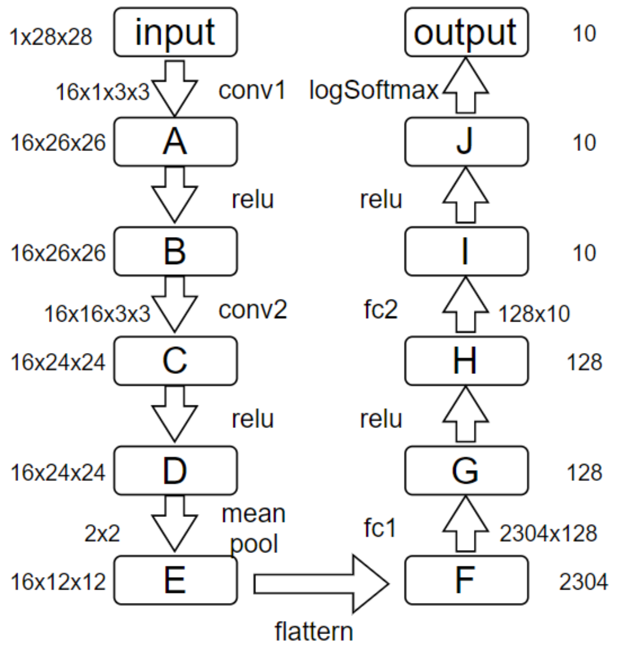


Fig. 5. Network Structure on MNIST

C. Forward Propagation

1) $INPUT$: At first, the input of image will be normalized which means

$$INPUT_{(i,j,k)} = (INPUT_{(i,j,k)} - mean)/std \tag{1}$$

where $mean$ equals the mean of $INPUT$ and std equals the standard deviation of $INPUT$.

2) $INPUT \xrightarrow{conv1} A$: There are some default rules in convolution layer(with no padding).

$$\begin{aligned} IN.shape_{(0)} &= CONVW.shape_{(1)} \\ OUT.shape_{(0)} &= CONVW.shape_{(0)} \\ OUT.shape_{(1)} &= IN.shape_{(1)} - CONVW.shape_{(2)} + 1 \\ OUT.shape_{(2)} &= IN.shape_{(2)} - CONVW.shape_{(2)} + 1 \\ CONVB.shape_{(0)} &= CONVW.shape_{(0)} \end{aligned} \tag{2}$$

where $shape$ means the dimension of that tensor and index starts from 0.(Eg. in this paper IN.shape(0)=1 IN.shape(1)=28 IN.shape(2)=28)

$$A_{(i)} = convb1_{(i)} + \sum_j INPUT_{(j)} \otimes convw1_{(i,j)} \tag{3}$$

where $\otimes$ means operation of convolution. Mind that $A_{(i)}$ is a tensor whose shape is (26,26), $INPUT_{(j)}$ is a tensor whose shape is (28,28) and $convw1_{(i,j)}$ is a tensor whose shape is (3,3).

3) $A \xrightarrow{relu} B$:

$$B = RELU(A) \tag{4}$$

where RELU is a common function shown in Fig.6.

4) $B \xrightarrow{conv2} C$:

$$C_{(i)} = convb2_{(i)} + \sum_j B_{(j)} \otimes convw2_{(i,j)} \tag{5}$$

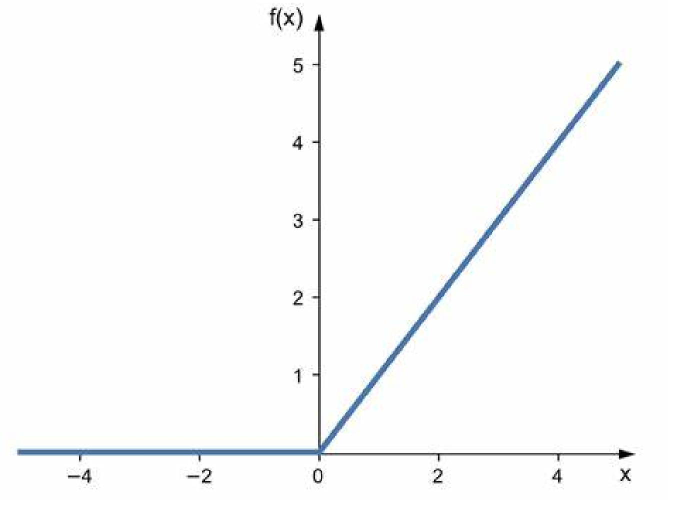


Fig. 6. RELU activation function

5) $C \xrightarrow{relu} D$:

