LightNet

[A Versatile, Standalone Matlab-based Environment for Deep Learning]

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ABSTRACT

LightNet is a **lightweight**, **versatile** and **purely Matlab-based** deep learning framework. The aim of the design is to provide an easy-to-understand, easy-to-use and efficient computational platform for deep learning research. The implemented framework supports major deep learning architectures such as Multilayer Perceptron Networks (MLP), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The framework also supports both CPU and GPU for computation and the switch between them is straightforward. Different applications in computer vision, natural language processing and robotics are demonstrated as experiments.

Categories and Subject Descriptors

D.0 [**Software**]: General; I.2.10 [**Artificial Intelligence**]: Vision and Scene Understanding

General Terms

Algorithm, Deep Leaning, Software prototype

Keywords

Computer vision; image understanding; machine learning; deep learning; convolutional neural networks; multilayer perceptrons

1. INTRODUCTION

Deep neural networks [8] have made significant breakthroughs in advancing machine intelligence. Most current implementations of the neural network models put the primary emphasis on efficiency. The implementation of each framework usually involves multiple programming languages [5, 13, 2], and it requires extensive efforts to thoroughly understand and modify the underlying models. A straightforward and self-explanatory deep learning framework is highly anticipated to accelerate the understanding and application of the deep neural network models.

We present LightNet, a **lightweight**, **versatile** and **purely Matlab-based** implementation of modern deep neural network models. Succinct and efficient Matlab programming techniques are used to implement all the computational modules. With a basic knowledge of Matlab programming, researchers can easily understand and modify any part of the framework to develop new network architectures and to adapt to new applications. Popular types of neural networks such as multilayer perceptrons, convolutional neural networks, and recurrent neural networks are fully implemented in LightNet, together with several variations of stochastic gradient descent (SDG) based optimization algorithms.

Aside from the simplicity and versatility of implementation, the highlights of LightNet include: 1. LightNet contains the most modern network architectures. 2. Applications in computer vision, natural language processing and reinforcement learning are demonstrated. 3. LightNet provides a comprehensive collection of optimization algorithms. 4. LightNet supports straightforward switching between CPU and GPU for the computation. 5. Efficient fast Fourier transform is used to calculate convolutions, leading to the support of large convolution kernels. 6. LightNet automates hyper-parameter tuning with a novel Selective-SGD algorithm.

2. USING THE PACKAGE

A simple template is provided to start the training process (Fig. 1). The user is required to fill in some critical training parameters, such as the training epochs and the training method. A Selective-SGD algorithm is provided to facilitate the selection of an optimal learning rate. The learning rate is selected automatically and can be adjusted in the middle of the training if the user enables this option. The framework support both GPU and CPU for the computation, through the *opts.use_gpu* option. Two additional functions are provided to prepare the training data and initialize the network structure.

3. BUILDING BLOCKS

The primary computational modules include a feed forward process and a backward/back propagation process. The feed forward process evaluates the model, and the back propagation reports the network gradients. Stochastic gradient descent based algorithms are used to optimize the model parameters.

3.1 Core Computational Modules

```
n_epoch=20; %training epochs
dataset_name='mnist'; %dataset name
network_name='cnn'; %network name
use_gpu=1; %use gpu or not

%function handle to prepare your data
PrepareDataFunc=@PrepareData_MNIST_CNN;
%function handle to initialize the network
NetInit=@net_init_cnn_mnist;

%automatically select learning rates
use_selective_sgd=1;
%select a new learning rate every n epochs
ssgd_search_freq=10;
learning_method=@sgd; %training method: @sgd

%sgd parameter
%(unnecessary if selective-sgd is used)
%sgd_lr=5e-2;

Main_Template(); %call training template
```

Figure 1: A basic example to train a CNN on the MNIST dataset with LightNet.

We explain the implementation details of the primary computational modules in this section. The notations below are chosen for simplicity. Readers can easily extend the derivations to the mini-batch setting.

3.1.1 Linear Perceptron Layer

A linear perceptron layer can be expressed as:

$$y = Wx + b, \tag{1}$$

Here, x denotes the input data of size $input\_dim \times 1$, W denotes the weight matrix of size $output\_dim \times input\_dim$, b is a bias vector of size $output\_dim \times 1$, and y denotes the linear layer output of size $output\_dim \times 1$.

The mapping from the input of the linear perceptron to the final network output can be expressed as:

$$z = f(y) = f(Wx + b), \tag{2}$$

where f is a non-linear function that represents the network's computation in the deeper layers and z is the network output, which is usually a loss value.

