Domino Saliency Metrics: Improving Existing Channel Saliency Metrics with Structural Information

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Abstract. Channel pruning is used to reduce the number of weights in a Convolutional Neural Network (CNN). Channel pruning removes slices of the weight tensor so that the convolution layer remains dense. The removal of these weight slices from a single layer causes mismatching number of feature maps between layers of the network. A simple solution is to force the number of feature map between layers to match through the removal of weight slices from subsequent layers. This additional constraint becomes more apparent in DNNs with branches where multiple channels need to be pruned together to keep the network dense. Popular pruning saliency metrics do not factor in the structural dependencies that arise in DNNs with branches. We propose Domino metrics (built on existing channel saliency metrics) to reflect these structural constraints. We test Domino saliency metrics against the baseline channel saliency metrics on multiple networks with branches. Domino saliency metrics improved pruning rates in most tested networks and up to 25% in AlexNet on CIFAR-10.

Keywords: Convolutional Neural Networks · Pruning · Machine Learning

1 Introduction

Deep neural networks can reach human level accuracy for many classification problems [31], but they have huge memory and computation cost. Pruning reduces the size of neural networks via the removal of unnecessary weights [27, 9]. Channel pruning removes weights corresponding to an entire channel in the output of a layer. When the weights of the entire channel are set to zero, the corresponding output feature map of the channel becomes zero. This zero output feature map feeds into subsequent layers which may allow the corresponding channel to be removed from these subsequent layers in a domino effect.

In a network architecture where each layer has exactly one output and one input layer, the removal of an output feature map leads to the following layer’s input feature map no longer contributing to the network. This scenario is illustrated in Figure 4 where the consumer layer is a convolution or fully-connected
layer, the resulting zero input channel allows the corresponding weights from the consumer layer to be pruned.

In networks with branches/splits, the output feature map from one layer may feed into multiple others. With joins, feature maps from different layers feed into a single layer. A common occurrence of split and join connections in CNNs is due to skip connections, which were first pioneered in ResNet architectures. The common structure of a ResNet block containing join and split connections is shown in Figure 1. The presence of these joins allows multiple output feature maps to be removed together when one feature map is considered for removal. Networks that offer state-of-the-art accuracy for image classification often contain skip connections [1,36,35,23,32]. ResNet architectures are also more difficult to prune for their lower redundancy [21,5,14]. Hence, improving pruning rates for networks containing skip connections can be very advantageous.

Another common occurrence of joins is group convolution. Group convolution was originally used in the AlexNet architecture [16] to parallelise convolution on multiple GPUs. Since, it has also been used in state of the art architectures [35,1].

Most approaches do not factor in the removal of different feature maps when computing the saliency metric used for pruning. We propose using Domino saliency metrics to factor in the saliency of feature maps and weights that need to removed together. We make the following contributions: (1) We propose Domino saliency metrics, where existing saliency metrics are combined together depending on the set of channels that need to be removed together. (2) Combining channel saliency metrics to obtain Domino saliency metrics, has a negligible computational cost to computing channel saliency metrics and requires very little modification to existing pruning strategies. (3) We experimentally evaluate two variants of Domino saliency metrics: Domino−o and Domino−io, and find that they significantly improve pruning.

Fig. 1: Structure of a block in ResNet-20. The direction of arrows show the direction in which data flows.
2 Data Flow Graph for Pruning

2.1 Background

Pruning is the removal of weights from the network. The pruned weights are set to zero. Pruning can be done in an unstructured or structured way. Unstructured pruning removes weights from the network without any given constraint in pattern. On the other hand, structured pruning removes weights in a chosen pattern. Common patterns for structured pruning are (in increasing size of pattern): intra-kernel, kernel, and channels (or filters).

Channel pruning removes entire channels from convolution layers of the network. By removing entire channels, the weight tensor remains dense, so existing DNN dense libraries can be used. The removal of an entire channel of convolution weights leads to the removal of its subsequent feature map. Removing a feature map may allow corresponding weights from subsequent layers to be removed. In a network where each layer has at most one input layer and output layer, this relationship is obvious.

2.2 Channel Pruning Networks with Splits and Joins

While simpler neural networks are often linear and acyclic [15][16], modern networks often contain join nodes and split nodes [16][11].

It is obvious which weights need to be removed when applying channel pruning to a network where each layer is fed to only one successor. However in networks with branches, feature maps are used by more than one layer. A layer can have multiple successors due to skip connections. Skip connections are elementwise additions between output feature maps of different convolutions to produce the input feature map of the following layer.

