Assignment 1 for COS598D: System and Machine Learning: Network Pruning

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1. Hyper-parameter tuning

1.1 Testing on different archietectures

Testing accuracy (top 1)

Data	Arch	Rand	Mag	SNIP	GraSP	SynFlow
Cifar10	VGG16	10.00	89.73	87.10	83.66	88.39
MNIST	FC	95.77	97.68	96.99	95.99	11.35

On Cifar10 dataset, we use the following commands to run the experiments, especially we only set post-pruning epochs to be 400 for GraSP, and 100 for all other pruners. This is because we observe that GraSP needs more epochs to converge.

```
python main.py --model-class lottery --model vgg16 --dataset cifar10 --experiment singleshot --pruner rand --compression 1 --expid 4 --post-epochs 100
python main.py --model-class lottery --model vgg16 --dataset cifar10 --experiment singleshot --pruner mag --compression 1 --expid 5 --post-epochs 100 --pre-epochs 200
python main.py --model-class lottery --model vgg16 --dataset cifar10 --experiment singleshot --pruner snip --compression 1 --expid 6 --post-epochs 100
python main.py --model-class lottery --model vgg16 --dataset cifar10 --experiment singleshot --pruner grasp  --compression 1 --expid 7 --post-epochs 400 --verbose
python main.py --model-class lottery --model vgg16 --dataset cifar10 --experiment singleshot --pruner synflow --compression 1 --expid 8 --post-epochs 100
```

On MNIST dataset, we use the following commands. Note that SyncFlow is not effective on MNIST dataset even if setting post-pruning epochs to be 150.

```
python main.py --model-class default --model fc --dataset mnist --experiment singleshot --pruner rand --compression 1 --expid 9 --post-epochs 20
python main.py --model-class default --model fc --dataset mnist --experiment singleshot --pruner mag --compression 1 --expid 10 --pre-epochs 20 --post-epochs 10
python main.py --model-class default --model fc --dataset mnist --experiment singleshot --pruner snip --compression 1 --expid 11 --post-epochs 30
```

```
python main.py --model-class default --model fc --dataset mnist --
experiment singleshot --pruner grasp  --compression 1 --expid 12 --post-
epochs 30
python main.py --model-class default --model fc --dataset mnist --
experiment singleshot --pruner synflow --compression 1 --expid 13 --post-
epochs 150
```

1.2 Tuning compression ratio

Prune models on CIFAR10 with VGG16, please replace {} with sparsity 10^-a for a \in {0.05,0.1,0.2,0.5,1,2}.

In this subsection, we set post-pruning epochs to be 300 for GraSP, and 100 for all other pruners as well. Other parameters are the same as the previous subsection.

1.2.1 *Testing accuracy (top 1)*

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	88.08	88.69	88.20	79.03	88.05
0.1	87.51	89.47	88.17	72.34	88.16
0.2	88.16	89.36	87.87	78.87	88.50
0.5	86.80	89.95	88.55	80.86	87.14
1	10.00	88.88	87.77	81.46	87.83
2	10.00	42.61	81.55	82.72	10.00

1.2.2 *Testing time (inference on testing dataset)*

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	0.608	0.658	0.583	0.624	0.828
0.1	0.689	0.598	0.674	0.709	0.763
0.2	0.694	0.646	0.702	0.580	0.714
0.5	0.613	0.700	0.672	0.609	0.714
1	0.630	0.666	0.705	0.705	0.640
2	0.627	0.713	0.605	0.794	0.679

1.2.3 *FLOP*

In the following table, the reported numbers are calculated with: `FLOP / 313478154` where `313478154` is the total FLOP of the unpruned model.

