TOWARDS THINNER CONVOLUTIONAL NEURAL NETWORKS THROUGH GRADUALLY GLOBAL PRUNING

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ABSTRACT

Convolutional neural networks (CNNs) are always trapped by their huge amount of parameters when faced with resource-limited devices. To handle this problem, we propose a pruning scheme for neuron level pruning, in which the redundant neurons were selected globally in the network. Our scheme could automatically find a thinner network structure with a given performance.

INTRODUCTION

- Three types of current pruning methods
  - **Approximation**: Weight matrices and tensors in deep model could be approximated using tensor decomposition techniques.
  - **Quantization**: By searching or constructing a finite set for candidate parameters, one could map parameters from real number to several candidates
  - **Pruning**: Reduce redundant connections, neurons or entire layers of the model.
- Pruning methods in different granularities:
  - Layer-level: Shallower networks
  - Neuron-level: Thinner networks
  - Connection-level: Sparser networks
- Main problems
  - How to evaluate the importance of a neuron
  - How to conduct the pruning process
- We refer neuron as a node in fully-connected networks or a filter in convolutional networks.

METHOD

- Redundant neurons selection (neuron importance evaluation)
  - $l = layer\ index, i = neuron\ index, N = \#neurons\ in\ a\ layer$
  - Mean of activations:

$$S_{\bar{R}}(l,i) = \sum_{j=1}^{N} R_{ij}^{l}$$

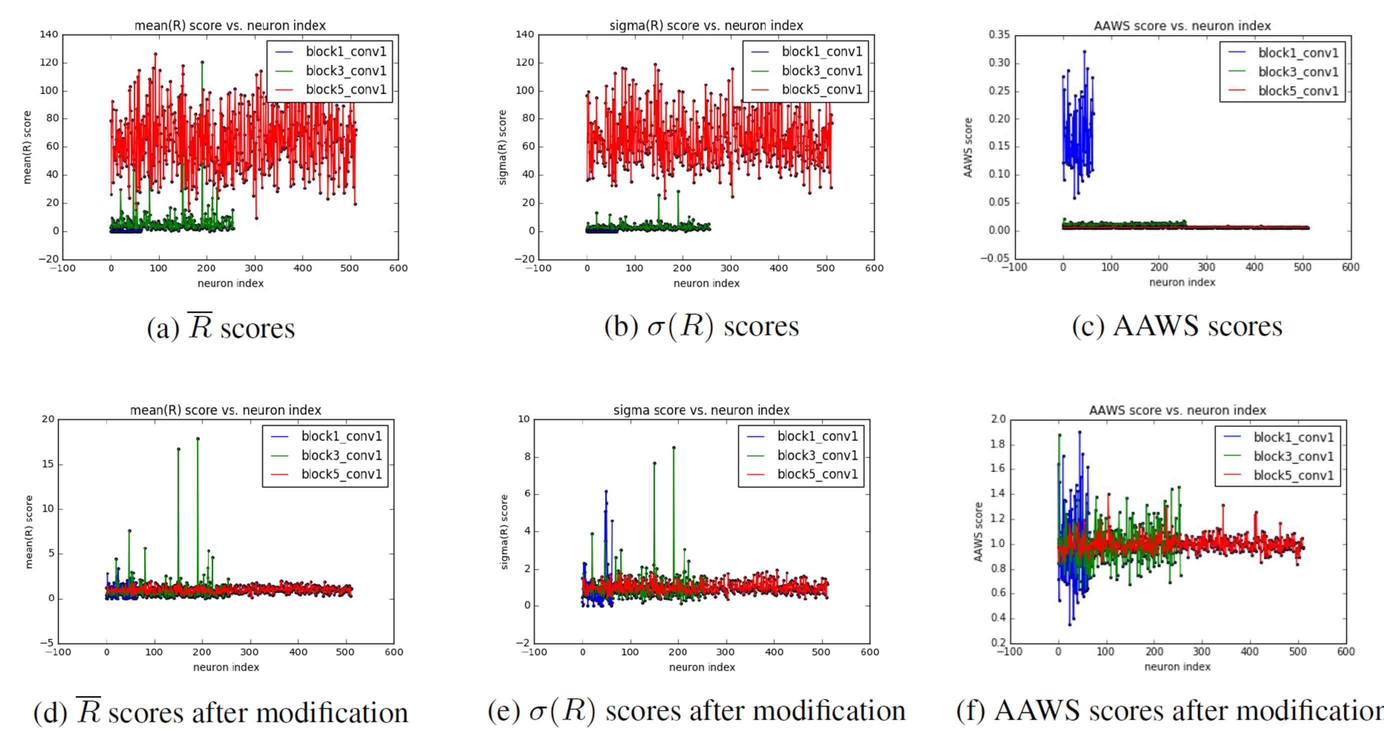
  - Standard derivation of activations:

$$S_{\sigma}(l,i) = \sqrt{\frac{\sum_{j=1}^{N}(R_{ij}^{l}-\bar{R})}{N}}$$

  - Average Absolute Weights Sum

$$S_{AAWS}(l,i) = \frac{1}{n_c \times n_m \times n_n} \sum_C \sum_M \sum_N |W_i^l|$$