In networks with branches, applying a reachability analysis such as is performed by a compiler on a more traditional computational structure, the control-flow graph, to uncover the weights that need to be pruned together to keep the network dense. The basic intuition here is that if the definition of some feature map reaches a layer, the pruning of that feature map may also imply the removal of more feature maps which are computed from it. While this seems trivial for linear networks, the introduction of splits and joins in the graph mean that extra care must be taken in order to exploit the dependence relationship to achieve better pruning results.

2.3 Data Flow Graph

Neural networks form a directed graph structure where simple input-output dependence exists between producer and consumer layers in the network (i.e. the network forms a data flow graph). When representing the data flow graph, we can make abstraction of activation layers (see Section 2.6). Hence, we only need to represent the data flow between a convolution or fully-connected layer to other convolution or fully-connected layers.
We introduce some notation to facilitate the description of the data flow graph. A layer $l$ has a set of 3-dimensional input feature maps $I(l)$, a set of 3-dimensional output feature maps $O(l)$ and weights $W^l$ (with shape $m_{out}^l \times m_{in}^l \times k_l^l \times k_l^l$). $O_i(l)$ and $I_i(l)$ refer to the $i^{th}$ 2-dimensional feature map of $O(l)$ and $I(l)$ respectively. We can describe the flow of information between layers with a successor relation $O(l) = I(\text{succ}(l))$ intuitively, the data flow successors $\text{succ}(l)$ of a layer $l$ are those layers whose input is the output of layer $l$.

When a layer in a neural network joins the output of multiple producer channels, we write $O(l) \subset I(\text{succ}(l))$ i.e. the successor relation extends to any channel which consumes the output of $l$. If $I(l+1)$ is the input feature map of the following, then it is the direct successor of $O(l)$.

### 2.4 Join and Split Nodes

$I(l+1)$ is not necessarily the only successor of $O(l)$. For example, in Figure 2a the elementwise sum of two layers $l$ and $l'$ is fed to layer $l+1$. $l+1$ satisfies $O(l) \subset I(l+1) \land O(l') \subset I(l+1)$. We can also consider data dependencies for a single channel, $C_i^l$, instead of an entire layer, $l$, with $O(C_i^l) = O_i(l)$. So we would say that both $\text{succ}(C_i^l) = \{C_i^{l+1}\}$ and $\text{succ}(C_i^{l'}) = \{C_i^{l'+1}\}$. Split, or broadcast relationships also exist, where the output of a layer is used by multiple consumers. An example of split in the data flow graph is seen in Figure 2b where $\text{succ}(C_i^l) = \{C_i^{l+1}, C_i^{l+2}\}$.

![Fig. 2: Data dependencies with join and split connections in CNNs. The arrows are in the direction of data flow.](image)

### 2.5 Group Convolution

Data dependencies at the entrance of group convolutions can be modeled using a simple convolution layer that has $g$ sets of input feature maps that result in $g$ sets of partial output feature maps. These partial output feature maps are then added together to create the final output feature map of the layer. We have $m_{in}^{l+1} = \frac{m_{in}^l}{g}$ with the group size, $g > 1$. Figure 3 illustrates a group convolution with a group size of 2.
Hence, \( O(C_{i-1}^l) \subset I(C_i^l) \land O(C_{i+1}^{l-1}) \subset I(C_i^l) \). In Figure 3b, \( \text{succ}(C_{i}^{l-1}) = \{C_i^l, C_{i+2}^l\} \).

Considering a neural network graph with \( G \) channels, we can define the successor relation as:

\[
\forall c \in G, \exists x \in G : O(c) \subset I(x) \Rightarrow x \in \text{succ}(c) \quad \text{(SUCCESSOR)}
\]

Let the predicate \( P(c) \) be true where a feature map \( c \) is being pruned, and false otherwise. The truth of \( P(c) \) is determined locally for the input or output feature maps of a specific layer by the pruning process.

We are interested in how the truth of \( P(c) \) locally in any single layer may influence the truth of \( P(c) \) for connected layers in the network, or more informally, how pruning some feature maps may imply the pruning of other feature maps.

\[
\forall c \in G, \forall x \in \text{succ}(c) : P(O(c)) \Leftrightarrow P(I(x)) \quad \text{(CHANNEL PRUNING)}
\]

Equation CHANNEL PRUNING states that the pruning an output feature map \( O(c) \) is materially equivalent to pruning the input feature map \( I(x) \), with \( x \) a successor of \( c \). This predicate is valid for all the channels in the network. Hence, in a typical ResNet style block this leads to the simultaneous pruning of multiple channels. In Figure 1, feature maps A-I need to be removed simultaneously.