The backward process calculates the derivative $\frac{\partial z}{\partial x}$, which is the derivative passing to the shallower layers, and $\frac{\partial z}{\partial W}$, $\frac{\partial z}{\partial b}$, which are the gradients that guide the gradient descent process.

$$\frac{\partial z}{\partial x} = \frac{\partial z}{\partial y} \times \frac{\partial y}{\partial x} = f'(y)^T \times W \tag{3}$$

$$\frac{\partial z}{\partial W} = \frac{\partial z}{\partial y} \times \frac{\partial y}{\partial W} = f'(y) \times x^T \tag{4}$$

$$\frac{\partial z}{\partial b} = \frac{\partial z}{\partial y} \times \frac{\partial y}{\partial b} = f'(y) \tag{5}$$

The framework adopts extensively optimized Matlab matrix operations.

3.1.2 Convolutional Layer

A convolutional layer maps N_{map_in} input feature maps to N_{map_out} output feature maps with a multidimensional filter bank k_{io}. The input feature maps are convolved with the corresponding filter bank k_{*o} with a bias value b_o added to the output, to generate the o-th output map:

$$y_o = \sum_{1 \le i \le N_{map\_in}} k_{io} * x_i + b_o \tag{6}$$

To allow using large convolution kernels, the fast Fourier transforms (FFT) are utilized to calculate convolutions (and correlations). According to the convolution theorem [10], convolution in the spatial domain is equivalent to point-wise multiplication in the frequency domain. Therefore, $k_i * x_i$ can be calculated with the Fourier transform: $k_i * x_i = F^{-1}\{F\{k_i\} \cdot F\{x_i\}\}$. Here, F denotes the Fourier transform and $\cdot$ denotes the point-wise multiplication operation. The convolution layer supports both padding and striding.

The mapping from the o-th output feature map to the network output can be expressed as:

$$z = f(y_o) = f(y_o). \tag{7}$$

Here f is the non-linear mapping from the o-th output feature map y_o to the final network output. Similar with Sec. 3.1.1, $\frac{\partial z}{\partial x_i}$, $\frac{\partial z}{\partial k_i}$, and $\frac{\partial z}{\partial b_o}$ need to be calculated in the backward process.

$$\frac{\partial z}{\partial x_i} = \frac{\partial z}{\partial y_o} \times \frac{\partial y_o}{\partial x_i} = f'(y_o) \star k_i \tag{8}$$

Here $\star$ denotes the correlation operation. According to the correlation theorem [10], the correlation can also be calculated in the frequency domain with the help of Fourier transform: $x \star k = F^{-1}\{F\{x\} \cdot conj(F\{k\})\}$.

$$\frac{\partial z}{\partial k_i^*} = \frac{\partial z}{\partial y_o} \times \frac{\partial y_o}{\partial k_i^*} = f'(y_o) \star x_i \tag{9}$$

The gradient $\frac{\partial z}{\partial k_i}$ can be calculated by flipping the correlation output.

$$\frac{\partial z}{\partial b_o} = \frac{\partial z}{\partial y_o} \times \frac{\partial y_o}{\partial b_o} = 1^T \cdot vec(f'(y_o)) \tag{10}$$

The gradient $\frac{\partial z}{\partial b_o}$ can be calculated by point-wise summing up the values in $f'(y_o)$. Moreover, the fast Fourier transform (FFT) implemented in Matlab is utilized on the batched data to calculate the convolutions and correlations.

3.1.3 Max-pooling Layer

The max pooling layer calculates the largest element in $P_r \times P_c$ windows, with stride size $S_r \times S_c$. A customized *im2col_ln* function is implemented to convert the stridden pooling patches into column vectors, to vectorize the pooling computation in Matlab. The built-in *max* function is called on these column vectors to return the pooling result and the indices of these maximum values. Then, the indices in the original batched data are recovered accordingly. Also, zero padding can be applied to the input data.

Without the loss of generality, the mapping from the max-pooling layer input to the final network output can be expressed as:

$$z = f(y) = f(Sx), \tag{11}$$

where S is a selection matrix, and x is a column vector who denotes the input data in this layer.