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.05	0.8916	0.9477	0.9377	0.8201	0.9488

Compression	Rand	Mag	SNIP	GraSP	SynFlow
0.1	0.7945	0.8991	0.9268	0.7295	0.9026
0.2	0.6310	0.8151	0.7812	0.5711	0.8217
0.5	0.3165	0.5634	0.4622	0.3781	0.6423
1	0.1009	0.2283	0.1979	0.1751	0.4571
2	0.0108	0.0322	0.0411	0.0586	0.1845

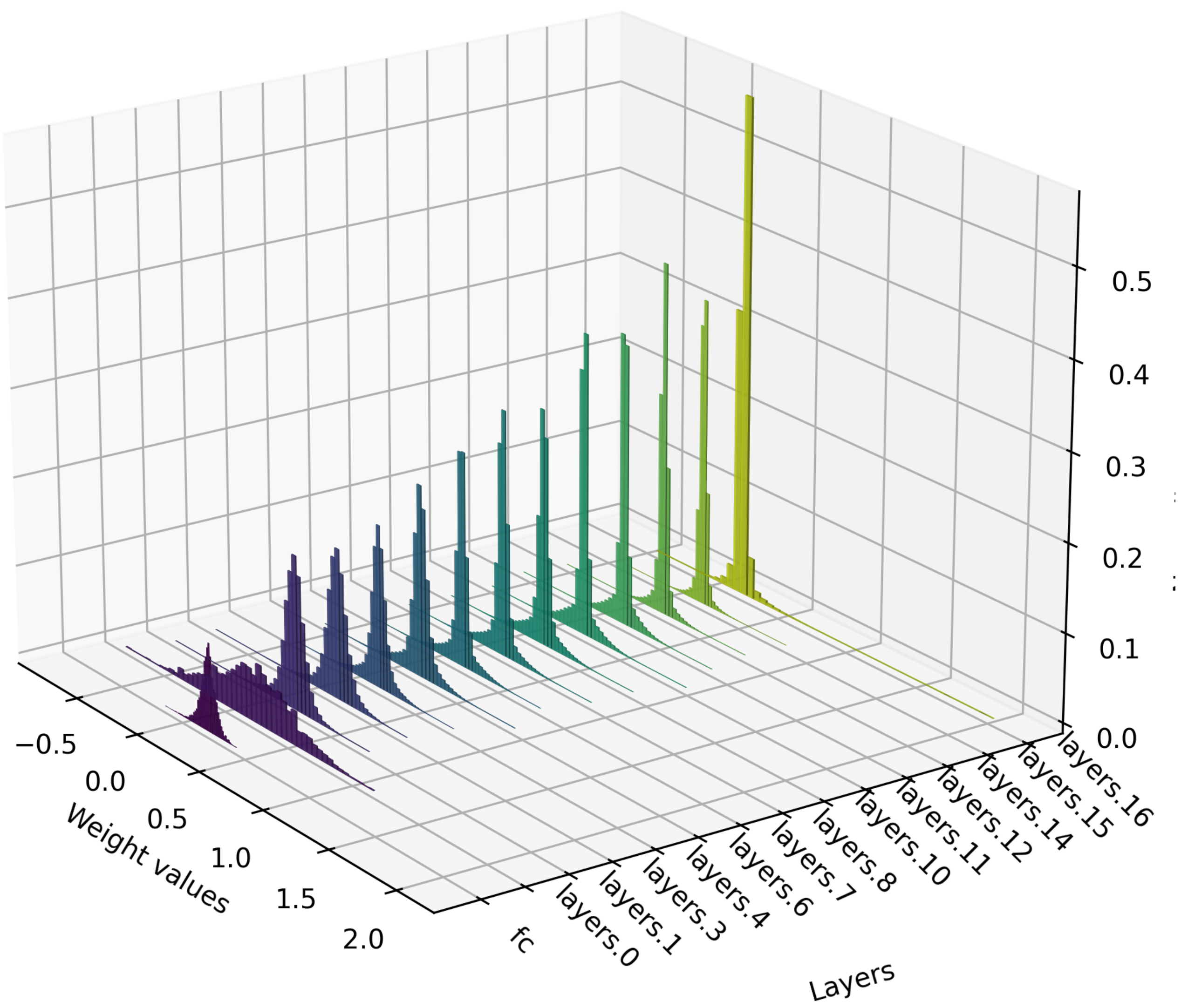
2. Compression ratio of each layer

2.1 Weight histograms

Report the sparsity of each layer and draw the weight histograms of each layer using pruner Rand | Mag | SNIP | GraSP | SynFlow with the following settings: `model = vgg16`, `dataset=cifar10`, `compression = 0.5`.