Equation CHANNEL PRUNING is used to propagate pruning of feature maps. However, for channel pruning we need to remove weights from the network. To prune an output channel, \( c = C_i^l \), from the network, weights \( W[l,i,:,:,] \) are removed from network with “:” representing all valid indices. Hence, when a feature map \( O(C_i^l) \) is pruned, \( W[l,i,:,:,] \) is pruned and when a feature map \( I(C_i^l) \) is pruned, \( W[l,:,i,:,:,] \) is pruned.

2.6 How to Prune Biases and Activation Layers

The output of a convolution is not often fed directly to the next convolution or fully-connected layer. Instead, at least one activation function is applied to the feature map before being fed to the next layer. Hence, the output feature map produced by a layer is not directly equivalent to the input feature map of the following layer.

For most activation functions, applying them to a zero feature map results in a zero feature map. ReLU, GELU, and max/average pooling layers, are examples of activation functions that output zero for a zero input. When these activation functions are used, a pruned output feature map results in pruned input feature maps of the subsequent layers. However, in the case of activation functions with biases such as Batch Norm or bias layers, a zero input does not always result into a zero output unless the biases are also set to zero. Hence, the pruned feature map and the pruned weights cannot be removed from the network. However, if the corresponding biases are set to zero, the weights can then be removed from the network.
Fig. 3: Data flow with group convolutions in CNNs. The arrows are in the direction of data flow.

Fig. 4: Channel pruning where the outputs of convolution $l$ are fed into an activation layer (with bias), $z^l$ before being fed to the successor $l+1$. 
A simple channel pruning case is shown in Figure 4. For the convolution layer \( l \), to produce a single \( O_i(l) \) each \( j^{th} \) input feature map is convolved with its corresponding 2D filter \( W_l[i, j, :, :] \) and summed together. In Figure 4, \( O_0(l) = z_l^{-1}(O_0(l-1))*W_l[0, 0, :, :] + z_l^{-1}(O_1(l-1))*W_l[1, 0, :, :] \) and \( O_1(l) = z_l^{-1}(O_0(l-1))*W_l[0, 1, :, :] + z_l^{-1}(O_1(l-1))*W_l[1, 1, :, :] \). To prune the output channel \( C_l0, W_l[0, 0, :, :] \) and \( W_l[0, 1, :, :] \) are set to zero. If the corresponding bias in the activation layer \( z_l(B_{l0}) \), is set to zero, then the input feature map \( z_l(O_0(l)) \) is also zero. Since convolution with a zero feature map results into a zero feature map, the values of \( W^l[0, 0, :, :] \) and \( W^l[1, 0, :, :] \) no longer influence feature maps \( O_0(l+1) \) and \( O_1(l+1) \). Hence, \( W^l[0, 0, :, :], W^l[0, 1, :, :], B_{l0}, W^{l+1}[0, 0, :, :], \) and \( W^{l+1}[1, 0, :, :] \), can be set to zero and removed.

If the biases are not set to zero, then feature maps filled with zeroes still need to be stored to keep the network dense. In practice, output feature maps filled with zeroes are removed from the network to increase memory savings. Hence, biases of activation functions are also set to zero and the obsolete parameters are removed to keep the network dense. Hence, to simplify the data flow graph, we can make abstraction of activation functions even if they contain biases. We can also assume that when a channel is pruned, weights, feature maps and activation layer parameters of that channel are set to zero.

3 Domino Pruning

When pruning neural networks with skip or group connections, most approaches use the same saliency metrics as for simple forward feed neural networks without any modification. The construction of these saliency metrics do not take into account the structural dependencies that may to be satisfied between layers to keep the network dense.

We argue that a more straightforward inspection of the data dependence structure may be more prudent. Using a reachability analysis such as may be performed by a compiler, we show how the removal of one set of parameter may be used to heuristically perform a cascade of removals of other reachable parameters. We refer to this technique as “Domino” saliency metrics. Any saliency metric that has been formulated to give each channel a saliency measure can be used with Domino saliency metrics.

\[
\forall x \in \text{succ}(c), \exists y : x \in \text{succ}(y) \Rightarrow y \in \text{coparent}(c) \quad \text{(COPARENT)}
\]

\[
\forall x \in \text{succ}(c), \exists y : y \in \text{succ}(c) \Rightarrow y \in \text{Sibling}(x) \quad \text{(SIBLING)}
\]

