CIFAR-10 Classification using VGG,ResNet,GoogLeNet

Author: Chi Zhang

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Figure 1: The Preview of Dataset

1 Introduction and Overview of Dataset

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class. The Fig 1 shows a preview of the dataset.

2 VGG

2.1 The Architecture of VGG

In Fig 2, we give the model construction diagram of VGG.

2.2 Features of VGG

- 1. Small convolution kernel : 3x3 convolution kernel
- 2. Small pooling kernel: 2x2 pooling kernel
- 3. Deeper layers with wider feature maps: Based on the first two points in addition to the convolution kernel focusing on expanding the number of channels and pooling focusing on narrowing the width and height, making the model architecturally deeper and wider while the computational effort slowly increases.

ConvNet Configuration										
A	A-LRN	В	С	D	E					
11 weight	11 weight 11 weight 13 weight		16 weight	16 weight	19 weight					
layers	layers	layers	layers	layers	layers					
input (224×224 RGB image)										
conv3-64	conv3-64	conv3-64	conv3-64	conv3-64	conv3-64					
	LRN	conv3-64	conv3-64	conv3-64	conv3-64					
	-	max	pool	-						
conv3-128	conv3-128	conv3-128	conv3-128	conv3-128	conv3-128					
		conv3-128	conv3-128	conv3-128	conv3-128					
		max	pool							
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256					
conv3-256	conv3-256	conv3-256	conv3-256	conv3-256	conv3-256					
			conv1-256	conv3-256	conv3-256					
					conv3-256					
		max	pool							
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512					
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512					
			conv1-512	conv3-512	conv3-512					
					conv3-512					
		max	pool							
conv3-512	conv3-512	conv3-512	conv3-512	conv3-512	conv3-512					
conv3-512	conv3-512 conv3-512 conv3		conv3-512	conv3-512	conv3-512					
			conv1-512	conv3-512	conv3-512					
					conv3-512					
maxpool										
FC-4096										
FC-4096										
FC-1000										
soft-max										

Figure 2: The Architecture of VGG

2.3 Why is VGG designed in such a way

In VGG16, the authors consider that the perceptual field size obtained by a stack of two 3x3 convolutions is equivalent to a 5x5 convolution; while the perceptual field obtained by a stack of three 3x3 convolutions is equivalent to a 7x7 convolution. This reduces the parameters and increases the network depth on the one hand, and corresponds to more nonlinear mappings on the other hand, which can increase the fitting ability of the network.

2.4 My Choice

I choose the VGG-16 network, which is the class D in Fig 2.

2.5 Experiment

We choose the optimizer as SGD, set the learning rate to 0.01, use the cross-entropy loss function, and cut the training set into 167 batches with 300 as the training set batch size, and the number of epochs is 20. The device we use is Nvidia Geforce RTX 3050 Laptop GPU.

In Fig 3,We plot the training loss, training accuracy, and testing accuracy during model training. In Table 1, we give the GPU time and final accuracy for a single epoch versus all (20) epochs.



Figure 3: Training loss, training accuracy, and testing accuracy during model training

Epoch	Computation time (ms)	Test accuracy (%)
1	49216.24	43.00
20	1132012.75	73.23

Table 1: Computational efficiency and Test accuracy

3 ResNet

3.1 The Architecture of ResNet

In Fig 4, we give the model construction diagram of ResNet.