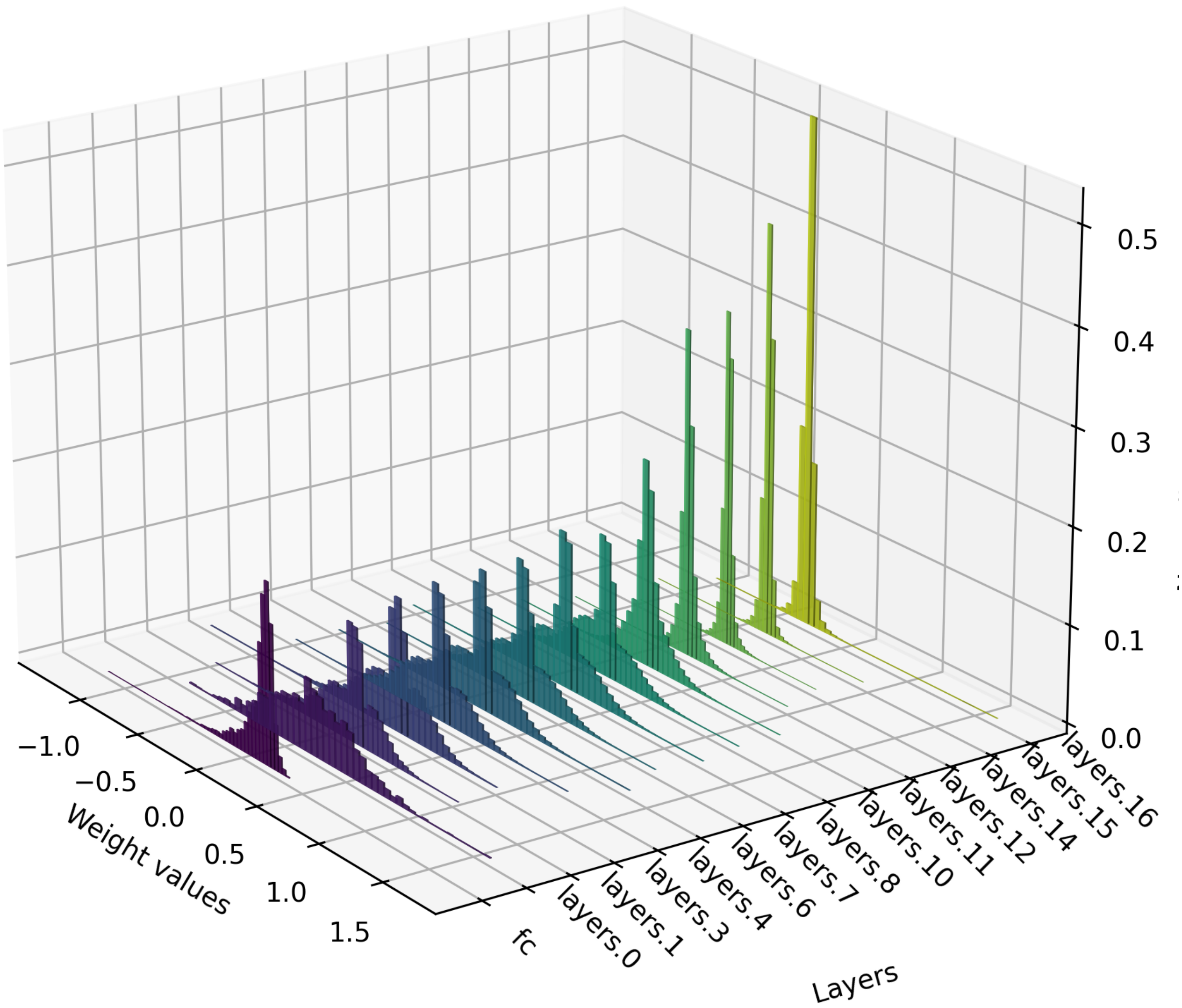
In all the figures, the x-axis is the weight value, y-axis is the name of the layer, and the z-axis is the frequency weights in the corresponding bin. Note that we normalize by deviding the total number of weights in each layer.

