Friedrich-Alexander-Universität
Technische Fakultät

RADL – GPU Group

Agenda

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02 Convolution Optimazition

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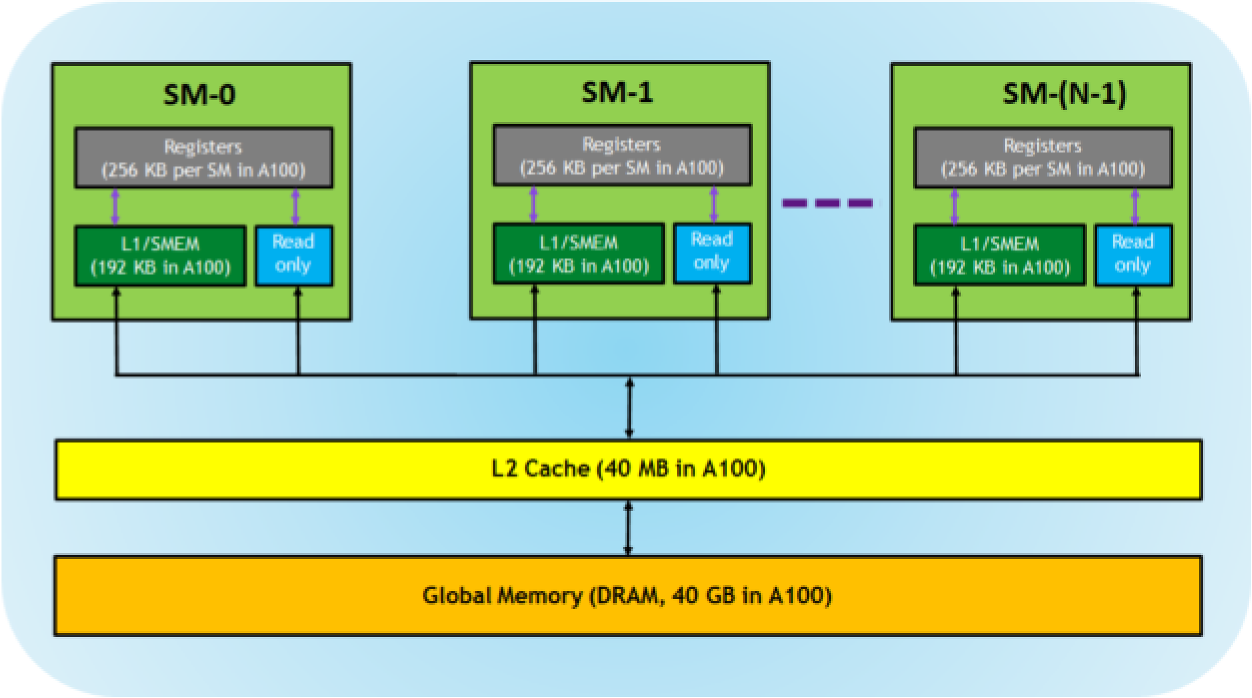
GEMM Optimization

Memory hierarchy



The following memories are exposed by the GPU architecture:

Registers; L1/Shared memory (SMEM); Read-only memory; L2 cache; Global memory

Optimization Strategy

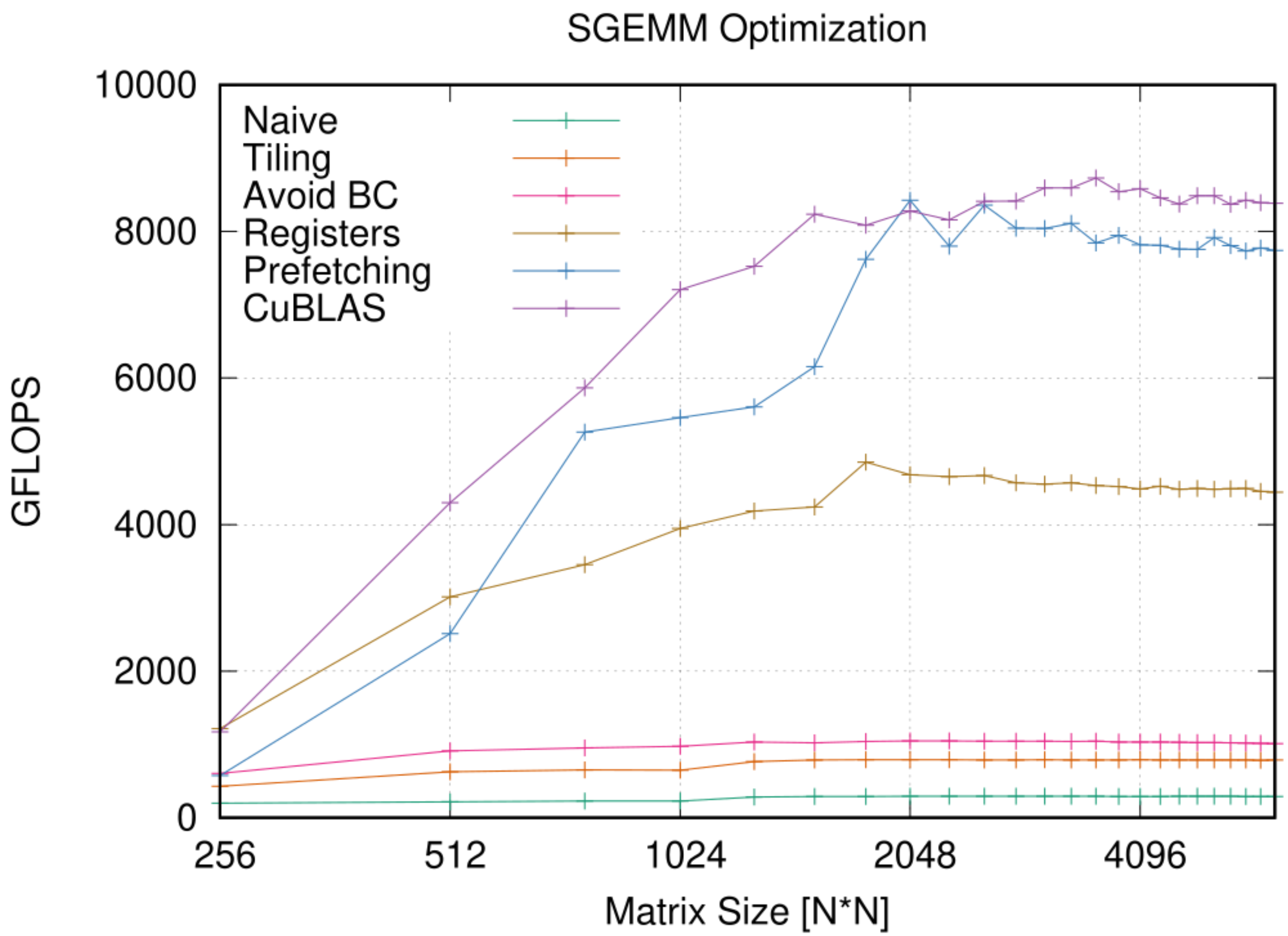
Optimizing GEMM on GPU and CPU platforms share the same idea:

- Hide the memory latency with massive parallelism
- Cache-/register-level data re-use
- Manual prefetching.

The major operations in convolutional neural networks consist of matrix multiplications in both the convolutional and the fully-connected layers.

