基于强化学习的模型压缩

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Introduction

Although the deep network model has been widely used in industry, it cannot be applied well to devices with limited memory or limited computing resources, such as mobile phones and satellites. Model compression technology can reduce the size of the model and runs better on devices with memory limitations. In this paper, we proposed a learning-based strategy leveraging reinforcement learning with compression ratio and accuracy exceeding those of current the rule-based policy.The reason why we achieved great progress of significant performance is that we leverage DDPG of reinforcement learning to provide the model compression strategy based on the pruned model. The proposed method shows that the model achieved more than 3.1% accuracy and more than 6.46X compression ratio compared with the hand-crafted model compression policy for ResNet20 on Ciar10.

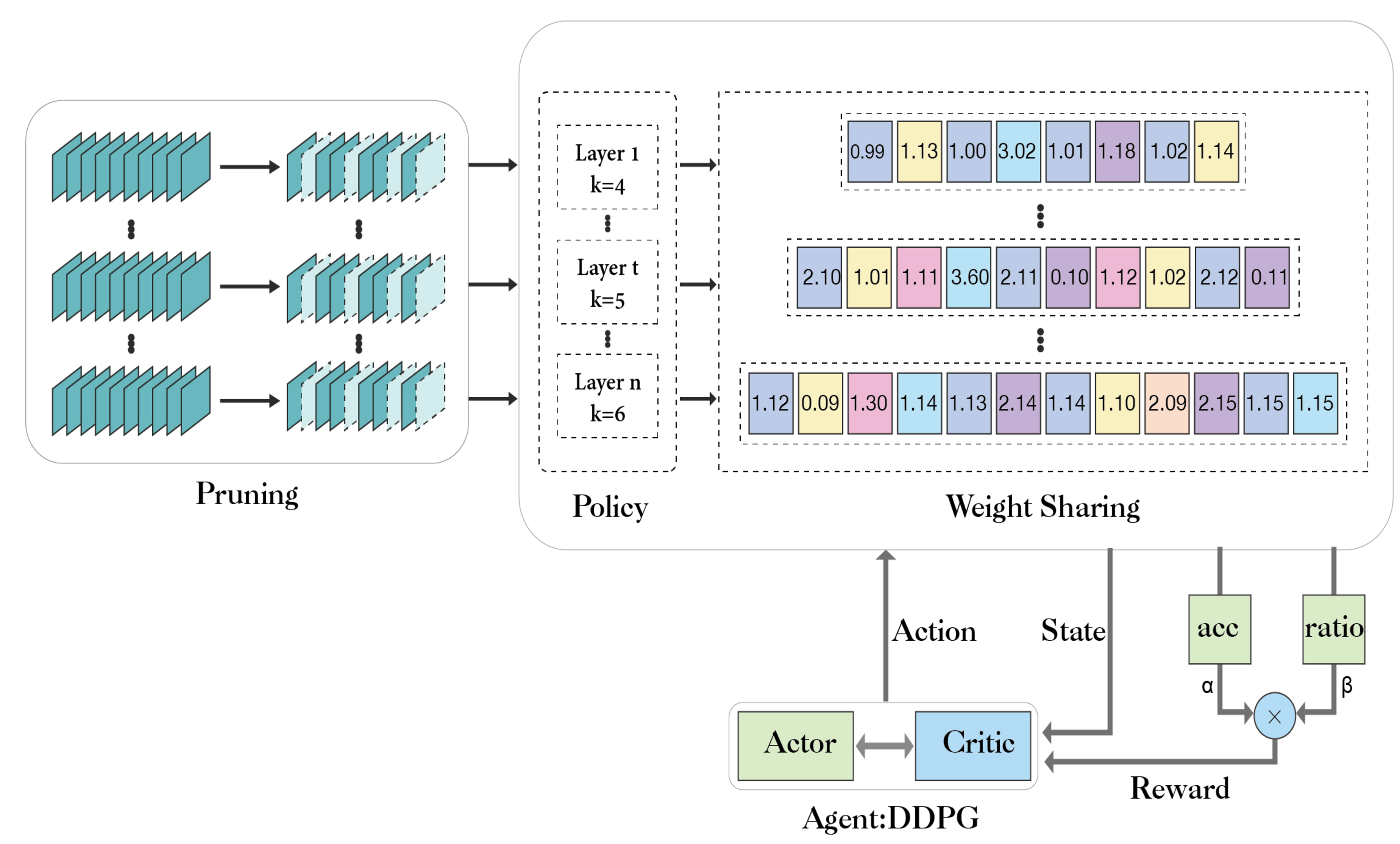

Figure 1. An overview of the framework which pruning the redundant structure of the model,then using DDPG of reinforcement learning to learn automatically the number of clusters k in each layer for weight sharing.

Measures

1、 the redundant structure of the trained model in the software was pruned by geometric median method,which aims to improve the model’s computational efficiency on satellite.

2、we leverage the DDPG of reinforcement learning to learn the number of clusters k automatically in each layer for weight sharing, which aims to reduce the models storage space on satellite.

3、we performed experiments for RestNet20 and RestNet32 on Cifiar10,which not only improves the model’s computational efficiency but also reduced the models storage space without manual design,and the result shows this learning-based compression policy which has a higher compression ratio, better retains accuracy and freeing human labor, is superior to rule-based compression policy.

Experimental Results

clusters	baseline	top1	top5	ratio
FPGM	92.20	90.62	99.87	1.67X
/16	92.20	90.48	99.77	5.73X
/32	92.20	89.41	99.52	6.25X
/64	92.20	87.30	99.52	7.30X
16	92.20	88.89	99.66	13.35X
32	92.20	89.89	99.79	4.72X
64	92.20	90.29	99.73	4.71X
ours	92.20	90.22	99.75	11.17X

Table 1. CIFAR-10 on Restnet20

clusters	baseline	top1	top5	ratio
FPGM	92.63	91.91	99.73	1.67X
/16	92.63	91.70	99.73	5.72X
/32	92.63	90.99	99.67	6.42X
/64	92.63	85.83	99.26	7.29X
16	92.63	89.67	99.56	13.35X
32	92.63	91.67	99.77	10.68X
64	92.63	91.87	99.75	8.90X
ours	92.63	91.13	99.72	12.03X

Table 2. CIFAR-10 on Restnet32