2.1.1 Rand

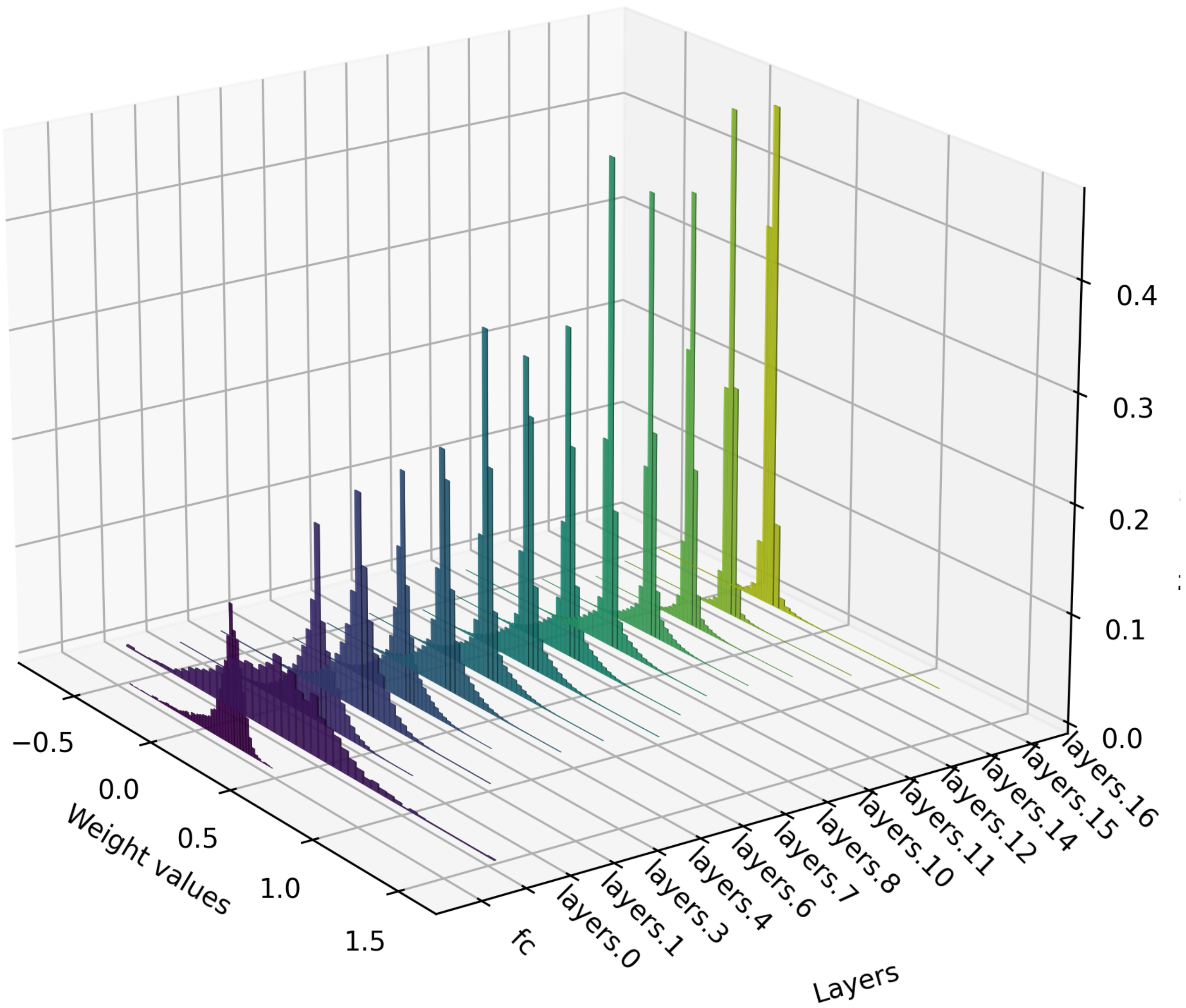


0.5
0.4
0.3
0.2
0.1
0.0
−0.5
0.0
0.5
1.0
1.5
2.0
Weight values
fc
layers.0
layers.1
layers.3
layers.4
layers.6
layers.7
layers.8
layers.10
layers.11
layers.12
layers.14
layers.15
layers.16
Layers

