[Supplementary]
Reproducibility Report
Rigging the Lottery: Making All Tickets Winners

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1 Architecture Specific Details—ResNet-50 on CIFAR100

Table 1: **ResNet-50 architecture used on CIFAR100**. Building blocks are shown in brackets, with the numbers of blocks stacked. Downsampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

Layer Name	Output Size	ResNet-50
conv1	32×32	3×3, 64, no stride
conv2_x	32×32	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3_x	16×16	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$
conv4_x	8×8	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$
conv5_x	4×4	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 100-d fc, softmax
FLOPs		2.59e9

We use a variant of the originally proposed ResNet architecture (He et al. [2016]). Particularly, we replace the initial 7×7 conv layer with a 3×3 conv layer. Here, "conv layer" refers to convolution followed by batchnorm (Ioffe and Szegedy [2015]) and ReLU activation. This is intended to not excessively downsample the image—CIFAR-100 (Alex Krizhevsky [2009]) has images of dimensions 32×32, compared to Imagenet's (Russakovsky et al. [2015]) 224×224. Each block used (conv2_x, conv3_x, etc.) is a bottleneck block, and uses the conv-batchnorm-ReLU ordering.

2 FLOP Counting Procedure

Following Evci et al. [2020], we base our counting procedure on the Micronet Challenge[1], which was conducted as a part of NeurIPS 2019. Support for unstructured sparsity is assumed while computing the number of additions and multiplication operations. The sum of these two gives us the theoretical FLOPs for a single forward pass through the model.

Concretely, let the FLOPs required for a forward pass through a dense model be f_d and the corresponding for a sparse model (or small-dense model) be f_s. Then, the FLOPs for training a dense model are $3f_d$—since the backward pass involves computing gradients with respect to each weight and activation. f_s can be computed for a model given its sparsity distribution via the counting procedure. The FLOPs required to train a sparse model depend on the technique used, as detailed below.

2.1 Inference FLOPs

Small-Dense, RigL, SET, Static These methods involve constant layer-wise sparsity throughout training, hence the FLOP count can be determined during any step. The FLOP count for Random initialized models are $(1-s)$ times the Dense FLOPs.

SNFS, Pruning Both methods involve varying layer-wise sparsity during training, and hence non-constant FLOP consumption. The final weights are used to determine inference FLOPs in this case.

2.2 Train FLOPs

Small-Dense, Static Dense gradients are not required by these models, and hence have a train FLOP count of $3f_s$.

SET Dense gradients are not required, and random growth can be implemented quite efficiently. Thus, the train FLOP count is $3f_s$.

RigL Dense gradients are required only every ΔT steps, hence the corresponding train FLOP count is: $\frac{3\Delta T f_s + 2f_s + f_d}{\Delta T + 1}$. We note that since ΔT is typically set between 100–1000, the preceding expression is quite close to $3f_s$.

SNFS Dense gradients are required at each training step, resulting in $2f_s + f_d$ FLOPs consumed at each step. Since the sparse FLOP count varies as we train, the average FLOP count is: $2\mathbb{E}[f_{s,t}] + f_d$, where $f_{s,t}$ is the sparse inference FLOPs at train step t.

Pruning Does not require dense gradients, but the sparsity increases smoothly from 0% to the target value as we train. The FLOP consumption here is $3\mathbb{E}[f_{s,t}]$, , where $f_{s,t}$ is the sparse inference FLOPs at train step t.

To determine $\mathbb{E}[f_{s,t}]$, we compute a running average of the FLOP consumption after every epoch. Notably, we find that the inference cost of Pruning is often close to a Random initialized sparse network, while SNFS, regardless of initiazation, is compute-intensive.

