Pruning Techniques for Convolutional Neural Networks based on Similarity of Hidden Units

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Abstract. When we solve a variety of problems using Convolutional Neural Networks (CNNs), we usually need to choose a moderate size of each layer in the net. Especially when there are complicated problems with large data, an appropriate size of network helps us reduce the running time and improve the efficiency of training process. In this situation, pruning techniques are essential as it can remove the excess units which perform no real function in the final output of the neural network. In this paper, I made a study of these hidden units and performed an easy but powerful pruning technique to remove one kind of them in CNNs with different size. After pruning, the network has a similar good performance as before. However, it performs worse when comparing to other modern pruning techniques these days.

1 Introduction

It is the generally assumption that a feed-forward CNN has two convolutional layers, two max-pooling layers and two fully connected layers in this paper. No lateral, backward or multilayer connections in the CNN. The CNN uses back-propagation for error measurement. General properties of excess units include low relevance, poor contribution, less sensitive and large badness. (T.D. Gedeon and D. Harris, 1991) When two units are too similar, one of them can be considered as an excess unit. According to Gedeon's article, vector angle is suggested as a measurement of similarity between units.

In this paper, I calculated the vector angle between pairs of hidden units in CNN's first fully connected layer and removed one of them when the angle is beyond some certain bounds. Size of the fully connected layer is considered and three networks with different size of hidden units are chosen in the experiment. After pruning on each network, the outcome is compared with other techniques from other published paper.

2 Method

Firstly, CNN basic structure with input layer, output layer, two convolutional layer, two pooling layer and two fully connected layer is built as in Figure1. MNIST is used as the dataset choice. Vector angle calculation is carried out on the first fully connected layer of each CNN. The parameter of the first CNN I chose is shown in Table1.

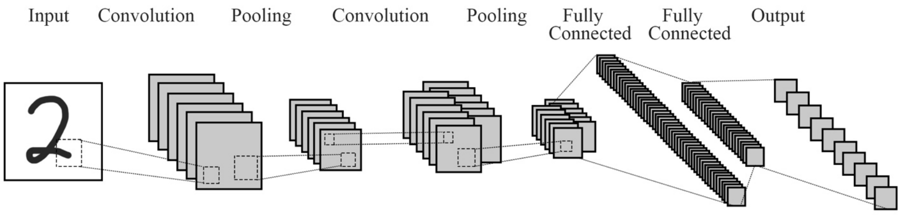


Figure 1. CNN Structure

Net1	Convolutional layer1	Pooling layer1	Convolutional layer2	Pooling layer2	Fully Connected layer1	Fully Connected layer2
input	1	10	10	20	320	50
output	10	10	20	320	50	10
Kernel	5*5	2*2	5*5	2*2		

Table 1. 1st CNN Parameters

Without any pruning, this network performed well and get 98% accuracy on test set after 5 epoch of training sessions. After the model finished its training, I calculated the vector angle on every pair of two hidden units on fully connected layer1. Then put the output in a sigmoid function to bound it between 0 and 1. After normalising the outcome from sigmoid function to 0.5, a bound is set. If the vector angle between two hidden units is less than the lower bound or larger than the upper bound, one of the two units will be deleted. The weight of the deleted unit was set to zero and its original weight will be added to the other unit which is preserved. The vector angle bounds I used in the pruning procedure are [60^o, 150 ^{o}], [65 ^{o}, 150 ^{o}], [70 ^{o}, 150 ^{o}], [75 ^{o}, 150 ^{o}], [80 ^{o}, 150 ^{o}].

3 Results and Discussions

The pruning result of the first network is shown in Table 2 and Figure 2.

From the results in Table 2 and Figure 2 below, it is easy to see that with appropriate pruning, the test accuracy can still stay high. And as every time at most one unit was removed from every pair if the vector angle reaches the bound, total pruning units will not exceed half of the total hidden units in fully connected layer 1. After removing almost half of the units, the network still performed well because I chose a large number of hidden units at initialization. So even half of the units are removed, it is sufficiently large number of units for CNN to predict the outcome. To prove my guess, I implemented the same pruning techniques on the other three networks. The parameters of these three networks are shown in Table 3 and Table 4.