3.2 Features of ResNet

- 1. ResNet follows the complete 3x3 convolutional layer design of VGG
- 2. Put forward the concept of residual blocks.Fig 5 shows the structure of the residual block.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer					
conv1	112×112	7×7, 64, stride 2									
			3×3 max pool, stride 2								
conv2_x	56×56	$\left[\begin{array}{c} 3\times3, 64\\ 3\times3, 64 \end{array}\right]\times2$	$\left[\begin{array}{c} 3\times3, 64\\ 3\times3, 64\end{array}\right]\times3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$					
conv3_x	28×28	$\left[\begin{array}{c} 3\times3,128\\3\times3,128\end{array}\right]\times2$	$\left[\begin{array}{c} 3\times3,128\\3\times3,128\end{array}\right]\times4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$					
conv4_x	14×14	$\left[\begin{array}{c} 3\times3,256\\3\times3,256\end{array}\right]\times2$	$\left[\begin{array}{c} 3\times3,256\\ 3\times3,256\end{array}\right]\times6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$					
conv5_x	7×7	$\left[\begin{array}{c} 3\times3,512\\ 3\times3,512\end{array}\right]\times2$	$\left[\begin{array}{c} 3\times3,512\\ 3\times3,512\end{array}\right]\times3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512\\ 3 \times 3, 512\\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$					
	1×1	, softmax									
FLOPs		1.8×10^{9}	3.6×10^{9}	3.8×10^{9}	7.6×10^{9}	11.3×10^{9}					

ures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of block

Figure 4: The Architecture of ResNet



Figure 5: The Architecture of residual block

Epoch	Computation time (ms)	Test accuracy (%)
1	49216.24	51.40
20	395522.34	67.67
50	979699.44	73.63

Table 2: Computational efficiency and Test accuracy

3.3 Why is ResNet designed in such a way

There are two main design ideas for residual blocks, shortcut connections and constant mappings. Shortcut connections make residuals possible, while constant mappings make the network deeper.

3.4 My Choice

I choose the ResNet18 network, which is second column in Fig 4.

3.5 Experiment

We choose the optimizer as SGD, set the learning rate to 0.01, use the cross-entropy loss function, and cut the training set into 167 batches with 300 as the training set batch size, and the number of epochs is 20. The device we use is Nvidia Geforce RTX 3050 Laptop GPU.

In Fig 6, We plot the training loss, training accuracy, and testing accuracy during model training. In Table 2, we give the GPU time and final accuracy for a single epoch versus all (20) epochs.

4 GoogLeNet

4.1 The Architecture of GoogLeNet

In Fig 7, we give the model construction diagram of GoogLeNet.



Figure 6: Training loss, training accuracy, and testing accuracy during model training

type	patch size/ stride	output	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool	params	ops
convolution	7×7/2	112×112×64	1		reduce		leader		proj	2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	$56 \times 56 \times 192$	2		64	192				112K	360M
max pool	3×3/2	$28 \times 28 \times 192$	0								
inception (3a)		$28 \times 28 \times 256$	2	64	96	128	16	32	32	159K	128M
inception (3b)		$28 \times 28 \times 480$	2	128	128	192	32	96	64	380K	304M
max pool	$3 \times 3/2$	$14 \times 14 \times 480$	0								
inception (4a)		$14 \times 14 \times 512$	2	192	96	208	16	48	64	364K	73M
inception (4b)		$14 \times 14 \times 512$	2	160	112	224	24	64	64	437K	88M
inception (4c)		$14 \times 14 \times 512$	2	128	128	256	24	64	64	463K	100M
inception (4d)		$14 \times 14 \times 528$	2	112	144	288	32	64	64	580K	119M
inception (4e)		$14 \times 14 \times 832$	2	256	160	320	32	128	128	840K	170M
max pool	$3 \times 3/2$	$7 \times 7 \times 832$	0								
inception (5a)		$7 \times 7 \times 832$	2	256	160	320	32	128	128	1072K	54M
inception (5b)		$7 \times 7 \times 1024$	2	384	192	384	48	128	128	1388K	71M
avg pool	$7 \times 7/1$	$1 \times 1 \times 1024$	0								
dropout (40%)		$1 \times 1 \times 1024$	0								
linear		$1 \times 1 \times 1000$	1							1000K	1M
softmax		$1 \times 1 \times 1000$	0								

Figure 7: The Architecture of GoogLeNet



Figure 8: The Architecture of Inception

4.2 Features of GoogLeNet

1. Put forward the concept of Inception.Fig 8 shows the structure of the Inception.