PRUNING CONVOLUTIONAL NEURAL NETWORKS FOR IMAGE INSTANCE RETRIEVAL

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ABSTRACT

In this work, we focus on the problem of image instance retrieval with deep descriptors extracted from **pruned** Convolutional Neural Networks (CNN). The objective is to heavily prune convolutional edges while maintaining retrieval performance. To this end, we introduce both data-independent and data-dependent heuristics to prune convolutional edges, and evaluate their performance across various compression rates with different deep descriptors over several benchmark datasets. Further, we present an end-to-end framework to fine-tune the pruned network, with a triplet loss function specially designed for the retrieval task. We show that the combination of heuristic pruning and fine-tuning offers $5 \times$ compression rate without considerable loss in retrieval performance.

Index Terms— CNN, Pruning, Triplet Loss, Image Instance Retrieval, Pooling

1. INTRODUCTION

Image instance retrieval is the problem of retrieving images from a large database that contain or depict similar objects to a target image. Convolutional Neural Networks (CNN)-based descriptors [1, 2, 3, 4, 5] have recently been used to generate compact image descriptors with high retrieval performance, and are rapidly becoming the dominant approach for retrieval problem. Their major drawback is the size of their models, running into hundreds of megabytes.

Smaller networks are desirable for use in mobile and embedded applications, where storage, transmission, and computational power is limited. For efficient hardware implementations of deep neural networks, smaller networks reduce cost and improve chip performance. Storing the entire network on-chip allows fast access and reduce processing latency. There are also gains in distributed training, where network latency bottlenecks the sharing of updated parameters, and smaller networks significantly improve speed. Finally, emerging MPEG standards like Compact Descriptors for Visual Search (CDVS) [6] and Compact Descriptors for Video Analysis (CDVA) [7] require memory-efficient models for streaming and hardware implementations.

Model compression strategies reduce the computational, memory, and bandwidth costs; and pruning is a common first technique. Pruning algorithms reduce network size by discarding edges or nodes, and can be heuristic or analytic [8]. Modern pruning algorithms have thus far been evaluated on CNN performing image classification with a softmax loss function; we investigate the adaptation of these algorithms to image instance retrieval problem, and present an empirical evaluation of their effectiveness.

1.1. Related Work

Image Instance Retrieval with CNN. Image retrieval systems generally construct a *global image descriptor*, a vector that represents the contents of an image. Instead of descriptor extracted from fully-connected layer, state-of-the-art use the intermediate output of CNN (e.g. convolutional layers) with additional pooling operations to generate descriptors [1, 2, 3]. The application of multi-scale and multi-rotation feature construction and pooling further improves scale- and rotation-invariance [4, 9]. Very recently, pre-trained CNNs for ImageNet classification are repurposed for the image retrieval problem, by fine-tuning them with retrieval specific loss functions such as triplet loss [10, 11, 12].

Network Pruning Heuristic pruning algorithms generally assign either nodes or edges *salience* scores and remove those with the lowest scores [8]. In early neural network literature there was a considerable interest in developing such algorithms. Heuristics include *Optimal Brain Damage* by LeCun et al. [13]; derivative-based methods by Mozer and Smolensky [14], and Karnin [15]. Other work removes nodes where the weights of incoming connections has the smallest variance, but this has been mostly studied in the realm of fault tolerance [16].

In current networks, a popular strategy is the removal of low-magnitude edges. Han et al. [17] demonstrates this simple strategy on AlexNet, reducing the number of free parameters by a factor of $9\times$ by pruning alone without any loss in image classification performance. Their reported results heavily prune edges from fully-connected layers (\sim 89% are pruned); on convolutional layers alone, 37% of convolutional edges are dropped. Thus, the majority of the savings comes from the fully-connected layers, which contain 96% of the parameters of the entire network.

There are also analytic algorithms compress networks layer-by-layer, replacing the convolution matrix with a compressed representation. This compression is achieved by removing redundancy in the function that each layer computes. This approach has been vigorously explored in recent years, with work by Kim et al. [18], Mariet and Sra [19], Lebedev et al. [20], and Denton et al. [21] each with different redundancy reduction mechanisms.

