Inter-layer Collision Networks

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Abstract

Deeper neural networks are hard to train. Inspired by the elastic collision model in physics, we present a universal structure that could be integrated into the existing network structures to speed up the training process and eventually increase its generalization ability. We apply our structure to the Convolutional Neural Networks (CNNs) to form a new structure, which we term the “Inter-layer Collision” (IC) structure. The IC structure provides the deeper layer a better representation of the input features. We evaluate the IC structure on CIFAR10 and Imagenet by integrating it into the existing state-of-the-art CNNs. Our experiment shows that the proposed IC structure can effectively increase the accuracy and convergence speed.

Introduction

In recent years, Convolutional Neural Networks (CNNs) have demonstrated remarkable successes in fields such as computer vision and speech recognition, attracting much research on improving the CNNs. A common trend is building larger and deeper networks ever since AlexNet (Krizhevsky, Sutskever, and Hinton 2012) and VGG (Simonyan and Zisserman 2015) showed the superiority of deep networks. However, deep neural networks bring high costs on time and memory, not to mention the difficulties of training deep models, such as vanishing/exploding gradients and degradation. To optimize the deep networks, a series of techniques have been suggested in the last few years (He et al. 2016a), (Ioffe and Szegedy 2015).

Neural Architecture Search (NAS), based on reinforcement learning (Zoph and Le 2017), is another technology which has achieved higher accuracy than manual architectures in image classification task. Although NAS can learn the structure automatically, its search space has to be defined manually. Much research concentrated on designing the effective atomic unit to add to the search space (Tan et al. 2018). Besides, in view of the excessive computation burden, NAS has not been a universal method.

Our research aims to develop a universal basic unit that could improve the networks’ convergence speed with little additional burden. We observe that, in elastic collision model, the way objects colliding with each others is like data exchanging between one another. Inspired by this, we design a basic structure, which we term the “Inter-layer Collision” (IC) unit. Our experiments show that this structure can team up with other networks to enhance their performance with little computation burden.

Fig. 1(a) shows the structure of IC unit. In this structure, we add a branch to a full-connection layer before the activation operation. This branch, which we use a manual function which built by $F(X)$, represents a kind of global information related to input $X$. In this way, we enhance the relationships between different dimensions of input. The IC unit can be easily integrated into convolution operation. We show this structure in Fig. 1(b). When the IC unit slides on the input, each dimension can be connected with the information of its neighboring fields, which we term “local information”. This operation also emphasises the small areas on input when capturing the features.

When we train a network combined with IC units, the local information can represent a rough feature, which can help the subsequent layers to learn. In order to represent the rough features in different channels, we divide the local information into each channel with a collection of per-channel weights. In this way, the subsequent layers can flexibly use the rough features, which can help to reduce the difficulty of learning, resulting in a faster training speed.

We integrate the IC unit into the state-of-the-art architectures. To compare the IC based model with its baseline model, we design a series of experiments on image classification task, which show that the networks with IC structure have an evident improvement on training speed. The experiments on Imagenet also shows that the IC structure can help to increase the final accuracy with little additional costs.

Our contribution can be summarized as below:

- In our research, we investigate the reasons why deep networks are hard to train. Then we analyse this problem in perspective of physics, and propose a method, which is based on the physical system, that partially solves this problem.
- We develop a universal structure that could be added to a majority of convolutional neural networks to improve their performance. Then we prove that our structure can increase the accuracy and convergence speed on image
classification tasks with little computational burden.

Related Work

Although AlexNet (Krizhevsky, Sutskever, and Hinton 2012) and VGGNet (Simonyan and Zisserman 2015) had shown the great power of deep convolutional networks (Szegedy et al. 2015), some research revealed that stacking convolutional layers caused some problems, such as degradation (He and Sun 2015), over-parameterization (Denton et al. 2014), etc. A rising trend was to optimize the network structures to build more effective models. ResNet (He et al. 2016a) used a skip connection structure to solve the degradation problem, leading a trend on designing skip connection structures. It also proposed a class of stronger artificial block structures that were widely used to design networks by later research. For instance, ResNext (Xie et al. 2017) designed a multi-branch architecture based on ResNet. Dual-path networks (Chen et al. 2017) proposed an effective architecture by combining the idea of ResNet and DenseNet (Huang et al. 2017).