In the backward process, $\frac{\partial z}{\partial x}$ is calculated and passed to the shallower layers:

$$\frac{\partial z}{\partial x} = \frac{\partial z}{\partial y} \times S = f'(y)^T S. \tag{12}$$

When the pooling range is less than or equal to the stride size, $\frac{\partial z}{\partial x}$ can be calculated with simple matrix indexing techniques in Matlab. Specifically, an empty tensor $dzdx$ of the same size with the input data is created. $dzdx(from) = dzdy$, where $from$ is the pooling indices, and $dzdy$ is a tensor recording the pooling results. When the pooling range is larger than the stride size, each entry in x can be pooled multiple times, and the back propagation gradients need to be accumulated for each of these multiple-pooled entries. In this case, the $\frac{\partial z}{\partial x}$ is calculated using the Matlab built-in function: $accumarray()$.

3.1.4 Rectified Linear Unit

The rectified linear unit (ReLU) is implemented as a major non-linear mapping function, some other functions including sigmoid and tanh are omitted from the discussion here. The ReLU function is the identity function if the input is larger than 0 and outputs 0 otherwise:

$$y = relu(x) = x \cdot ind(x > 0) \tag{13}$$

In the backward process, the gradient is passed to the shallower layer if the input data is non-negative. Otherwise, the gradient is ignored.

3.2 Loss function

Usually, a loss function is connected to the outputs of the deepest core computation module. Currently, LightNet supports the softmax log-loss function for classification tasks.

3.3 Optimization Algorithms

Stochastic gradient descent (SGD) algorithm based optimization algorithms are the primary tools to train deep neural networks. The standard SGD algorithm and several of its popular variants such as Adagrad [3], RMSProp [12] and Adam [6] are also implemented for deep learning research. It is worth to mention that we implement a novel Selective-SGD algorithm to facilitate the selection of hyper-parameters especially the learning rate. This algorithm selects the most efficient learning rate by running the SGD process for a few iterations using each learning rate from a discrete candidate set. During the middle of the neural net training, the Selective-SGD algorithm can also be applied to select different learning rates to accelerate the energy decay.

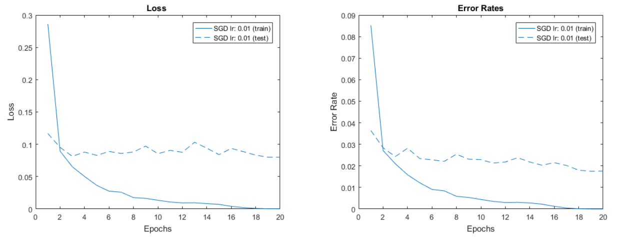
4. EXPERIMENTS

4.1 Multilayer Perceptron Network

A multilayer perceptron network is constructed to test the performance of LightNet on MNIST data [9]. The network takes 28×28 inputs from the MNIST image dataset and has 128 nodes respectively in the next two layers. The 128-dimensional features are then connected to 10 nodes to calculate the softmax output. See Fig. 2 for the experiment results.

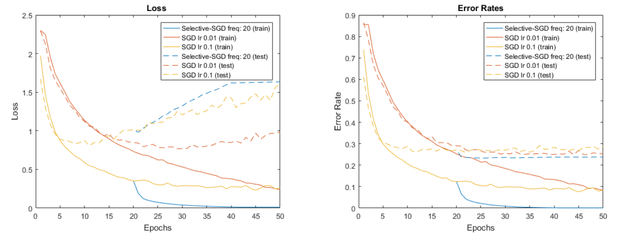
4.2 Convolutional Neural Network

A convolutional network with 4 convolution layers is constructed to test the performance of LightNet on CIFAR-10 data [7]. The architecture is the same as the one reported from MatConvNet [13]. There are $32, 32, 64, 64$ convolution kernels of size 5×5 in the first three layers, the last layer has kernel size 4×4. $relu$ functions are applied after each convolution layer as the non-linear mapping function. LightNet automatically selects and adjusts the learning rate and can achieve state-of-the-art accuracy with this architecture. Selective-SGD leads to better accuracy compared with standard SGD with a fixed learning rate. Most importantly, using Selective-SGD avoids manual tuning of the learning rate. See Fig. 3 for the experiment results. The computations are carried out on a desktop computer with an Intel i5 6600K CPU and a Nvidia Titan X GPU with 12GB memory. The current version of LightNet can process 750 images per second with this network structure on the GPU, around $5\times$ faster than using CPU.



(a) (b)

Figure 2: Loss and error rates during training and testing phases using LightNet on the MNIST dataset.



(a) (b)

Figure 3: Loss and error rates of training and testing with LightNet on the CIFAR-10 dataset.