Benckmarkting

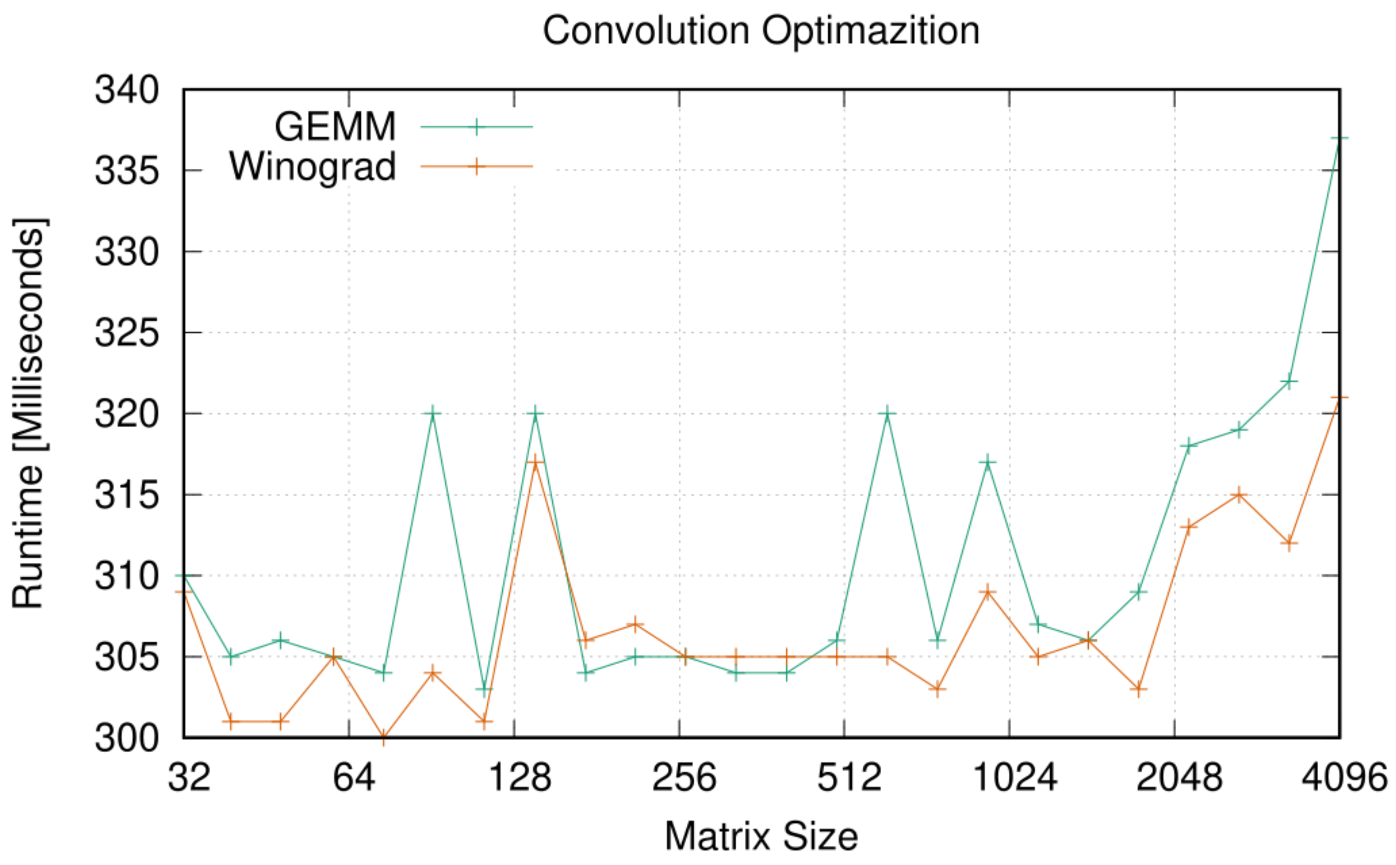
RTX 2080



Convolution Optimazition

Benckmarkting

RTX 2080

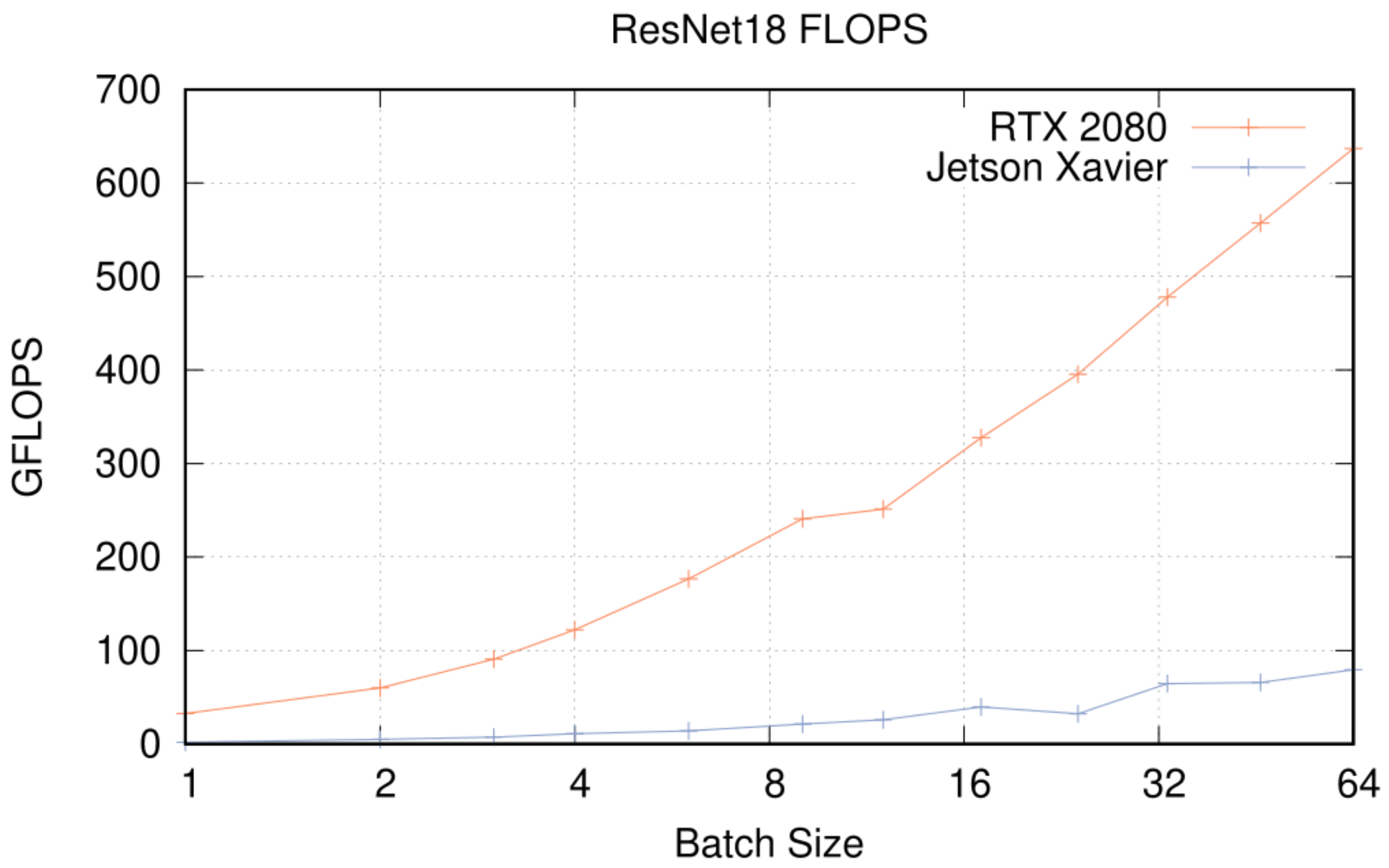


CNN Benchmark

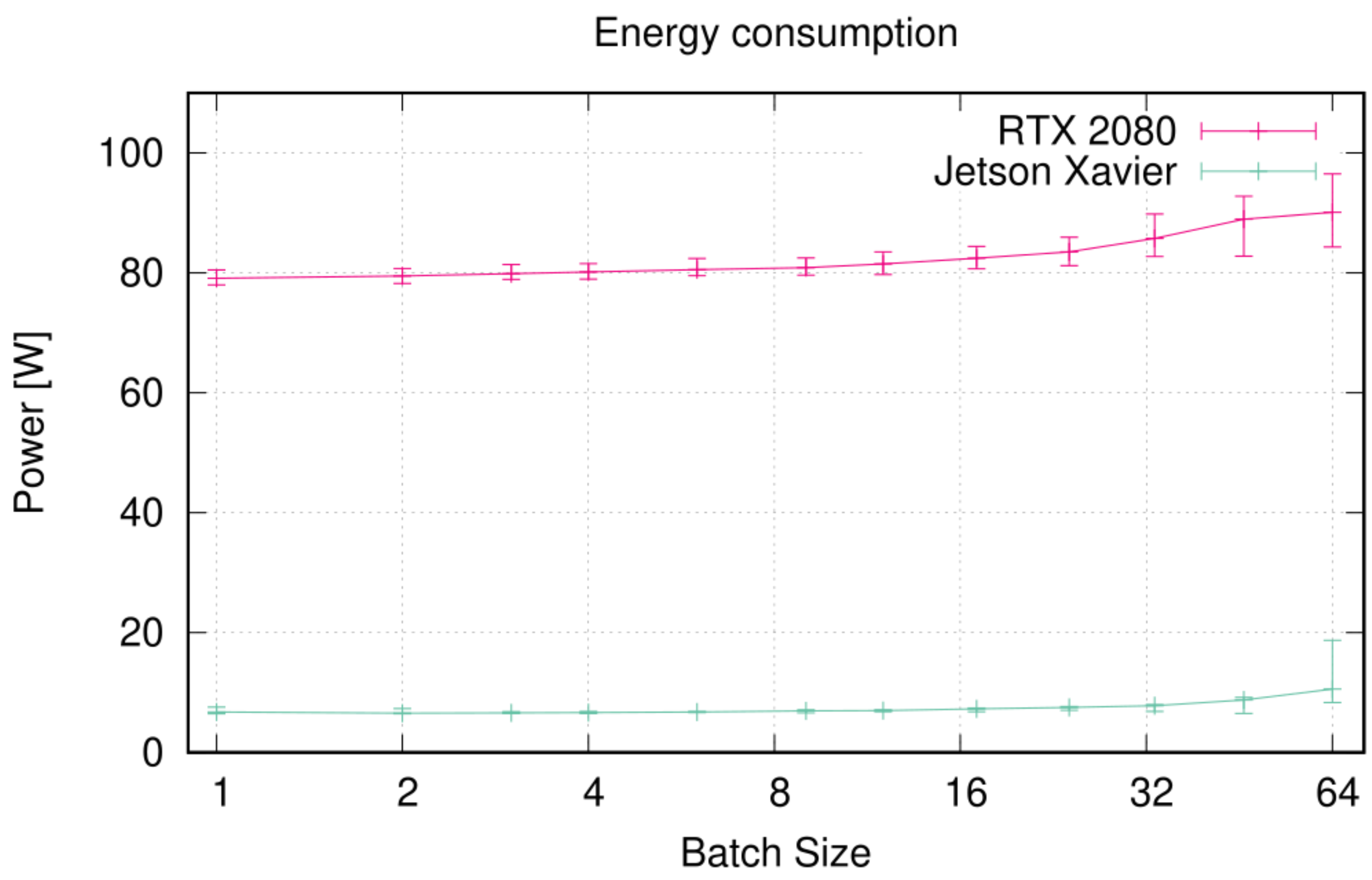
Benchmarketing

- Implemented FC, Conv, ReLU, BN and a Pooling Layer using CUDA
- Benchmarked on GPGPU(RTX 2080) and Embedding GPU(Jetson Xavier)
- Compared the throughput and power consumption of two different platforms
- Model: ResNet18
- Dataset: CIFAR-10

FLOPS


ResNet18 FLOPS
GFLOPS
700
600
500
400
300
200
100
0
1
2
4
8
16
32
64
Batch Size
RTX 2080
Jetson Xavier