1.2. Contributions

Compared to fully-connected layers that contain the most redundancy, heavily pruning edges on convolutional layers is more challenging. In this work, we focus on heuristic criteria to prune convolutional edges especially for image instance retrieval. We make the following contributions:

 We investigate both data-independent and data-dependent heuristics to prune convolutional edges. We perform a thorough evaluation across various compression rates and deep pooled descriptors over several benchmark datasets. Results

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suggest that heuristic pruning is capable of reducing the network size by $2\times$ without retrieval performance loss.

 We introduce an end-to-end framework for fine-tuning pruned network, specially tailored to image instance retrieval with a triplet loss function. Combining pruning and rank-based finetuning can provide a factor of 5× compression with minimal loss in retrieval performance.

2. METHOD

2.1. Pruning Convolutional Edges

We consider different heuristics to assign salience scores[8] to edges. Consider an arbitrary layer in a neural network, N_i is a random variable following the activation of the i^{th} node when presented with data from a training set, $w_{i,j}$ is the weight of the edge connecting that node to the j^{th} node in the next layer, \mathcal{L} is the value of the loss function when run on some data. From existing literature, we consider computing the following heuristics for each edge:

- 1. $|w_{i,j}|$, the simplest heuristic, requiring no data. This was recently popularized by Han et al. [17].
- 2. $\frac{d\mathcal{L}}{dw_{i,j}}w_{i,j}$, which was recently used by Molchanov et al. [22] to prune networks for transfer learning. This is justified as the Taylor expansion of the function computing the difference in loss function with and without the weight $w_{i,j}$, and is shown to be applicable to transfer learning.
- 3. $\langle |N_i| \rangle \cdot |w_{i,j}|$ Mean activation.
- 4. $Var[N_i] \cdot w_{i,j}^2$ Variance of activation.

One may notice that heuristic 2 requires data with ground-truth labels to compute the loss-function term $(\frac{d\mathcal{L}}{dw_{i,j}})$. Computing heuristic 3 and 4 requires data, but does not require that it have labels.

In order to prune the network to a fraction t of its original size, we first compute the salience score for each edge in the network. We then sort all salience scores across all layers and select the threshold salience value, τ , such that (1-t) of the salience scores are below this value. We then remove all edges with salience scores less than τ . Throughout our experiments, we report the network size as the total fraction of edges removed. We do not prune bias nodes or report them in the network size.

2.2. Convolutional Feature Pooling

In constructing the global image descriptor we append a pooling layer to the pruned network. The pooling function employed is critical to the performance of the model. In this work, we consider Square-root pooling (SQP) [23] and Regional-Maximum Activations of Convolutions (R-MAC) [4] pooling functions. Consider an arbitrary image X, with C feature maps $\{x_1,...,x_C\}$ extracted from intermediate layer, x_c is a feature map of width W and height H. Square-root pooling, $f_2(\cdot)$ is defined as

$$f^{\text{SQP}}(\boldsymbol{x}_c) = \sqrt{\frac{1}{W \cdot H} \sum_{i=1}^{W \cdot H} x_{c,i}^2}.$$
 (1)

R-MAC [4] pooling is computed by first performing maximum pooling over regions of interest (ROI), then average pooling.

$$f^{\text{R-MAC}}(\boldsymbol{x}_c) = \frac{1}{N_{\text{ROI}}} \sum_{i=1}^{N_{\text{ROI}}} \max_{j \in [1, S_{\text{ROI}}]} (x_{c,j}^i), \tag{2}$$

where S_{ROI} is the number of ROIs, and \boldsymbol{x}_c^i denotes the i^{th} ROI sampled from feature map \boldsymbol{x}_c , with size $S_{\text{ROI}} < W \cdot H$.

2.3. Triplet-based Fine-tuning

To fine-tune remaining parameters in an end-to-end manner, we need to design a loss function for the pruned network. Following existing work by Arandjelović et al. [11], Gordo et al. [12], we define a triplet (X^q, X^+, X^-) that contains the query image X^q , a positive matching image X^+ and a negative, non-matching image X^- . The images are selected so that query image X^q is more similar to positive image X^+ than to the negative image X^- . The triplet should meet the condition that $K(X^q, X^+) > K(X^q, X^-)$, where K is a function computing pairwise image similarity.

Accordingly, we define the triplet loss as:

$$L_{q,+,-} = \max\{0, m + K(X^q, X^-) - K(X^q, X^+)\}, \quad (3)$$

where m is a positive margin parameter.