4.3 LSTM Network

The Long Short Term Memory (LSTM) [4] is a popular recurrent neural network model. Because of LightNet's versatility, the LSTM network can be implemented in the LightNet package as a particular application. Notably, the core computational modules in LightNet are used to perform time domain forward process and back propagation for LSTM.

The forward process in an LSTM model can be formulated as:

$$i_t = sigmoid(W_{ih}h_{t-1} + W_{ix}x_t + b_i), \tag{14}$$

$$o_t = sigmoid(W_{oh}h_{t-1} + W_{ox}x_t + b_o), \tag{15}$$

$$f_t = sigmoid(W_{fh}h_{t-1} + W_{fx}x_t + b_f), \tag{16}$$

$$g_t = tanh(W_{gh}h_{t-1} + W_{gx}x_t + b_g), \tag{17}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t, \tag{18}$$

$$h_t = o_t \odot tanh(c_t), \tag{19}$$

$$z_t = f(h_t), \tag{20}$$

$$z = \sum_{t=1}^{T} z_t. \tag{21}$$

Where $i_t/o_t/f_t$ denotes the response of the input/output/forget gate at time t. g_t denotes the distorted input to the memory cell at time t. c_t denotes the content of the memory cell at time t. h_t denotes the hidden node value. f maps the hidden nodes to the network loss z_t at time t. The full network loss is calculated by summing the loss at each individual time frame in Eq. 21.

To optimize the LSTM model, back propagation through time is implemented and the most critical value to calculate in LSTM is:

$$\frac{\partial z}{\partial c_s} = \sum_{t=s}^{T} \frac{\partial z_t}{\partial c_s}. \tag{22}$$

A critical iterative property is adopted to calculate the above value:

$$\frac{\partial z}{\partial c_{s-1}} = \frac{\partial z}{\partial c_s}\frac{\partial c_s}{\partial c_{s-1}} + \frac{\partial z_{s-1}}{\partial c_{s-1}}. \tag{23}$$

A few other gradients can be calculated through the chain rule using the above calculation output:

$$\frac{\partial z_t}{\partial o_t} = \frac{\partial z_t}{\partial h_t}\frac{\partial h_t}{\partial o_t}, \tag{24}$$

$$\frac{\partial z}{\partial \{i,f,g\}_t} = \frac{\partial z}{\partial c_t}\frac{\partial c_t}{\partial \{i,f,g\}_t}. \tag{25}$$

The LSTM network is tested on a character language modeling task. The dataset consists of $20,000$ sentences selected from works of Shakespeare. Each sentence is broken into 67 characters (and punctuation marks), and the LSTM model is deployed to predict the next character based on the characters before. 30 hidden nodes are used in the network model and RMSProp is used for the training. After 10 epochs, the prediction accuracy of the next character is improved to 70%.

4.4 Q-Network

As an application in reinforcement learning, We created a Q-Network [11] with the MLP network. The Q-Network is then applied to the classic Cart-Pole problem [1]. The dynamics of the Cart-Pole system can be learned with a two-layer network in hundreds of iterations. One iteration of the update process of the Q-Network is:

$$\begin{aligned} Q_{new}(state_{old}, act) &= reward + \gamma Q_{current}(state_{new}, act_{best}) \\ &= reward + \gamma max_a Q_{current}(state_{new}, a) \\ &= reward + \gamma V(state_{new}). \end{aligned} \tag{26}$$

The *action* is randomly selected with probability *epsilon*, otherwise the *action* leading to the highest score is selected. The desired network output Q_{new} is calculated using the observed reward and the discounted value $\gamma V(state_{new})$ of the resulting state, predicted by the current network through Eq. 26.

By using a least squared loss function:

$$\begin{aligned} z &= (y - Q_{current}(state_{old}, act))^2 \\ &= (Q_{new}(state_{old}, act) - Q_{current}(state_{old}, act))^2, \end{aligned} \tag{27}$$

the Q-Network can be optimized using the gradient:

$$\frac{\partial z}{\partial \theta} = \frac{\partial z}{\partial Q_{current}}\frac{\partial Q_{current}}{\partial \theta}. \tag{28}$$

Here θ denotes the parameters in the Q-Network.

5. CONCLUSION

LightNet provides an easy-to-expand ecosystem for the understanding and development of deep neural network models. Thanks to its user-friendly Matlab based environment, the whole computational process can be easily tracked and visualized. These set of the main features can provide unique convenience to the deep learning research community.

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