With Domino pruning, the output channels that are considered coparents are considered as a single pruning choice. Hence, they cannot be removed without the other coparent output channels. Output channels are considered coparent if they share a common successor as shown in Equation COPARENT. Similarly Equation SIBLING is used to find siblings of direct successors. We
consider the coparent and sibling relationships to be bi-directional and transitive, i.e., if $A \in \text{coparent}(B)$ then $B \in \text{coparent}(A)$ and if, $C \in \text{coparent}(B)$ then $C \in \text{coparent}(A)$. coparents$^+$ and siblings$^+$ are the transitive closure of the coparent and sibling relationships. When $c$ is an output channel, then siblings$^+(c)$ represents the transitive closure of any of $c$’s successors and when $c$ is an input channel, coparents$^+(c)$ represents the transitive closure of any output channel that is used to produce $c$. The feature maps and weights removed when one output channel is removed is given by Equation [CHANNEL PRUNING]. The set of parameters coparents$^+(c) \cup$ siblings$^+(c)$ is pruned when the output channel $c$ is pruned. In the case of a network with no joins and no splits $\text{coparents}^+(c) = \{c\}$ and $\text{siblings}^+ = \text{succ}(c)$.

Saliency metrics are traditionally computed for a single output channel. This is also true for networks with skip connections (ResNets). With Domino metrics we combine the channel saliency of channels that are removed together.

We propose two variants of Domino saliency: Domino $- o$ and Domino $- io$. Domino $- o$ adds the saliency of all output channels that are removed together. Since most channel pruning algorithms use the channel saliency of output channels, Domino $- o$ has negligible cost and require minimal change to the pruning algorithm. Equation [1] describes how to compute Domino $- o$ for a channel using coparents$^+$ and their channel saliency $S$.

\[
\text{Domino}(c) = \sum_{x \in \text{coparents}^+(c)} S(x) \quad (1)
\]

As illustrated in Figure [4], the output feature produced by a convolution channel ultimately becomes the input feature map for the following layer. Few approaches apart from feature reconstruction based metrics, exploit this relationship for saliency computation. With Domino $- io$, we add the saliency of all the weights or feature maps that are removed when a channel is removed to get the saliency of the channel to be pruned. Equation [2] shows how to compute Domino $- io$ using the channel saliency of coparents$^+$ (output feature maps or weights) and siblings$^+$ (input feature maps or weights) using a channel saliency $S$.

\[
\text{Domino} - io(c) = \sum_{x \in \text{coparents}^+(c)} S(x) + \sum_{x \in \text{siblings}^+(c)} S(x) \quad (2)
\]

4 Experimental Evaluation

Channel saliency is the use of the saliency metric of a single output channel to prune all the dependent weights and feature maps. This is the common strategy when pruning networks. In practice, this leads to the lowest saliency of the output channels that are pruned together to be used as saliency metric of the set of weights or feature maps to be pruned. This baseline is denoted $S$.

We compare Domino saliency metrics constructed using a channel saliency against the use of the base channel saliency.
A Domino saliency metric is built using a baseline channel saliency metric. If the saliency of all channels are roughly of the same order and positive, their addition is of greater order than channels that are not part of split or join nodes. We use an average of the number of weights or output points to avoid favoring isolated channels for pruning. Saliency metrics that use feature maps are scaled using the number of pixels in the feature maps. For example, if two saliency $S(c)$ and $S(z)$ are computed using $N_c$ and $N_z$ weights then, the Domino-scaled metric is $\frac{S(c)+S(z)}{N_c+N_z}$ instead of $S(c) + S(z)$. The scaled channel metrics are $\frac{S(c)}{N_c}$ and $\frac{S(z)}{N_z}$. Metric with this average is suffixed with -avg.

4.1 Pruning Algorithm

The saliency metric is one component of the pruning algorithm. We choose a pruning algorithm that heavily relies on the choices of the saliency metric to determine the improvement brought by changing the saliency metric. Since our aim is to find better saliency metrics, we avoid obfuscating the contribution of the saliency metric by not retraining after each pruning step. If a saliency metric is able to achieve higher pruning rates without retraining, then it can also be used to reduce the cost of retraining\(^\text{29}\).

For each pruning iteration we compute the saliency of every output channel. The lowest saliency channel is then pruned according to Equation \text{Channel Pruning}. This process is repeated until the test accuracy falls under 5% of its initial value.

4.2 Networks

We evaluate Domino saliency metrics on popular architectures with split and join nodes. We evaluate the original ResNet architecture\(^\text{11}\) and a state-of-the-art ResNet-inspired architecture, NFNET-F0\(^\text{1}\). We also evaluate Domino saliency metrics on AlexNet\(^\text{16}\). The join and split connections in ResNet arise due to skip connections. The join connections in AlexNet arise due to group convolutions. NFNET-F0 contain both skip connections and group convolutions.