Following [2], we define the similarity measure K as:

$$K(X,Y) = \beta(X)\beta(Y)\sum_{c=1}^{C} k(f(\boldsymbol{x}_c), f(\boldsymbol{y}_c)), \tag{4}$$

where f(.) denotes the pooling operation applied on feature maps, $k(f(\boldsymbol{x}_c), f(\boldsymbol{y}_c)) = \langle f(\boldsymbol{x}_c), f(\boldsymbol{y}_c) \rangle$ is the scalar product of the pooled features, $\beta(.)$ is a normalization term computed by $\beta(X) = \sqrt{\sum_{c=1}^C k(f(\boldsymbol{x}_c), f(\boldsymbol{x}_c))}$.

3. EXPERIMENTS

We begin with a VGG-VeryDeep-16 network [24] pre-trained on ImageNet, and keep only the layers from the input up to and including the last pooling layer pool5. Convolutional layers are pruned using each of the four heuristics, then fine-tuned for 20 epochs on the image retrieval task using the triplet loss function discussed earlier. All pruning and fine-tuning, are implemented with the MatConvNet library, with the 3D-Landmarks [25] dataset. Testing is performed on the INRIA Holidays [26], Oxford5k [27] and Paris6k [28] datasets which consist of outdoor scenes and buildings; and the UKbench [29] dataset which features close-up shots of objects in indoor environments.

In all reported results, the accuracy metric for the Holidays, Oxford5k, and Paris6k datasets is the mean average precision (MAP), and the metric for the UKbench dataset is 4×recall@4. Note that we report results without post-processing (e.g., PCA whitening) on pooled features.

3.1. Pooling Features

We first pruned the convolutional layers of VGG-VeryDeep-16 using the four heuristics discussed earlier. Each network was pruned to five different sizes, from 10% to 50% of the original network size. The performance of each pruned network on each of the four datasets is presented in Figure 1.

From Figure 1, we observe that heuristic 1 (magnitude of edge) consistently performs better than the other heuristics. In fact, until about 40% of the edges are remaining, networks pruned with heuristic 1 perform not significantly worse than unpruned networks. This corresponds to a $2.5\times$ savings in size for minimal computational and implementation effort.

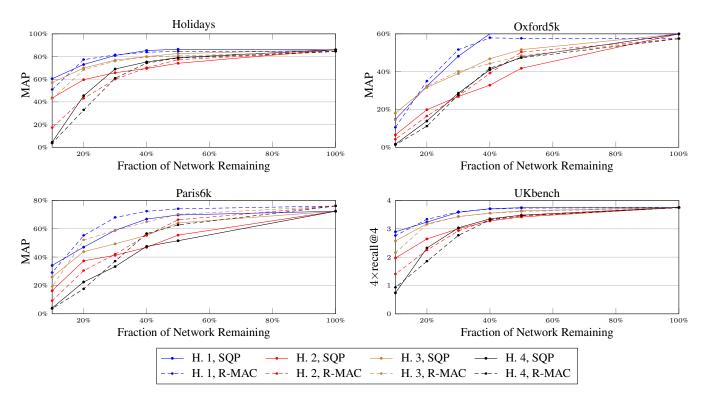


Fig. 1. Performance of pruned networks by remaining network size across different datasets. In each dataset, lines are colored by pruning heuristic and dashed by pooling feature (solid lines use SQP pooling, dashed lines use R-MAC). No fine-tuning was performed. We observe that Heuristic 1 consistently performs better than the other heuristics, and the use of SQP features over R-MAC improves performance.

Additionally, we observe that the accuracy graphs of networks seldom intersect, and so heuristic 1 dominates the entire domain. This, along with the advantage of requiring minimal computation and no data, suggests that heuristic 1 is better suited to practical implementations than the other heuristics proposed.

We also use the data in Figure 1 to compare the performance of SQP and R-MAC features. Across three out of four datasets, SQP features perform better than networks with R-MAC features pruned to the same size. From this, we observe that SQP features are generally superior, providing around 2 percentage points' performance gain over R-MAC. Thus, we choose SQP for fine-tuning in the subsequent sections.

3.2. Fine-tuning

As established by Han et al. [17, 30], fine-tuning pruned networks can recover image classification performance lost in pruning. To investigate this effect for image instance retrieval, we fine-tuned networks pruned with each heuristic, and then evaluated their performance. These networks were pruned to 50% of their original size, and evaluated with SQP. Figure 2 shows the performance of these networks before and after fine-tuning.