Bound	Pruning units (Total: 320)	Accuracy After Pruning
[60°, 150 °]	37	96%
[65°, 150 °]	92	95%
[70°, 150 °]	137	83%
[75°, 150 °]	146	81%
[80°, 150 °]	158	87%

Table2. Pruning statistics on 1st CNN

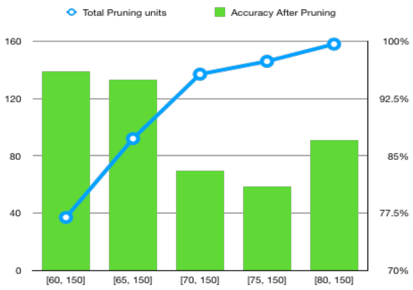


Figure2. Relationship between pruning number and test accuracy on 1st CNN

Net2	Convolutional layer1	Pooling layer1	Convolutional layer2	Pooling layer2	Fully Connected layer1	Fully Connected layer2
input	1	10	10	40	640	50
output	10	10	40	640	50	10
Kernel	5*5	2*2	5*5	2*2		

Table3. 2nd CNN Parameters

Net3	Convolutional layer1	Pooling layer1	Convolutional layer2	Pooling layer2	Fully Connected layer1	Fully Connected layer2
input	1	10	10	10	160	50
output	10	10	10	160	50	10
Kernel	5*5	2*2	5*5	2*2		

Table4. 3rd CNN Parameters

By applying 5 epoch of training and choosing the same pruning technique with same parameters as the first neural network, the pruning results of these two networks are illustrated in Table 5, Figure 3 and Table 6, Figure 4. The test accuracy of 2nd and 3rd network without any pruning are both 97%.

Bound	Pruning units (Total:640)	Accuracy After Pruning
[60^{o}, 150^{o}]	128	94%
[65^{o}, 150^{o}]	230	84%
[70^{o}, 150^{o}]	299	90%
[75^{o}, 150^{o}]	317	89%
[80^{o}, 150^{o}]	319	87%

Table5. Pruning statistics on 2nd CNN

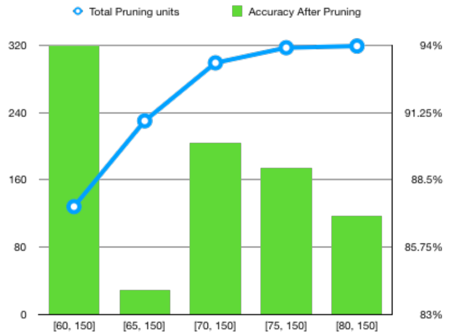


Figure3. Relationship between pruning number and test accuracy on 2nd CNN

Bound	Pruning units (Total : 160)	Accuracy After Pruning
[60^{o}, 150^{o}]	22	93%
[65^{o}, 150^{o}]	42	93%
[70^{o}, 150^{o}]	60	81%
[75^{o}, 150^{o}]	75	66%
[80^{o}, 150^{o}]	79	76%

Table6. Pruning statistics on 3rd CNN

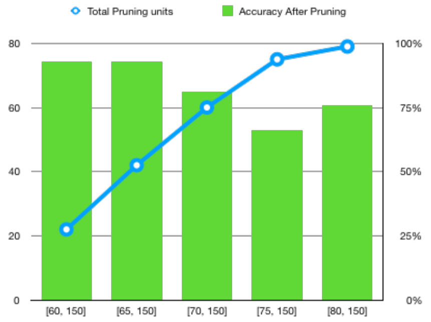


Figure4. Relationship between pruning number and test accuracy on 3rd CNN

To make it more clear, the test accuracy after same pruning technique implemented on 3 CNNs with different unit size is shown as below.

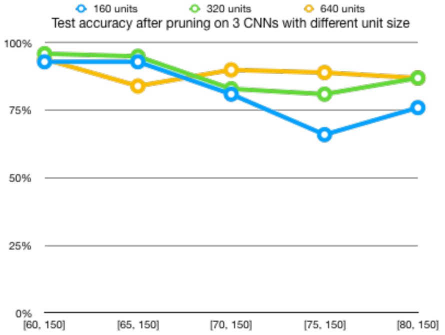
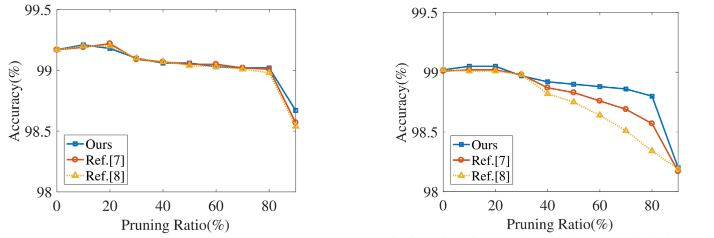


Figure5. Comparison of the pruning influences between 3 networks with different unit size

From the diagram above, it is clear that my guess mentioned before is correct. When the CNN has sufficient number of hidden units, the pruning operation does little bad influence on the final prediction result. However, when the number of hidden units is relatively small, the pruning implemented on it may decrease the final prediction accuracy. In other words, it is better to use the pruning technique on CNNs with larger number of hidden units.