2.1.2 Mag

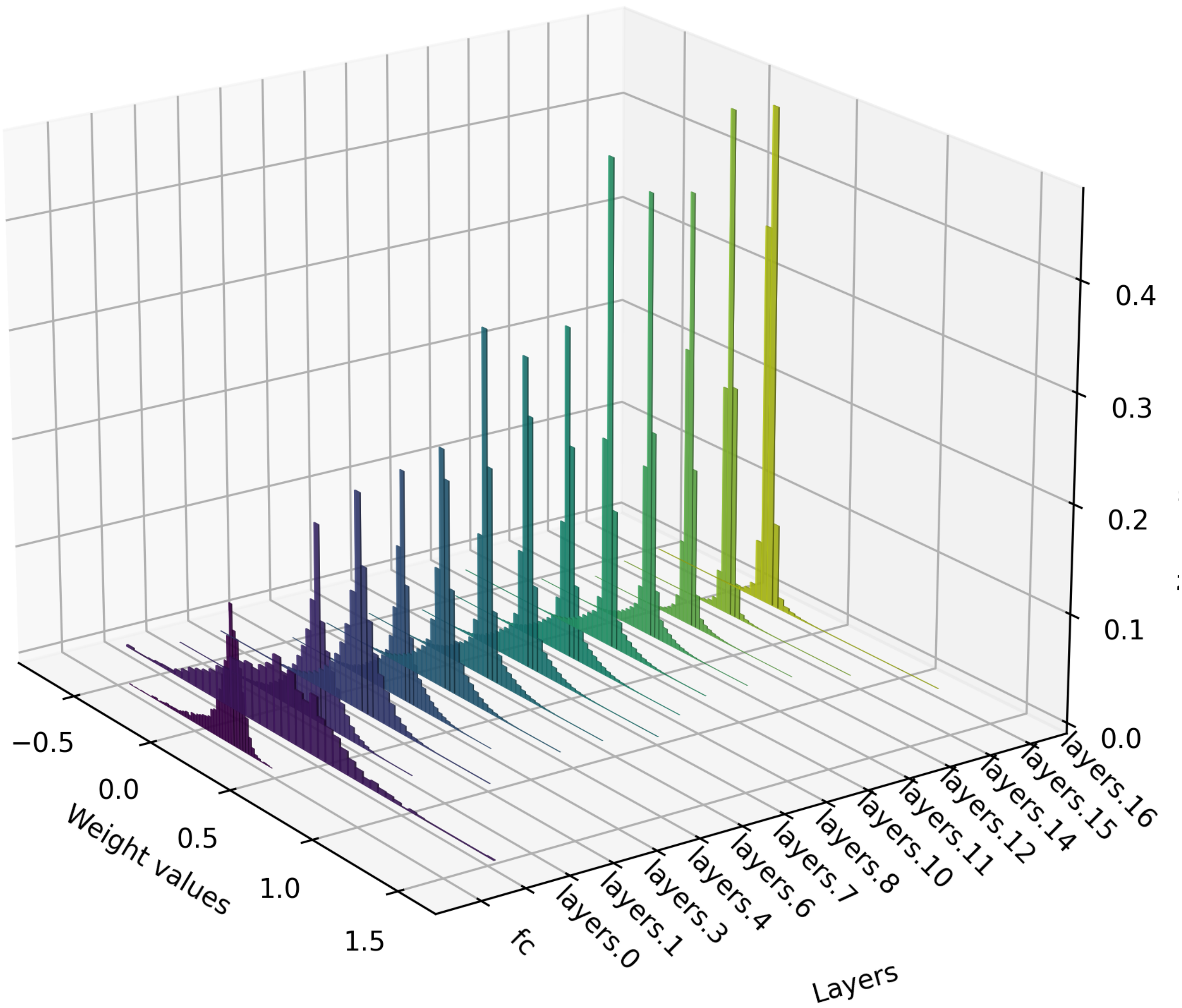

0.5
0.4
0.3
0.2
0.1
0.0
−1.0
−0.5
0.0
0.5
1.0
1.5
Weight values
fc
layers.0
layers.1
layers.3
layers.4
layers.6
layers.7
layers.8
layers.10
layers.11
layers.12
layers.14
layers.15
layers.16
Layers