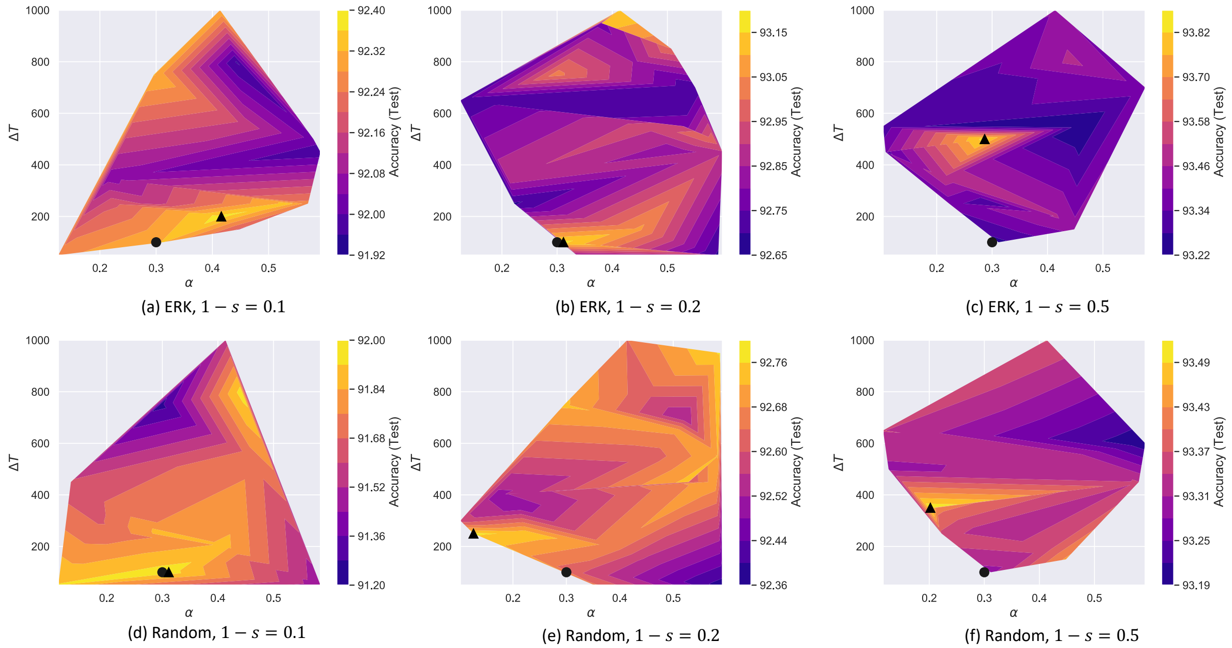
3 Trial Space of Hyperparameter Tuning

Figure 1 shows the hyper-parameter study for tuning $(\alpha, \Delta T)$ as a contour plot. We observe that for multiple initialization-density configurations, the reference choice ($\alpha = 0.3, \Delta T = 100$), is quite close to the optimal hyper-parameters. Furthermore, where they differ, the difference is within standard deviation bounds (Table 4 of the main report).

4 Dynamic Structured Sparsity

Present hardware accelerators lack efficient implementations for unstructured sparsity. As a result, in practice, the reduced FLOP requirement of sparse methods rarely translate to wall-clock improvements. In comparison, there are efficient implementations available for structured (or block) sparsity which reach theoretical speedups (Gray et al. [2017], Teja Vooturi et al. [2019]). Motivated by this, we try modifying *RigL* to explicitly work on structured sparsity.

[1] https://micronet-challenge.github.io/



(a) ERK, $1-s=0.1$ (b) ERK, $1-s=0.2$ (c) ERK, $1-s=0.5$

(d) Random, $1-s=0.1$ (e) Random, $1-s=0.2$ (f) Random, $1-s=0.5$

Figure 1: **Trial space of tuning** $(\alpha, \Delta T)$, shown as a countor plot. Here, black circle corresponds to $(\alpha = 0.3, \Delta T = 100)$, while black triangle corresponds to the optimal hyper-parameter pair found. We plot the convex hull of the trial space, so in a few cases the reference point lies on the border of this space.

Table 2: **Modifying *RigL* for structured sparsity, compared on CIFAR-10 and CIFAR-100 datasets.** *RigL*-struct fails to match the accuracy of *RigL* and just matches Small-Dense in performance.

Method	CIFAR-10				CIFAR-100			
	$1-s=0.1$		$1-s=0.2$		$1-s=0.1$		$1-s=0.2$	
	Accuracy ↑ (Test)	Wall Time ↓	Accuracy ↑ (Test)	Wall Time ↓	Accuracy ↑ (Test)	Wall Time ↓	Accuracy ↑ (Test)	Wall Time ↓
Small-Dense	89.0 ± 0.35	0.11x	91.0 ± 0.07	0.20x	70.8 ± 0.22	0.11x	72.6± 0.93	0.20x
Random Initialization								
RigL	91.7 ± 0.18	1.0x	92.9 ± 0.10	1.0x	71.8 ± 0.33	1.0x	73.5 ± 0.04	1.0x
RigL-Struct	87.0 ± 0.09	0.10x	90.4 ± 0.27	0.20x	69.1 ± 0.11	0.10x	71.9 ± 0.13	0.20x
ERK Initialization								
RigL	92.4 ± 0.06	1.0x	93.1 ± 0.09	1.0x	72.6 ± 0.37	1.0x	73.4 ± 0.15	1.0x
RigL-Struct	89.6 ± 0.16	0.17x	91.3 ± 0.18	0.35x	71.1 ± 0.15	0.23x	72.9 ± 0.08	0.38x

We promote channel sparsity for convolutional layers and keep fully connected layers dense. Mask update steps also operate at the channel level, based on *RigL*'s growth and pruning criterion. We name this method as *RigL*-struct. Such an approach is enticing, as we can remove masked-out channels, and obtain practical speedups on accelerators without needing support for unstructured sparsity.

Unfortunately, *RigL*-struct does not preserve the performance of originally proposed *RigL* (Table 2). In fact, it performs only as good as Small-Dense models, which negates the motivation behind such an experiment—Small-Dense models already achieve the intended speedups.

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