  - $n_c \times n_m \times n_n$ is the number of elements in a filter, W_i^l is a parameter in the filter. We omit indexes for simplicity.
- The imbalance of scores in different layers



(a) $\bar{R}$ scores (b) $\sigma(R)$ scores (c) AAWS scores

(d) $\bar{R}$ scores after modification (e) $\sigma(R)$ scores after modification (f) AAWS scores after modification

Fig. 1: The score distribution of different metrics

- Adjust scores in different layers for feasible global pruning.

$$S_{modified}(l,i) = \frac{S(l,i)}{\frac{1}{N_l}\sum_{j=0}^{N_l} S(l,j)}$$

FRAMEWORK

Algorithm 1 Gradually global pruning scheme.

Input: A trained Model: M
Given performance target: P_t
Contribution score evaluator: $E(\cdot)$
Pruning ratio generator: r
Training set: X
Validation set: V
Output: A thinner model: M

```
Compute the performance P_m of M using V
while P_m ≥ P_t do
    Compute the contribution scores of all neurons in M with evaluator E(·)
    Sort the scores
    Select N × r neurons to be prune, where N is the number of neurons in current model
    Drop the selected neurons in the network, get M_drop, update M by M_drop
    Fine-tune M with training set X
    Update P_m by the performance of M over V
end while
return M
```

EXPERIMENT RESULTS

- Pruning VGG-like network for CIFAR-10 classification(Prop. for "proportional pruning neurons in each layer, not proposed.")

name	org.	$\bar{R}$	$\sigma(R)$	AAWS	Prop.
conv1_1	64	35(54.7%)	3(4.7%)	33(51.6%)	45(70.31%)
conv1_2	64	52(81.3%)	14(21.9%)	34(53.1%)	45(70.31%)
conv2_1	128	85(66.4%)	70(54.9%)	83(64.8%)	89(69.5%)
conv2_2	128	72(56.3%)	70(54.9%)	128(100.0%)	89(69.5%)
conv3_1	256	93(36.3%)	168(65.6%)	254(99.2%)	179(69.9%)
conv3_2	256	173(67.6%)	194(75.8%)	256(100.0%)	179(69.9%)
conv3_3	256	169(66.0%)	218(85.2%)	256(100.0%)	179(69.9%)
conv4_1	512	257(50.2%)	314(61.3%)	486(94.9%)	357(69.7%)
conv4_2	512	405(79.1%)	395(77.1%)	500(97.7%)	357(69.7%)
conv4_3	512	490(95.7%)	382(74.6%)	448(87.5%)	357(69.7%)
conv5_1	512	468(91.4%)	452(88.3%)	321(62.7%)	357(69.7%)
conv5_2	512	436(85.2%)	434(84.8%)	276(53.9%)	357(69.7%)
conv5_3	512	398(77.7%)	397(77.5%)	229(44.7%)	357(69.7%)
fc1	512	177(34.6%)	199(38.9%)	6(1.2%)	357(69.7%)
total	4736	3310(69.9%)	3310(69.9%)	3310(69.9%)	3304(69.8%)
acc.	87.32%	84.35%	81.88%	86.89%	86.54%

- Pruning VGG network for Kaggle cat/dog classification(transfer learning)

name	org.	neurons	name	org.	neurons
conv1_1	64	28(43.8%)	conv4_3	512	512(100.0%)
conv1_2	64	28(43.8%)	conv5_1	512	512(100.0%)
conv2_1	128	59(46.1%)	conv5_1	512	512(100.0%)
conv2_2	128	74(57.8%)	conv5_2	512	512(100.0%)
conv3_1	256	169(66.1%)	conv5_3	512	506(98.8%)
conv3_2	256	192(75.0%)	fc1	4096	4096(100.0%)
conv3_3	256	216(84.4%)	fc2	4096	392(9.6%)
conv4_1	512	495(96.7%)	total	12416	8302(66.9%)
conv4_2	512	511(99.8%)	acc.	98.24%	97.22%