Except for the skip connections, there were a variety of methods to improve the effectiveness of networks. Batch Normalization (BN) introduced an operation to make the learning process more stable (Ioffe and Szegedy 2015). To a certain extent, BN can help to solve the vanishing gradients in deep architectures (Santurkar et al. 2018). This operation was popular and became ubiquitous in the state-of-the-art networks. Besides, Grouped convolution was another popular method concentrating on improving the functional form of the computational elements (Sun et al. 2018), (Ioannou et al. 2017). It divided the feature map into several groups that could provide more flexible operations for the convolution operation. It could also be used to construct lightweight networks (Howard et al. 2017). These prior works completely divided the feature map into separated channels and used pointwise convolutions to connect different features.

In recent years, using NAS to search the best model had become a trend (Liu, Simonyan, and Yang 2018), (Zoph et al. 2018). The result of NAS had outperformed the artificial architecture on image classification tasks, which didn’t mean that continuing to design artificial architecture makes no sense. On one hand, NAS occupied huge computing resources. Although (Pham et al. 2018) proposed a method to reduce the computational burden, the NAS was still more difficult to train compared to manual architectures. On the other hand, recent research of NAS used reinforcement learning to search architectures (Zoph and Le 2017), where the search space has to be defined manually. Besides, some other research focused on designing an effective basic unit that can be added into the search space.

Similar to our purpose, SENets (Hu, Shen, and Sun 2018) proposed a manual basic unit to improve the representations of CNNs, which got a high accuracy. It also proposed a SE block that can be integrated into most of the standard convolution architectures. Furthermore, (Tan et al. 2018) demonstrated that the SE block was useful in NAS. Although our purpose is similar to SENets, the method is different. SENets focused on the relationship between different channels, while our method focused on strengthening the relationship between a single input and its neighboring fields.

Inter-layer Collision Structure

In this section, we first introduce the mathematical form of the elastic collision model inspired by which we build the basic IC unit. Then we propose two kind of block structures showing how the IC method could be combined with the CNN models. Finally, we analyze the computational overhead brought by the IC unit.

Elastic Collision Model

In this section, we briefly introduce the elastic collision model and its physical significance. Considering two objects in a 1D space where objects could only move to the left (−) or to the right (+), the mass of them are $m_1$ and $m_2$ respectively. Initially, $m_1$ lies to the left of $m_2$ and they both have a velocity of zero. When $m_1$ is given a speed $v_1$ toward $m_2$, according to the laws of energy conservation and momentum conservation, the velocity of $m_1$ and $m_2$ after collision are:

$$v'_1 = \frac{m_1 - m_2}{m_1 + m_2}v_1, \quad v'_2 = \frac{2m_1}{m_1 + m_2}v_1,$$

(1)

According to our analysis, the object $m_2$ will always move to the right while the moving direction of object $m_1$...
IC Unit

Considering a network with multiple input neurons and output neurons, we build the IC unit based on the collision based structure. We use $w$ to denote the learnable coefficient $\frac{2m_1}{m_1 + m_2}$, and $w - 1$ to denote $\frac{m_1 - m_2}{m_1 + m_2}$. $X, Y$ to denote the input and output $v_1, v''$. Each output $y_j$ is calculated by:

$$y_j = \sum_{i=1}^{N} w_{ij} x_i + \text{relu}\left(\sum_{i=1}^{N} (w_{ij} - 1)x_i\right)$$