$$D = RELU(C) \tag{6}$$

6) $D \xrightarrow{meanpool} E$:

$$E_{(i,j,k)} = (\sum_{m=j*2}^{j*2+1} \sum_{n=k*2}^{k*2+1} D_{(i,m,n)})/4 \tag{7}$$

7) $E \xrightarrow{flattern} F$:

$$F_{(i*12*12+j*12+k)} = E_{(i,j,k)} \tag{8}$$

8) $F \xrightarrow{fc1} G$:

$$G_{(i)} = fcb1_{(i)} + \sum_j F_{(j)} * fcw1_{(j,i)} \tag{9}$$

There are some default rules in full connection layer.

$$\begin{aligned} fcw.shape_{(1)} &= fcb.shape_{(0)} \\ IN.shape_{(0)} &= fcw.shape_{(0)} \\ OUT.shape_{(0)} &= fcw.shape_{(1)} \end{aligned} \tag{10}$$

9) $G \xrightarrow{relu} H$:

$$H = RELU(G) \tag{11}$$

10) $H \xrightarrow{fc2} I$:

$$I_{(i)} = fcb2_{(i)} + \sum_j H_{(j)} * fcw2_{(j,i)} \tag{12}$$

11) $I \xrightarrow{relu} J$:

$$J = RELU(I) \tag{13}$$

12) $J \xrightarrow{logSoftmax} OUTPUT$:

$$OUTPUT_{(i)} = log_e(\frac{e^{J_{(i)}}}{\sum_k e^{J_{(k)}}}) \tag{14}$$

where e means natural logarithm.

D. Backward propagation

1) ΔJ:

$$\Delta J_{(i)} = \begin{cases} 1 - \frac{e^{J_{(i)}}}{\sum_k e^{J_{(k)}}} & i = label \\ -\frac{e^{J_{(i)}}}{\sum_k e^{J_{(k)}}} & i \neq label \end{cases} \quad (15)$$

2) ΔI:

$$\Delta I_{(i)} = \begin{cases} \Delta J_{(i)} & I_{(i)} > 0 \\ 0 & I_{(i)} \leq 0 \end{cases} \quad (16)$$

3) $\Delta fcw2$:

$$\Delta fcw2_{(i,j)} = H_{(i)} * \Delta I_{(j)} \quad (17)$$

4) $\Delta fcb2$:

$$\Delta fcb2_{(i)} = \Delta I_{(i)} \quad (18)$$

5) ΔH:

$$\Delta H_i = \sum_j \Delta I_{(j)} * fcw2_{(i,j)} \quad (19)$$

6) ΔG:

$$\Delta G_{(i)} = \begin{cases} \Delta H_{(i)} & G_{(i)} > 0 \\ 0 & G_{(i)} \leq 0 \end{cases} \quad (20)$$

7) $\Delta fcw1$:

$$\Delta fcw1_{(i,j)} = F_{(i)} * \Delta G_{(j)} \quad (21)$$

8) $\Delta fcb1$:

$$\Delta fcb1_{(i)} = \Delta G_{(i)} \quad (22)$$

9) ΔF:

$$\Delta F_{(i)} = \sum_j \Delta G_{(j)} * fcw1_{(i,j)} \quad (23)$$

10) ΔE:

$$\Delta E_{(i,j,k)} = \Delta F_{(i*12*12+j*12+k)} \quad (24)$$

11) ΔD:

$$\Delta D_{(i,j,k)} = \Delta E_{(i,j/2,k/2)}/4 \quad (25)$$

12) ΔC:

$$\Delta C_{(i,j,k)} = \begin{cases} \Delta D_{(i,j,k)} & C_{(i,j,k)} > 0 \\ 0 & C_{(i,j,k)} \leq 0 \end{cases} \quad (26)$$