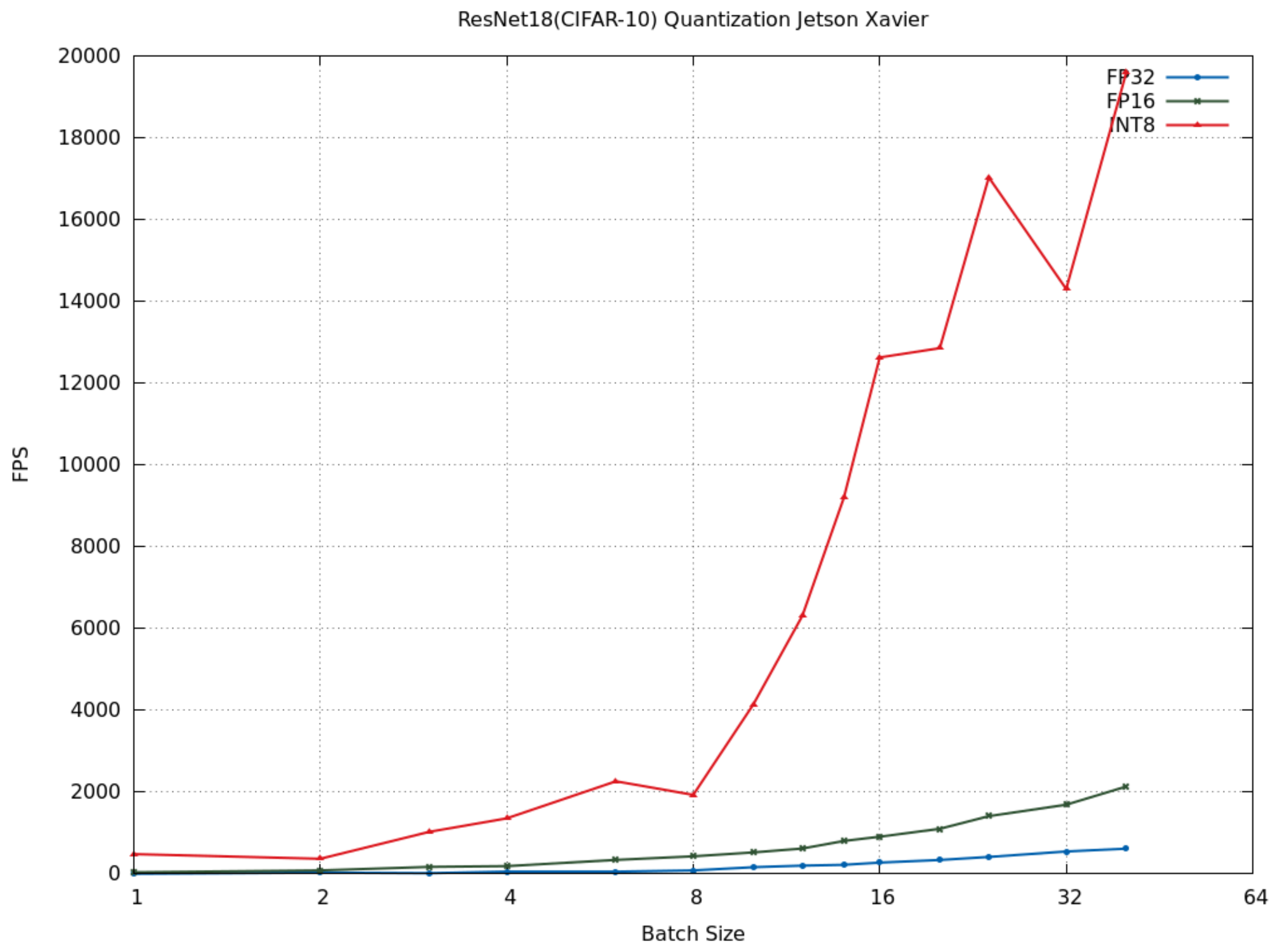
Energy consumption



FLOPS/W

Quantization

Quantization



Pruning

L1/L2 norm

Getting faster/smaller networks is important for running these deep learning networks on mobile devices.