We observe that in two of the four datasets, fine-tuning improves performance significantly, regardless of the pruning heuristic. Even after 50% pruning, the mean average precision of these networks approaches 80%. Also, after fine-tuning, heuristic 1 reports higher performance in all datasets. This further supports our earlier recommendation of heuristic 1, and corroborates the work of Han et al. [17, 30].

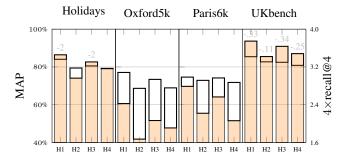


Fig. 2. Performance of 50% pruned networks on different heuristics, grouped by dataset. The colored bar represents performance before fine-tuning, and the clear bar represents the change in performance with fine-tuning for 20 epochs. The number above each bar is the change in percentage points or value. We observe that fine-tuning greatly improves the performance across Oxford5k and Paris6k datasets, suggesting that it is an important step in our pruning pipeline.

We note that fine-tuning decreases the $4 \times recall@4$ score on the UKbench dataset, regardless of heuristic used. This is likely because fine-tuning on the building-centric 3D-Landmarks dataset transfers well to Oxford5k and Paris6k, but poorly to the object-centric UKbench dataset.

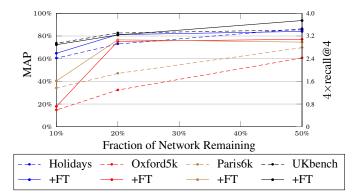


Fig. 3. Performance (with SQP pooling) of networks pruned by heuristic 1, before and after fine-tuning (FT). Pruning the network reduces performance significantly, but fine-tuning can generally restore most of the performance.

3.3. Pruned Network Size

We now investigate the size of the network pruned and its effect on accuracy. As per our earlier recommendation, we choose several networks pruned (to different sizes) with heuristic 1, pooled with SQP, and fine-tuned. We evaluate their performance on each of testing datasets before and after fine-tuning, and present the results in Figure 3.

We note that networks pruned to 20% of the initial model size exhibit poor performance compared to networks pruned to 50%, but this gap in performance diminishes upon fine-tuning. Fine-tuning allows us to improve compression rate from a factor of $2\times$ to $5\times$ with minimal performance penalty.

This performance improvement does not extend to networks pruned to 10% of their initial size. While these networks generally exhibit improvement in performance, their performance does not reach the performance of networks pruned to 50% of their size. This discontinuity suggests that the pruning algorithms are no longer able to exploit redundancy in the model, and further pruning will worsen performance. The minimum model size without loss of performance lies between 10-20% of the original model size.

Further investigation in this threshold is warranted. We observe this transition at around the same range in all datasets, suggesting that this is a property of the network or the heuristic. Further experiments may show that the heuristics perform differently at extremely small sizes and with little redundancy.

3.4. Pruned Layer Sizes

We chart the size of each convolutional layer in the network in Figure 4 for three different sizes when pruned with heuristic 1. As the network size shrinks, layers further up the network lose convolutional edges disproportionately more quickly. Even when the network is pruned to 10% of its original size, the lowest layer still retains 95% of its edges, and the highest layers retain only about 8% of their edges. This same trend is observed across all heuristics.

4. CONCLUSIONS

Pruning edges on convolutional layers is a more challenging operation than on fully-connected layers. In this work, we presented an end-to-end framework for compressing CNN, specially tailored to

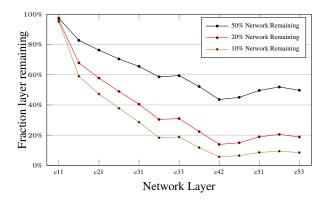


Fig. 4. Fraction of each layer remaining after different amounts of pruning (with heuristic 1). We observe that the layers closest to the data are pruned the least, a pattern that is consistent with all heuristics. This is likely because our pruning leverages the increasing redundancy in higher layers.

efficiently pruning convolutional edges with a triplet loss function. We present thorough evaluation across varied pruning parameters and deep features on several datasets. Our experiments suggest that pruning and fine-tuning can provide a factor of $2\times$ to $5\times$ compression with minimal loss in performance.

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