(3)

where $N, M$ denotes the number of input and output neurons. $x_{\text{sum}}$ denotes the sum of $x_1, x_2, \ldots , x_N$. To simplify, we omit the bias term and the activation operation. As shown in Fig. 1(a), the structure above the dotted line is the same as a standard full-connection layer, which means that the IC unit keeps the structures of traditional networks, that is it doesn’t hurt the generalization ability of the network. The structure under the dotted line refers to the relu function item, passing useful information for the subsequent layers. We further relax the fixed threshold $1$ to a learnable value $w'_j, j \in \{0, 1, \ldots , M\}$ to improve the learning ability of the IC unit. The reformulation is given by:

$$y_j = \sum_{i=1}^{N} w_{ij} x_i + \text{relu}(w'_j x_{\text{sum}}).$$

(4)

$$y_j = \sum_{i=1}^{N} w_{ij} x_i + \text{relu}(\sum_{i=1}^{N} w_{ij} x_i).$$

$w'_j$ represents an inherent parameter of each output neuron, modulating the corresponding $w_{ij}$ to increase the network capacity. We use $F(X, W, W')$ to denote the relu function item. The IC unit can be expressed by matrixes and vectors:

$$Y = WX + B + F(X, W, W').$$

(5)

We use $[w, w']$ to denote the weights of the IC unit. By adding $F(X, W, W')$, the IC unit strengthens the relationship between the individual input neuron and the whole input neurons, reducing the difficulties of learning.

From IC Unit to CNN

We apply the IC unit to the convolutional structure to form a new structure shown in Fig. 1(b). The convolution operation in CNN transforms the input feature $X \in \mathbb{R}^{H \times W \times C}$ into feature maps $U \in \mathbb{R}^{H \times W \times C'}$. We use $\ast$ to denote the operation that maps the input to one channel of output. Its corresponding convolutional kernel is denoted by $w_i \in W, W = [w_1, w_2, \ldots, w_C]$. The structure is built replacing the convolutional kernel $w_i$ with an IC unit $[w_i, w'_i]$ (Thin symbol refers to a scalar). Therefore, the output of one channel can be represented below:

$$u_i = [w_i, w'_i] \ast X$$

$$= w_i \ast X + \text{relu}(w_i \ast X - w'_i \ast (I \ast X)),$$

(6)

where the shape of the kernel $w_i$ is $3 \times 3 \times C'$. $u_i$ denotes one channel of the feature maps and $U = [u_1, u_2, \ldots, u_C]$ is computed by different IC kernels. Besides, $I$ is an all-one tensor which has the same size as $w_i$. Fig. 2(a) shows how
tensor \( I \) calculates the result. In this way, the IC unit connects the individual input with its \( 3 \times 3 \) neighboring fields. The relu item is termed “local information” in the following.

Although \( I \) and \( w'_i \) can represent the local information, this operation in Fig. 2(a) will mix different features. In the convolution operation, channels are specialized for images and feature maps that filters can capture features recorded on different channels. Therefore, the IC unit separates the local information to keep the independence of features, which is shown in Fig. 2(b). In order to capture the local information of each input channel, we separate the all-one kernel \( I \) into many 2D tensors \([i_1, i_2, \ldots, i_C]\), which is a grouped convolution, which denoted by **. Besides, \( w'_i \) should be adjusted to \( w'_i \in \mathbb{R}^{C' \times 1} \) to match the new form of local information, where

\[
u_i = w_i \ast X + \text{relu}(w_i \ast X - (I \ast \ast X)w'_i).
\]

Eq. 7 describes the calculation procedure of one layer, which we term “IC layer” in the following notation. When considering the whole kernel \([W, W']\), The IC layer uses an all-one kernel \( I \) to conduct a grouped convolution and a \( 1 \times 1 \) convolution \( W' \) to combine the local information. We term this \( 1 \times 1 \) convolution “pointwise convolution”(Howard et al. 2017) in the following. The usage of pointwise convolution is to combine different features in IC structure.

In the IC-based network, the subsequent layers are provided with rough features by the IC layer, which makes the subsequent layers easier to learn. It also avoids the impact of information redundancy which may be caused by using the structure depicted in Fig. 2(a). For instance, some features may not be significant or even negative for representations. The pointwise convolution can emphasize the positive feature maps and suppress negative ones. By those operations, The IC layer improves the learning ability of the network without increasing its depth or width.