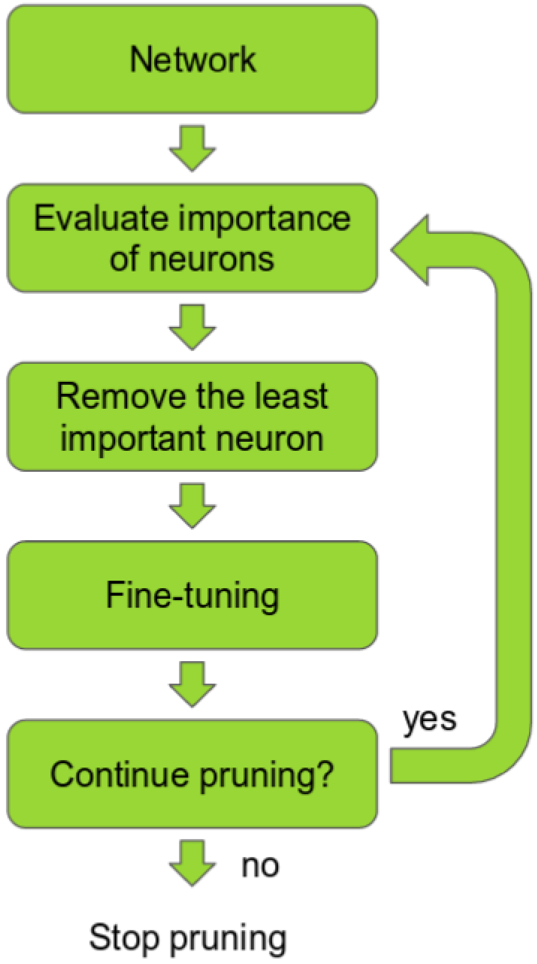
The ranking can be done according to the L1/L2 norm of neuron weights, their mean activations, the number of times a neuron wasn't zero on some validation set, and other creative methods . After the pruning, the accuracy will drop

```
def apply(self, weights, amount=0.0, round_to=1) -> Sequence[int]:  # return index
    if amount<=0: return []
    n = len(weights)

    l1_norm = torch.norm( weights.view(n, -1), p=self.p, dim=1 )

    n_to_prune = int(amount*n) if amount<1.0 else amount
    n_to_prune = round_pruning_amount(n, n_to_prune, round_to)
    if n_to_prune == 0: return []
    threshold = torch.kthvalue(l1_norm, k=n_to_prune).values
    indices = torch.nonzero(l1_norm <= threshold).view(-1).tolist()
    return indices
```