2.1.3 SNIP

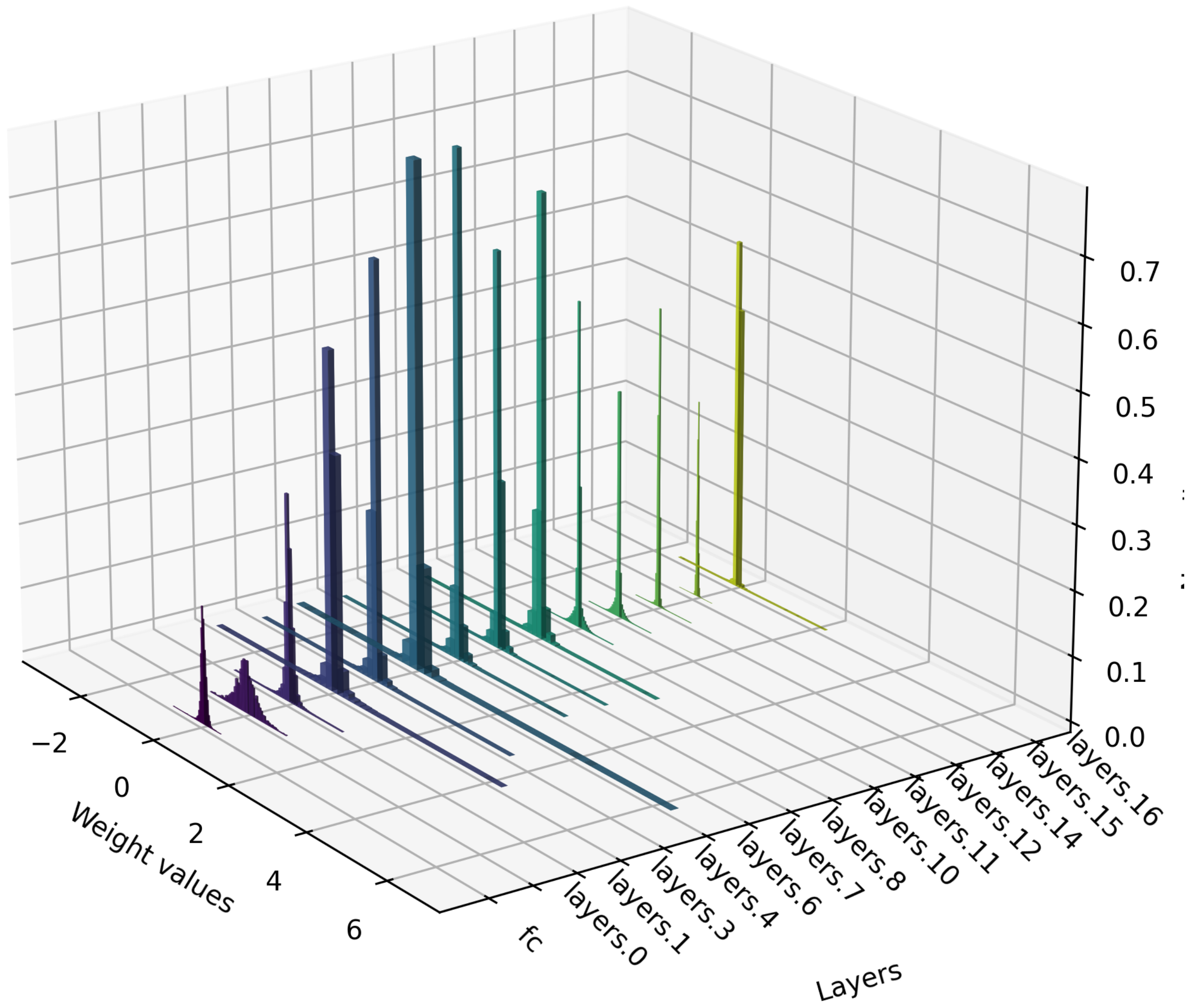


0.4
0.3
0.2
0.1
0.0
−0.5
0.0
0.5
1.0
1.5
Weight values
fc
layers.0
layers.1
layers.3
layers.4
layers.6
layers.7
layers.8
layers.10
layers.11
layers.12
layers.14
layers.15
layers.16
Layers

2.1.4 GraSP


0.4
0.3
0.2
0.1
0.0
−0.5
0.0
0.5
1.0
1.5
Weight values
fc
layers.0
layers.1
layers.3
layers.4
layers.6
layers.7
layers.8
layers.10
layers.11
layers.12
layers.14
layers.15
layers.16
Layers

2.1.5 SynFlow



2.2 FLOPs (optional)

Report the FLOP of each layer using pruner Rand | Mag | SNIP | GraSP | SynFlow with the following settings: `model = vgg16`, `dataset=cifar10`, `compression= 0.5`.

Layers	Unpruned	Rand	Mag	SNIP	GraSP	SynFlow
layers.0.conv	1769472	541695	1501183	1704960	985088	1765376
layers.1.conv	37748736	11867135	27796479	29917183	18281471	37137408
layers.3.conv	18874368	5992704	14198528	12952831	8534271	18300928
layers.4.conv	37748736	11856127	28079361	20818944	15328512	35502079
layers.6.conv	18874368	5943296	14003136	9233535	7212287	16645631
layers.7.conv	37748736	11949055	27708608	14927487	13233983	28944256

Layers	Unpruned	Rand	Mag	SNIP	GraSP	SynFlow
layers.8.conv	37748736	11956288	27095935	16215359	14178047	28932671
layers.10.conv	18874368	5974976	13638895	7740864	6951488	10316815
layers.11.conv	37748736	11935391	20104512	11484336	12541855	8774719
layers.12.conv	37748736	11964463	8695023	12011791	13159455	8783952
layers.14.conv	9437184	2980576	1030796	3001123	2925716	1995555
layers.15.conv	9437184	2982560	749572	2290064	2429731	1996460
layers.16.conv	9437184	2982684	1139607	2320448	2471884	1982292
fc	5120	1620	2201	4572	2810	5107

3. Summary