**Application in Different Models**

In this section, we combine the IC structure with some of the state-of-the-art models. The new network can be easily built by replacing only the standard convolution layers with IC layers, making it very applicable to a majority of convolution networks.

We first consider IC-VGGNet. VGGNet(Simonyan and Zisserman 2015) consisting of convolution, BN, and pooling layers, is a classic convolution network. In this architecture, the BN layers increase the stability of training. The use of pooling layers is to scale the size of feature maps and enhance its robustness. In our research, we only replace the convolution layers with IC layers(Fig. 3(a)) while others are unchanged. By stacking IC layers, the local information can be transmitted to deeper layers.

Building networks with a block structure is a popular approach. Based on the block structure reported by ResNet paper(He et al. 2016a), we build two IC block structure. The first structure termed “IC block” is built by replacing the convolution layers with IC layers shown in Fig. 3(b). Note that the shortcut branch from the original ResNet block is kept.

The second structure shown in Fig. 3(c) differs from the first structure that it connects the local information of input with the output of the second layer. We named it “IC block” because only one local information is used in this block.

IC block also contains a shortcut that uses identify mapping. Much research proves that the identify mapping is the most effective shortcut(He et al. 2016b),(Zagoruyko and Komodakis 2016). There are two kind of skip connections(identify mapping and local information) in IC block. We believe that the local information branch may not take advantage of the skip connection. However, our experiments have proven that the IC block can also improve the original network with identify mapping shortcuts. We argue that this is because the rough features provided by input are also useful for deeper layers.

**Parameters and Complexity Analysis**

For the standard convolutional layer with \( 3 \times 3 \) receptive field, the transformation

\[
X \in \mathbb{R}^{H' \times W' \times C'} \xrightarrow{\text{conv}} U \in \mathbb{R}^{H \times W \times C}
\]

needs \( 3 \times 3 \times C' \times C \) parameters. In the IC layer, we calculate the sum of each channel without additional parameters. The pointwise convolution \( W' \) adds \( 1 \times 1 \times C'' \times C \) parameters. Therefore, the number of parameters added by the IC layer is only \( \frac{1}{3} \) of the original layer. For the IC block, there is only one pointwise convolution in each block. The number of increased parameters is about \( \frac{1}{50} \) of the original layer. If we use a bigger receptive field, the ratio can be further reduced.

The IC layer adds a grouped convolution and a pointwise convolution. The grouped convolution is used to calculate the element-wise sum of input by an all-one kernel. The increased computational complexity is the same as adding a convolutional kernel because we only need to do this operation once. Therefore, the increased complexity by grouped convolution is \( \frac{1}{3} \) of the original layer. The pointwise convolution is a \( 1 \times 1 \) convolution which uses approximately \( \frac{1}{3} \) computation of the \( 3 \times 3 \) convolution(Sifre and Mallat 2014). We get an addition in computation of \( \frac{1}{50} + \frac{1}{3} \). Similar to the parameter analysis, the IC block will reduce about half of the additional computation costs.

**Experiments**

In this section, different IC architectures will be evaluated on the task of image classification. We investigate the effectiveness of the IC structure by a series of comparative experiments detailed below.

**Datasets and Evaluation Metrics**

We use CIFAR10 and Imagenet 1K classification dataset to investigate the effectiveness. The CIFAR-10 dataset consists of 60000 \( 32 \times 32 \) colour images in 10 classes divided into 50000 training images and 10000 test images, while the Imagenet dataset consists of more than 1 million colour images in 1000 classes divided into 1.28 million training images and 50K validation images.
Table 1: Architectures used in CIFAR10 experiments. Bracket denotes the same structure and the following numbers denotes the number of structure stacked.