13) $\Delta convw2$:

$$\Delta convw2_{(i,j)} = B_{(j)} \otimes \Delta C_{(i)} \quad (27)$$

14) $\Delta convb2$:

$$\Delta convb2_{(i)} = \sum_j \sum_k \Delta C_{(i,j,k)} \quad (28)$$

15) ΔB:

$$\Delta B_{(i)} = \sum_j PAD(\Delta C_{(j)}) \otimes ROT(convw2_{(j,i)}) \quad (29)$$

where PAD operation is shown in Fig.8 and ROT operation is shown in Fig.7.

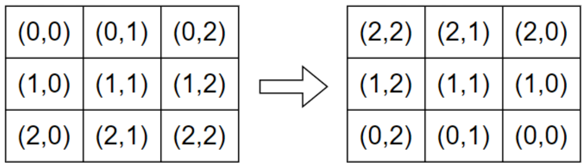


Fig. 7. ROT operation

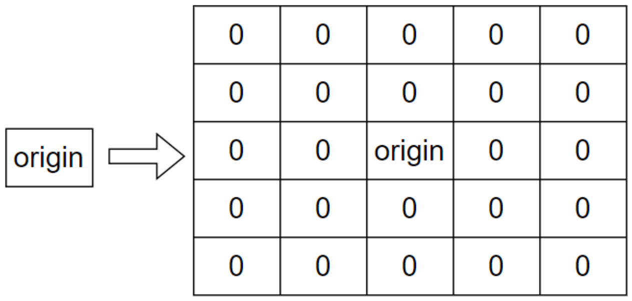


Fig. 8. PAD operation

16) ΔA:

$$\Delta A_{(i,j,k)} = \begin{cases} \Delta B_{(i,j,k)} & A_{(i,j,k)} > 0 \\ 0 & A_{(i,j,k)} \leq 0 \end{cases} \quad (30)$$

17) $\Delta convw1$:

$$\Delta convw1_{(i,j)} = INPUT_{(j)} \otimes \Delta A_{(i)} \quad (31)$$

18) $\Delta convb1$:

$$\Delta convb1_{(i)} = \sum_j \sum_k A_{(i,j,k)} \quad (32)$$

E. Other details about ConvNN

The loss of built ConvNN is defined as follows

$$Loss = OUTPUT_{(label)} \quad (33)$$

Due to the $LogSoftmax$ operation, OUTPUT will all be negative. And the closer the loss is to zero, the better result is. The model's parameters are updated in a way as follows

$$P_{i+1} = P_i + \Delta P_i * lr \quad (34)$$

where lr means learning rate of the model. In this paper, learning rate is set to $5e^{-3}$. And the model is trained with fixed learning rate. The model parameters were initialized with a normal distribution with a mean of 0 and a standard deviation of 0.1.

F. Evaluation

From Fig.9 and Fig.10, we can see the convergence of the model is fast at the beginning, and then gradually becomes slower. So dynamically updating learning rate is future work. After 10000 images' training, the model can achieve 96%