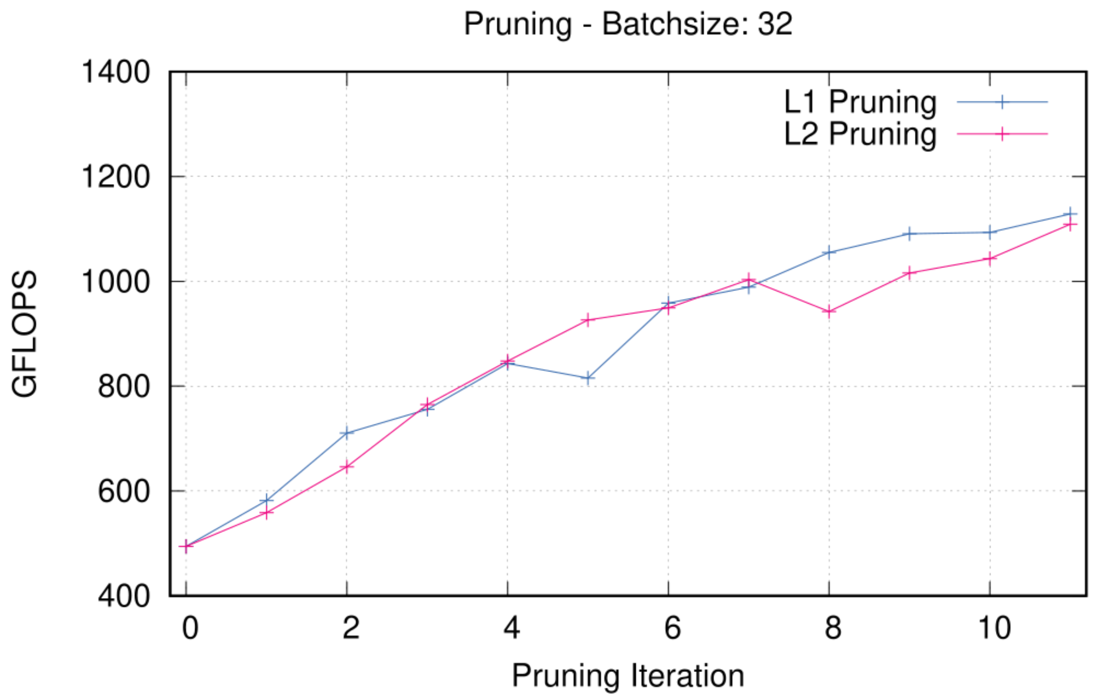
Retraining

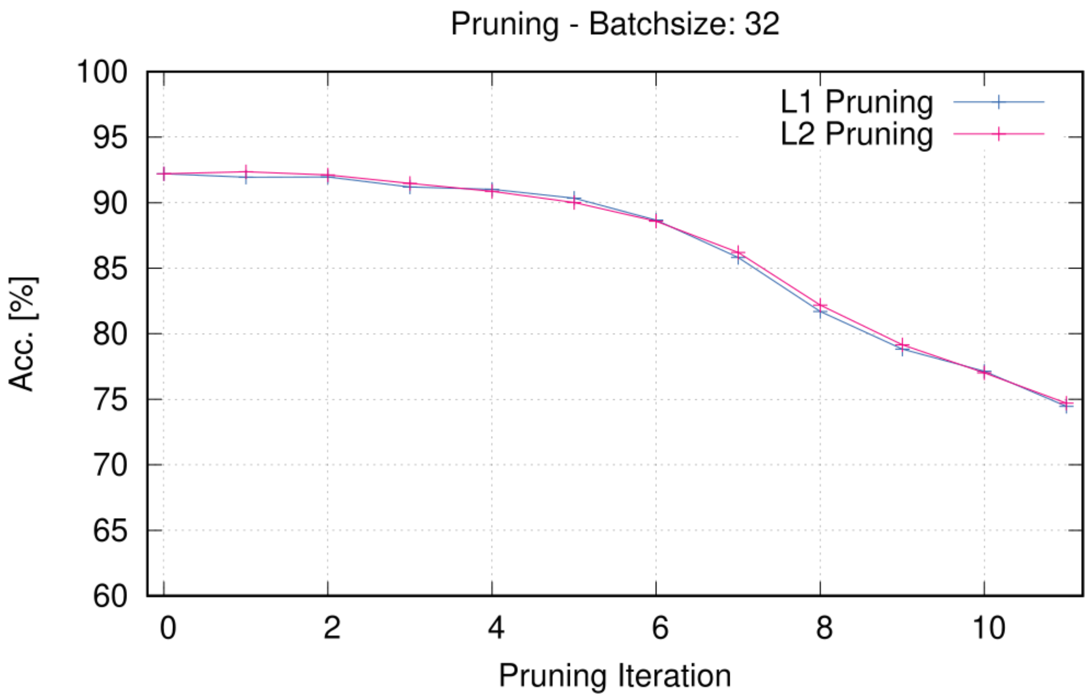
If we prune too much at once, the network might be damaged so much it won't be able to recover.

So, in practice this is an iterative process - often called 'Iterative Pruning': Prune / Train / Repeat.