| output size | IC-VGG16 | IC-ResNet18 |
|-------------|----------|-------------|
| 32 × 32     | 3 × 3, 64, conv | 3 × 3, 64, conv |
|             | 3 × 3, 64, IC | 3 × 3, 64, IC |
| 16 × 16     | maxpool, (3 × 3, 128, IC) × 2 | 3 × 3, 128, IC | × 2 |
| 8 × 8       | maxpool, (3 × 3, 256, IC) × 3 | 3 × 3, 256, IC | × 2 |
| 4 × 4       | maxpool, (3 × 3, 512, IC) × 3 | 3 × 3, 512, IC | × 2 |
| 2 × 2       | maxpool, (3 × 3, 512, IC) × 3 | - |
| 1 × 1       | maxpool, average pool, 4 × 4 | - |

IC-VGG19 is constructed and evaluated the same way. Similar to the structure of IC-VGG16 in Table. 1, IC-VGG19 uses a different stacking numbers of [2, 4, 4, 4]. To simplify, we use IC-VGGNets to represent both IC-VGG16 and IC-VGG19.

The training curve, depicted in Fig. 4(a, d), indicates that the IC structure can accelerate the convergence speed. This improvement is observed since the beginning of the training, even with an unsatisfactory initialization. Table. 2 shows the final accuracy and FLOPs. Moreover, IC-VGG16 and IC-VGG19 reach a higher accuracy with only a small increase on computational costs, IC-VGG16 with 12.9% and IC-VGG19 with 10.0%.

Based on ResNet18(He et al. 2016a) and the basic block depicted in Fig. 3(b, c), we build IC-ResNet18 and IC-ResNet18−, the layers and filters of which are shown in Table. 1(IC-ResNet18− replaces the structure in bracket with the structure inFig. 3(c)). Note that ResNet18 changes the size of feature maps by using a convolutional layer with bigger stride instead of a pooling layer so that the operation $I * * (X)$ uses the same stride in the parallel convolutional layer. In the same way, we build and evaluate IC-ResNet34 and IC-ResNet34−, both of which use a stacking numbers of [3, 4, 6, 3].

We first evaluate IC-ResNet18 and IC-ResNet34. The error rate cures are depicted in Fig. 4(b, e). Compared to their original models, both models have faster convergence speed. The final accuracy and FLOPs are shown in Table. 3. We observe that both IC-ResNet18 and IC-ResNet34 reach a higher accuracy compared to their original models. The additional computation costs, which are 0.13 GFLOPs(≈ 10.7%) of IC-ResNet18 and 0.13 GFLOPs(≈ 11.2%) of IC-ResNet34, is trivial compared to the increased...
Figure 4: Training on CIFAR10. Dotted line denote training top-1 error, and solid curves denote top-1 test error. Left column: IC-VGGNets. Middle column: IC-ResNets. Right column: IC-ResNets−.

Table 3: Error rates on CIFAR10 test dataset and complexity comparisons.

| method       | top-1 err.(%) | GFLOPs |
|--------------|---------------|--------|
| ResNet-18    | 4.98          | 0.56   |
| IC-ResNet-18 | 4.58          | 0.62   |
| IC-ResNet-18−| 4.70          | 0.58   |
| ResNet-34    | 4.52          | 1.16   |
| IC-ResNet-34 | 4.43          | 1.29   |
| IC-ResNet-34−| 4.53          | 1.22   |

accuracy. Moreover, IC-ResNet18 reaches a top-1 error of 4.58%, approaching the performance achieved by IC-ResNet34 (4.52%) with about half of the total computational burden (IC-ResNet18 is 0.62 GFLOPs, ResNet-34 is 1.16 GFLOPs).

We then evaluate IC-ResNet18− and IC-ResNet34−, which use fewer parameters compared to IC-ResNet18 and IC-ResNet34. Considering that IC-ResNets− use skip connections to transmit local information, we build a BN layer behind the local information branch (Fig. 3(c)) to increase the stability of training. The top-1 error, depicted in Fig. 4(c, f), shows that both models have a higher convergence speed, demonstrating that the IC structure could effectively speed up the training process. Table 3 shows that IC-ResNet18− reach a higher accuracy than ResNet18 even with less local information compared to IC-ResNet18. Whatmore, IC-ResNet18− has an additional computation costs of 3.6% which is less than half of that of IC-ResNet18. Base on the above discussion, we can conclude that the IC structure (Fig. 3(c)) could increase the model generalization ability with little computation costs.