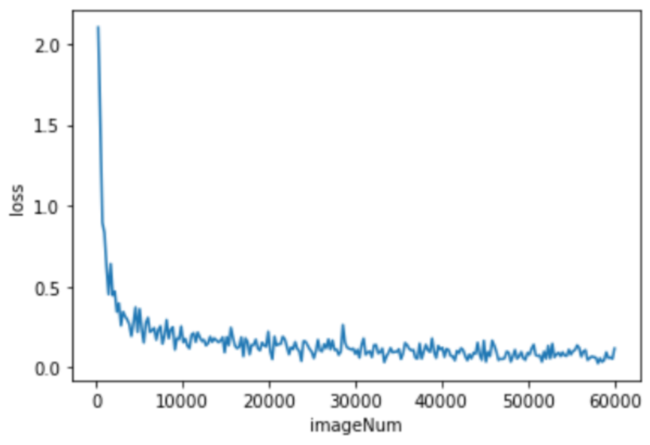


Fig. 9. Loss while training on MNIST

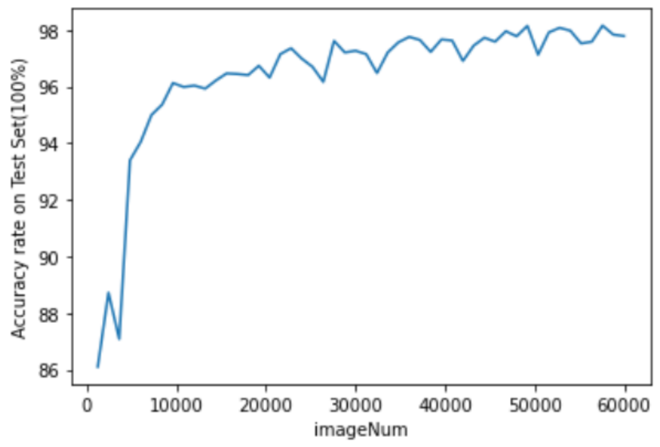


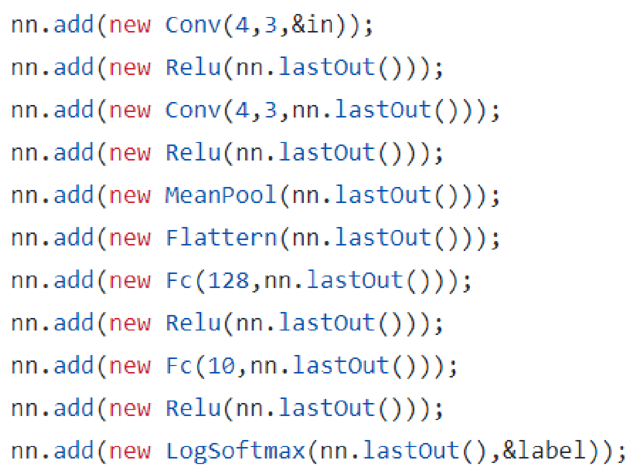
Fig. 10. Accuracy rate on test set while training on MNIST

accuracy. This shows that the model does not need a lot of training data to achieve good results.

IV. Framework support on CPU

Why I call that a framework? Because you can set up a convolution network with simple codes through framework like Fig.11. And you can train the network by just calling nn.forward() and nn.backward(). I abstract each Layer in the network into a subclass of Layer. They implement their own forward and backward methods, respectively. In this case, the NN class only needs to call the forward and backward methods at each layer. And you don't need to give full detail information about each layer but the basic information. Because it will automatically calculates the dimensions of this layer based on the input from the previous layer and given information. So you can build convolution network just like using other AI framework.

To validate the correctness and ease of use, I use it to solve MNIST and achieve 98% accuracy just like before. And I also use it to train CIFAR-10 which is far harder to train than MNIST. I try to build a complicated network like VGG-16 to solve CIFAR. It turns out that it's very slow and I give up and



```
nn.add(new Conv(4,3,&in));
nn.add(new Relu(nn.lastOut()));
nn.add(new Conv(4,3,nn.lastOut()));
nn.add(new Relu(nn.lastOut()));
nn.add(new MeanPool(nn.lastOut()));
nn.add(new Flattern(nn.lastOut()));
nn.add(new Fc(128,nn.lastOut()));
nn.add(new Relu(nn.lastOut()));
nn.add(new Fc(10,nn.lastOut()));
nn.add(new Relu(nn.lastOut()));
nn.add(new LogSoftmax(nn.lastOut(),&label));
```