Pruning the similar hidden units using vector angle calculation is an easy but very efficient way. There are also many other ways discussed and implemented by other people. For example, with the same MNIST dataset I used in this paper, filter level pruning based on similar feature extraction using k-means++ algorithm is carried out and performed really well. (Lianqiang LI and Yuhui XU, 2018) According to Lianqiang's paper, similar feature extraction are pruned on two convolutional layers and the test accuracy is shown below:



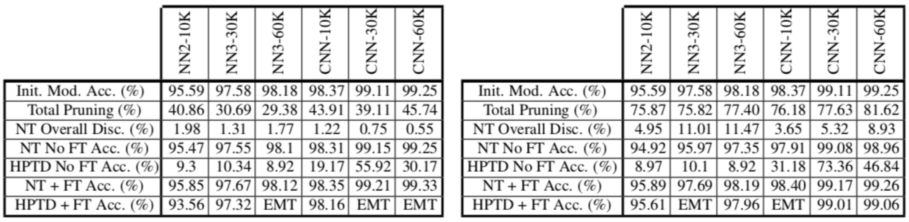
(a) Comparison of accuracy loss with the same sparsity in the first convolutional layer

(b) Comparison of accuracy loss with the same sparsity in the second convolutional layer

Figure6. Outcome of similar feature extraction pruning technique

From the trend graph above, we can see that similar feature extraction method using k-means++ algorithm perform better than the vector angle calculation method used in this paper. As the pruning ratio reaches 80% in Lianqiang's paper, the accuracy of network prediction still holds a high level around 99%.

And in another paper, convex optimization program is solved at each layer of CNNs to achieve pruning. (Alireza Aghasi and Afshin Abdi) According to that study, they use the MNIST dataset too and by doing the convex optimization on different-structured CNNs, they successfully finish the pruning work with an accuracy guarantee. The tables below show their works. On each CNN with distinctive complicated structure, the prediction accuracy remains pretty high after doing a 30%~82% pruning.



	NN2-10K	NN3-30K	NN3-60K	CNN-10K	CNN-30K	CNN-60K
Init. Mod. Acc. (%)	95.59	97.58	98.18	98.37	99.11	99.25
Total Pruning (%)	40.86	30.69	29.38	43.91	39.11	45.74
NT Overall Disc. (%)	1.98	1.31	1.77	1.22	0.75	0.55
NT No FT Acc. (%)	95.47	97.55	98.1	98.31	99.15	99.25
HPTD No FT Acc. (%)	9.3	10.34	8.92	19.17	55.92	30.17
NT + FT Acc. (%)	95.85	97.67	98.12	98.35	99.21	99.33
HPTD + FT Acc. (%)	93.56	97.32	EMT	98.16	EMT	EMT

(a)

	NN2-10K	NN3-30K	NN3-60K	CNN-10K	CNN-30K	CNN-60K
Init. Mod. Acc. (%)	95.59	97.58	98.18	98.37	99.11	99.25
Total Pruning (%)	75.87	75.82	77.40	76.18	77.63	81.62
NT Overall Disc. (%)	4.95	11.01	11.47	3.65	5.32	8.93
NT No FT Acc. (%)	94.92	95.97	97.35	97.91	99.08	98.96
HPTD No FT Acc. (%)	8.97	10.1	8.92	31.18	73.36	46.84
NT + FT Acc. (%)	95.89	97.69	98.19	98.40	99.17	99.26
HPTD + FT Acc. (%)	95.61	EMT	97.96	EMT	99.01	99.06

(b)

Figure7. Outcome of convex optimization pruning technique

A paper suggested that Neuron Importance Score Propagation (NISP) is a better way to do the pruning as compared to other pruning, the CNN with NISP pruning method converge fastest with lowest accuracy loss when the network is in re-trained session.

4 Conclusion and Future Work

Based on the work described above in this paper, similar and complementary hidden units at first fully connected layer of CNN are removed and the accuracy remains relatively high after the pruning. However, the pruning technique is better applied on a CNN with larger hidden unit number as we need to guarantee there are sufficient number of hidden units for basic model fitting.

With comparison to other pruning techniques, I found there are still many future works worth exploring. For instance, although the prediction accuracy stays high after pruning, we have no idea if the pruned model is strong noise resistant and this is certainly a future work area. And in this paper, a simple structured CNN model is used to do the pruning works. In the future, more complicated CNNs are going to be considered. Also, instead of one step pruning, multiple pruning steps are worth trying in the future.

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