Compared to baselines. Although these methods surpass the trivial baseline of random pruning, they do not apparently surpass magnitude pruning after training.

Accuracy. No one method is SOTA in all settings and sparsities. SNIP consistently performs well, with SynFlow frequently competitive. Magnitude pruning is surprisingly effective against more complicated heuristics. Especially, for normal sparsities, GraSP performs worst but surprisingly it excels at extreme sparsities (`compression=2`). Overall, the methods generally outperform random pruning; however, they cannot match magnitude pruning after training in terms of either accuracy or the sparsities at which they match full accuracy.

Time and FLOP. SynFlow has the highest FLOP, SNIP and GraSP have low and comparable FLOP. In terms of time, the GPU server I am using is not powerful enough to show the difference in time. Moreover, note that the GPU/CPU communication overhead is affected by other processes, thus I believe the time statistics are not meaningful enough. To have a more accurate time statistics, I think it is essential to send numerous runs on a more powerful server, while trying to avoid simultaneous processes.

Layer-wise weight distribution. Experimentally, we observe that advanced methods tend to prune more in the deeper layers. Specifically, SynFlow has very centered weight distributions, while random pruning has more spread-out weight distributions.

Layer-wise compression. The layer-wise sparsity is not consistent across different methods. For example, SynFlow has a higher sparsity in the first layer, while SNIP has a higher sparsity in the last 5 conv layer. This is consistent with the fact that different methods have different heuristics and objectives.