Fig. 11. The code used to build NN on cifar-10

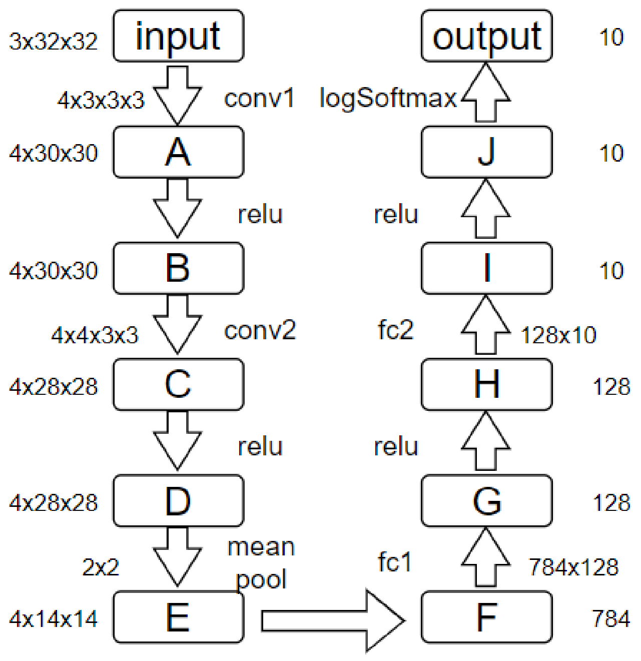


Fig. 12. The model used to train CIFAR-10

train a simple network. The network structure used to train CIFAR-10 is shown at Fig.12 . The result is shown at Fig.14 and Fig.13. Although the result is not very good, but it verify correctness and ease of the use to build CNN.

V. Framework support on GPU

To solve the problem of slow training time, I implement the GPU version of framework by calling CUDNN or kernels which I wrote. And the training time drops greatly. But after that I met many challenges about solving CIFAR-10.

A. *Gradient explosion*

After I build network like VGG-16, no matter how you adjust the learning rate, the training will soon be saturated.

TABLE V
COMPARISON WITH PYTORCH

metric	this paper(CPU)	this paper(GPU)	Pytorch(CPU)	Pytorch(GPU)
training time	about 7min	about 14s	about 1min	about 18s
accuracy rate on test set	about 98%	about 98%	about 98%	about 98%