The error curves (Fig. 5(e, f)) show that IC-ResNet34 and IC-ResNet34− have no obvious improvement at the third stage. We have mentioned that the IC structure will not destroy the generalization ability of the convolutional models, which is also confirmed by the previous experiments. We argue that this is because of the over-fitting caused by the 34 layered model. The final accuracy also reveals the overfitting phenomenon on the CIFAR10 dataset.

Large Dataset
To further verify the effectiveness of the IC structure. We evaluate IC-ResNet-18 and IC-ResNet18− on Imagenet. Although the IC structure shows impressing result on the CIFAR10 dataset, the dataset is relatively easy to learn that it can not fully validate the effectiveness of the IC structure. In this experiment, the baseline network is an 18 layered architecture reported in ResNet paper (He et al. 2016a). We use SGD with a weight decay of 0.0001 and a momentum of 0.9 to train the models and set the size of mini-batch to 512. The whole training process takes 60 epochs, which is averaged into four stages. The learning rate of each stage is set...
Figure 5: Training the two IC structures and their basic model on ImageNet. The both IC structures show improved performance in each learning stage.

Table 4: Random crop error rates (%) on the ImageNet validation set.

| method           | top-1 err. (%) | top-5 err. (%) |
|------------------|----------------|---------------|
| ResNet-18        | 31.96          | 11.95         |
| IC-ResNet-18     | 31.45          | 11.50         |
| IC-ResNet-18−    | 31.08          | 11.49         |

to 0.1, 0.01, 0.001 and 0.0001. The original images are preprocessed by a random crop for it is a universal method for image preprocessing.

The top-1 error, depicted in Fig. 5, shows that both models have a higher convergence speed, demonstrating that the IC structure could effectively speed up the training process. Table 4 shows that IC-ResNet18− reach a higher accuracy than ResNet18 even with fewer local information compared to IC-ResNet18. Moreover, IC-ResNet18− has additional computation costs of 3.6% which is less than half of that of IC-ResNet18. Base on the above discussion, we can conclude that the IC structure (Fig. 3(c)) could increase the model generalization ability with little computation costs.

Compared to the basic model, as shown in Fig. 5, both of IC-ResNet18 and IC-ResNet18− outperform the basic model in terms of convergence speed at each learning stage and end with a higher accuracy. As is shown in Table 4, IC-Resnet18− outperforms the basic network with 0.88% and IC-ResNet18 with 0.41% in terms of top-1, strongly demonstrating the effectiveness of our proposed models.

When we train a network combined with IC units, the local information can represent a rough feature, which can help the subsequent layers to learn. In order to represent the rough features in different channels, we divide the local information into each channel accompanied by a per-channel weight. In this way, the subsequent layers can flexibly use the rough features. In this way, the IC unit can help to reduce the difficulty of learning, resulting in a faster training speed.

The experiment results prove that our proposed model is not only applicable to small datasets, but also very effective on large datasets, further demonstrating the universality of our method. We also notice that IC-ResNet18− performs better compared to IC-ResNet18, which we believe is caused by the reason that the rough feature is passed to deeper layers that improves the final results. Besides, the skip connections in IC-ResNet− help reducing the impact of the degradation problem. We conjecture that the IC-ResNet− is more applicable in deeper networks.

**Conclusion and Future Work**

Inspired by the elastic collision model, we propose the IC structure that could be used to improve the performance of convolution networks. We build the IC networks by replacing the convolution layers of the state-of-the-art models with the IC layers. Our experiments show that the IC networks could effectively improve the convergence speed with little additional computational burden. Besides, our IC network reaches a higher accuracy compared to the baseline in the Imagenet experiment.

In the work, we have not fully explored the applicability to other networks that the IC structure potentially enables. Our future work includes applications to other network structures and tasks beyond image classification.

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