We use the CIFAR-10\(^\text{15}\), CIFAR-100\(^\text{17}\), ImageNet-32\(^\text{32}\) (a downsized ImageNet variant), and ImageNet\(^\text{3}\) datasets. ResNet-20\(^\text{3}\) on ImageNet, ResNet-50\(^\text{30}\) on ImageNet and NFNET-F0\(^\text{1}\) on ImageNet are pretrained networks. The remaining networks are trained from scratch.

4.3 Saliency Metrics

The most popular pruning saliency metrics are either a derivative of the L1 or L2 norm of weights\(^\text{9,13,6,7,24,20,33,17,12}\) or Taylor expansions\(^\text{19,10,26,25,28,14}\). With channel pruning, Taylor Taylor expansions can be applied to either weights or feature maps.

The channel saliency metrics that we evaluate are: Taylor expansion using weights, Taylor expansion using feature maps, and L1 norm of weights.\(^\text{1}\) https://github.com/HolmesShuan/ResNet-18-Caffemodel-on-ImageNet
5 Results

We measure the improvement of Domino saliency metrics by comparing the percentage of convolution weights removed for a drop of 5% in test accuracy. The results are an average from 4 runs.

Figures 5, 6, and 7 show the percentage of convolution weights removed. In most cases, we observe an improvement by using the Domino saliency metrics. Domino−io significantly improves the pruning rates for AlexNet on CIFAR-10, AlexNet on ImageNet-32 and ResNet-20 on CIFAR-10. Domino−io includes the saliency of input feature maps or input channel weights in addition to Domino−o. The larger improvement brought by Domino−io suggests that the saliency of input feature maps or input channel weights contain relevant information for pruning.

From Figure 5, we see that using Domino−io on AlexNet for CIFAR-10 and ImageNet greatly improves the base saliency metric. A notable result is the L1 norm of weights (with averaging) which can match the pruning rates of Taylor expansion based methods with Domino−io. The L1 norm of weights is a very popular metric for pruning for its low computational cost and good pruning rates. Domino−io has a negligible cost overhead while greatly improving the L1 norm of weights (with averaging).

From Figure 6, we observe a similar trend where the L1 norm of weights (with averaging) can be improved to match and exceed the pruning rates of Taylor based method on ResNet-20 on ImageNet.

Figure 7 shows that the improvement of Domino saliency metrics are marginal on NFNET-F0. However since the pruning rates are also extremely low, the results are inconclusive for this network. On the other hand, ResNet-50 benefits from the additional structural information used by Domino saliency metrics. The pruning rates on ResNet-50 can be improved by a few percentage points with either Domino−o or Domino−io.
The average improvement of using Domino metrics over channel metrics for each network, is shown in Figure 8a. On all the networks, except AlexNet on CIFAR-100, Domino – io on average improves the baseline channel metric. Domino – io can be used to push the pruning rate of a network farther. The improvement shown in Figure 8b corresponds to the difference between the maximum percentage of weights removed between the best Domino metric and the best channel metric for a given network. With Domino – io, up to 25% and 15% more weights can be respectively removed from AlexNet on the CIFAR-10 dataset and the ImageNet-32 dataset.

6 Related Work

When pruning networks with branch connections, multiple channels are removed to keep the network dense. However, most channel pruning approaches use the same saliency metric \(^{25,24}\) as for simple forward feed networks. These saliency
metrics do not factor in the other output channels that need to be removed when one channel is removed. Some pruning approaches that are based on feature-map reconstruction \cite{14,22} explicitly describe how branches are taken in account. He et al.\cite{14} and Thinet \cite{22} remove output channels by considering the effect on the next layer’s input feature map. For the ResNet architecture, He et al.\cite{14} consider the input feature map after the skip connection. ThiNet \cite{22} avoid pruning layers that could result in mismatching number of feature maps in the network. Feature maps reconstruction-based approaches are computationally expensive. They are poor candidates for elaborate pruning schemes \cite{13,12,34} that rely on computationally cost effective saliency metrics.

### 7 Conclusion

Most popular channel saliency metrics do not take into account structural constraints that can arise when pruning join and split connections. We propose two Domino saliency metrics to add structural information to the saliency measure by combining channel saliency of multiple channels. Domino – o adds information about the other output feature maps that are removed together and Domino – io adds information about output and input feature maps that are removed together. We observe a small improvement when using Domino – o over the baseline channel saliency metric and a significant improvement when using Domino – io. Domino – io can be use to improve the pruning rates by 25% and 15% for AlexNet on CIFAR-10 and ImageNet-32. In conclusion, the use of Domino – io can significantly improve pruning rates for networks with join/split connections. This suggests that, in addition to output feature maps or weights, information about input feature maps or weights is relevant for pruning.
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