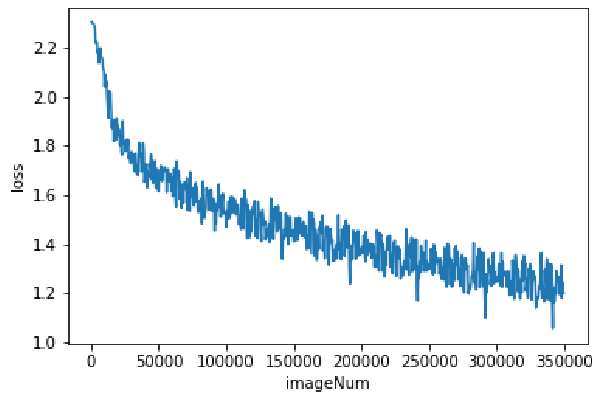


Fig. 13. Loss while training on CIFAR-10 on CPU

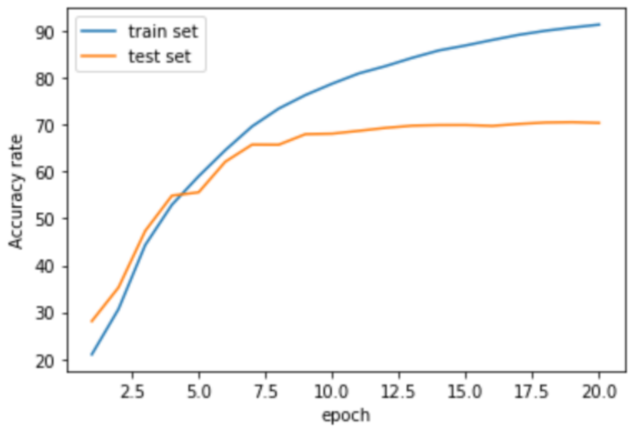


Fig. 15. Accuracy on train and test set training on GPU

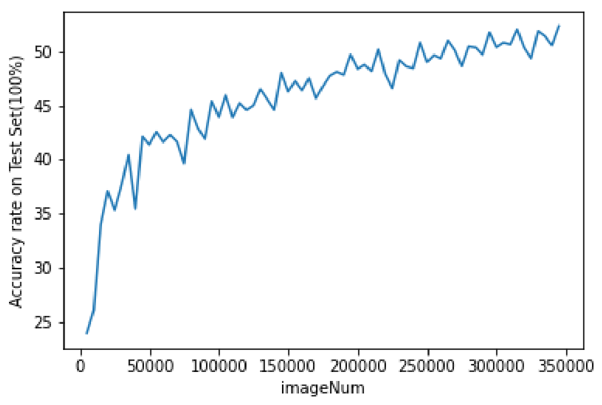
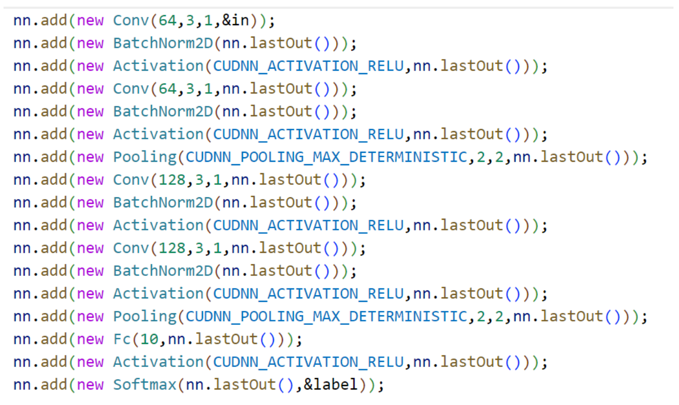


Fig. 14. Accuracy rate on test set while training on CIFAR-10 on CPU



```
nn.add(new Conv(64,3,1,&in));
nn.add(new BatchNorm2D(nn.lastOut()));
nn.add(new Activation(CUDNN_ACTIVATION_RELU,nn.lastOut()));
nn.add(new Conv(64,3,1,nn.lastOut()));
nn.add(new BatchNorm2D(nn.lastOut()));
nn.add(new Activation(CUDNN_ACTIVATION_RELU,nn.lastOut()));
nn.add(new Pooling(CUDNN_POOLING_MAX_DETERMINISTIC,2,2,nn.lastOut()));
nn.add(new Conv(128,3,1,nn.lastOut()));
nn.add(new BatchNorm2D(nn.lastOut()));
nn.add(new Activation(CUDNN_ACTIVATION_RELU,nn.lastOut()));
nn.add(new Conv(128,3,1,nn.lastOut()));
nn.add(new BatchNorm2D(nn.lastOut()));
nn.add(new Activation(CUDNN_ACTIVATION_RELU,nn.lastOut()));
nn.add(new Pooling(CUDNN_POOLING_MAX_DETERMINISTIC,2,2,nn.lastOut()));
nn.add(new Fc(10,nn.lastOut()));
nn.add(new Activation(CUDNN_ACTIVATION_RELU,nn.lastOut()));
nn.add(new Softmax(nn.lastOut(),&label));
```

Fig. 16. The network to solve CIFAR-10 training on GPU

Then I found that the gradient is very large. To solve gradient explosion, I use batch normalization [4] which is a great solution. The operation of batch normalization is as follows.

$$y = \frac{x - E[x]}{\sqrt{Var[x] + \epsilon}} * \gamma + \beta$$

where y is the output, x is the input, E[x] is the expectation of x, Var[x] is the variance of x, γ and β arelearnable parameters.

B. Overfitting

After adding batch normalization to the network, I found that it shows great overfitting when using VGG-16. I tried to add momentum when updating gradient and augmenting the input image by randomly cropping or horizon flipping. But it turns out that it didn't work well either. In the end, I simplify the network structure and achieve 70% accuracy which is shown at Fig.15. I believe and know this is not the best result so it is left to the future work.

VI. RELATED WORK

Pytorch gives an example to build convolution neural network on MNIST. The structure of that network is a little different from this paper which is the number of kernel of convolution. Tab.V gives a comparison with Pytorch. And the biggest difference is in training time. For gpu version, they both achive similar accuracy at similar time. But for CPU, Pytorch uses less time. I guess Pytorch use openmp to accelerate the training on CPU. This is left to the future work.

VII. Conclusion

This paper introduces and achieves the construction of a convolutional neural network, the process of forward propagation and back propagation in detail. This paper also explore the possibility of building convolutional network framework support on CPU and GPU. The GPU version can greatly reduce the training time. I also use the framework to solve MNIST and CIFAR-10 and achieve 98% and 70% accuracy respectively.

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