Pruning Benchmarket

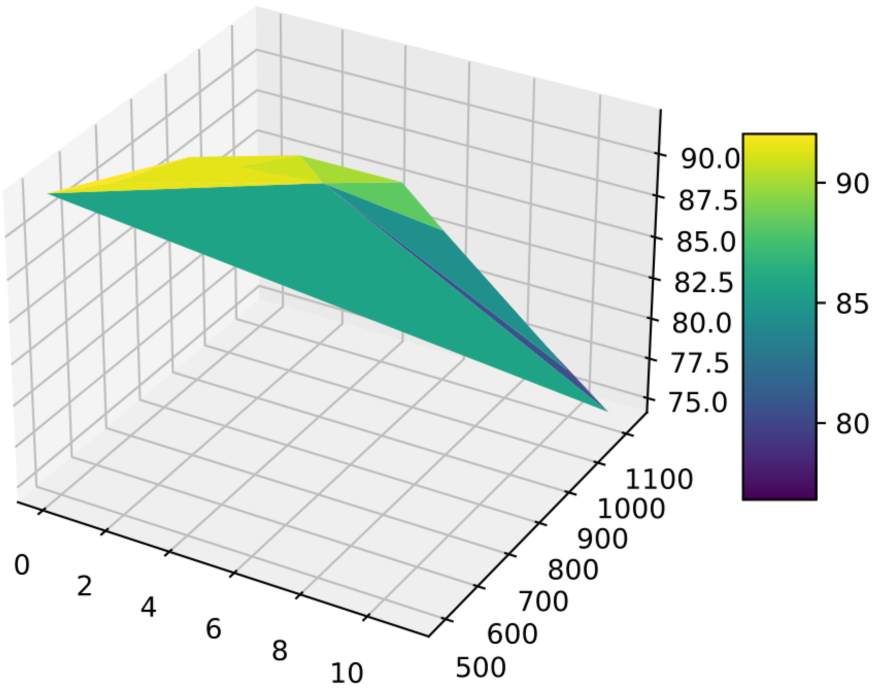




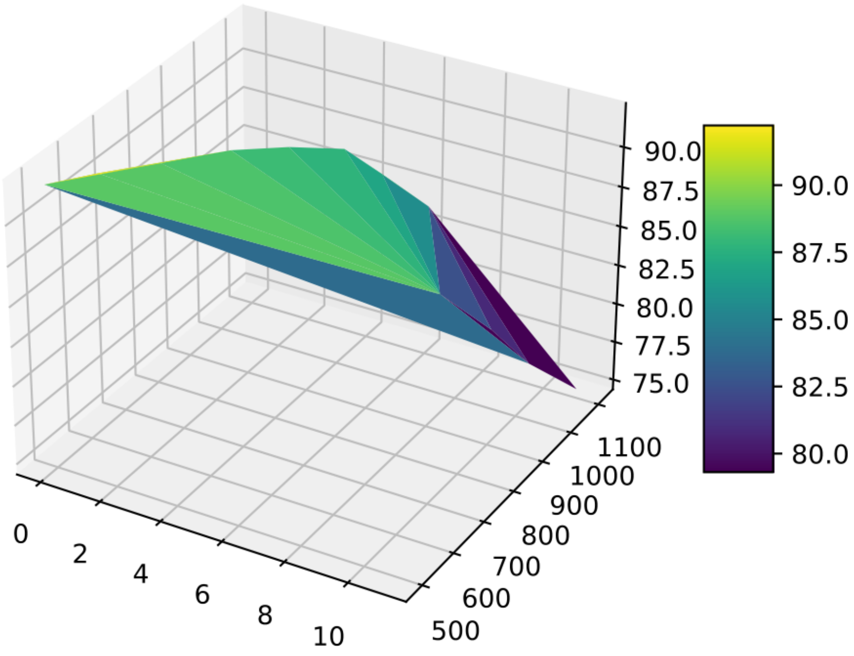
Pruning Benchmarket

Round	Params[K]	Reduced[%]	L1 Acc.[%]	L2 Acc.[%]
0	11181.642	0	92.2	92.2
1	4499.885	59.75	91.94	92.36
2	1904.148	82.97	91.96	92.11
3	850.709	92.39	91.20	91.48
4	408.764	96.34	91.03	90.87
5	210.707	98.11	90.35	90.02
6	118.955	98.93	88.68	88.59
7	70.37	99.37	85.82	86.20
8	46.003	99.58	81.70	82.19
9	32.347	99.71	78.83	79.16
10	23.606	99.78	77.14	77.02
11	17.706	99.84	74.46	74.71

Pruning Benchmarket



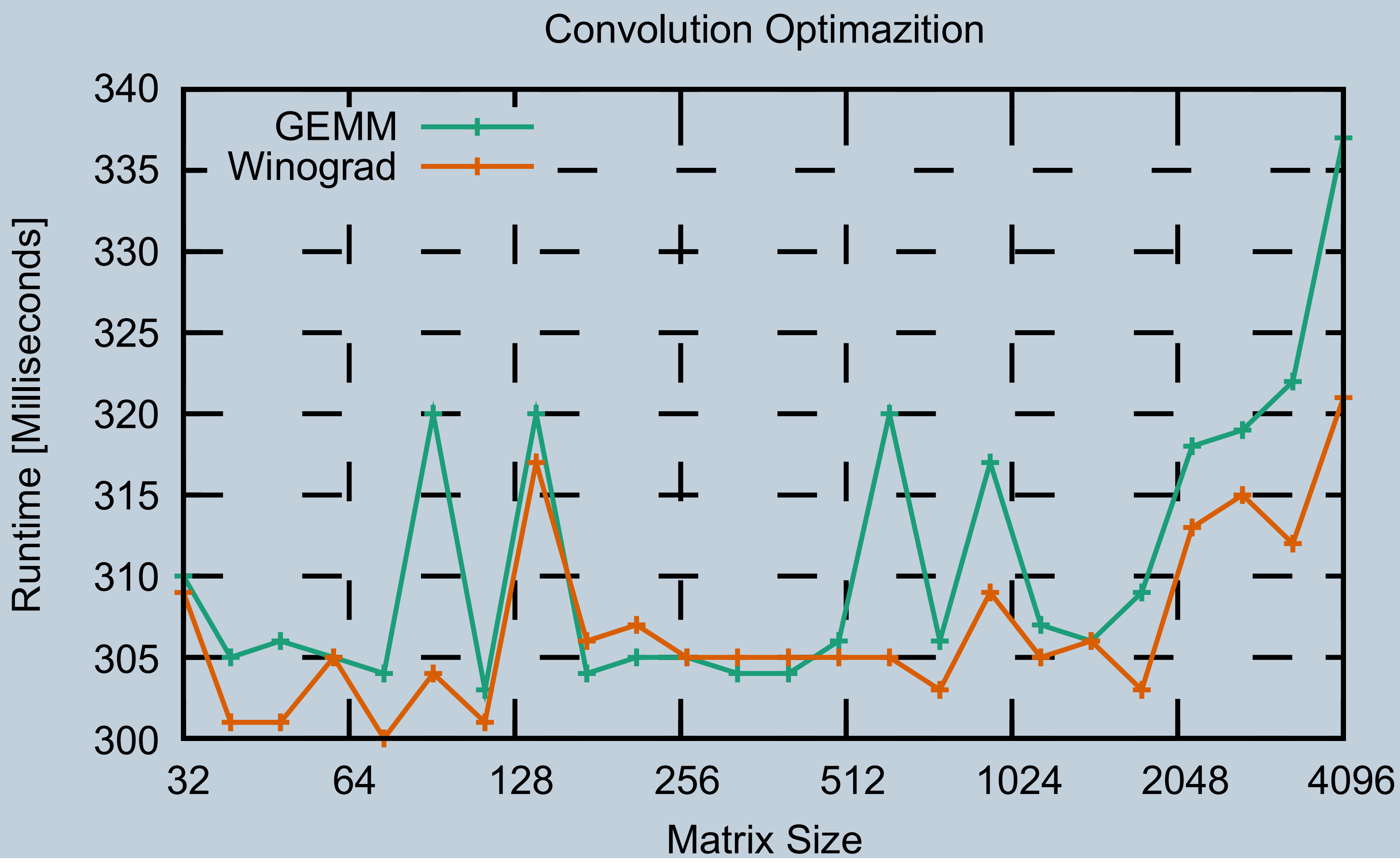
L1 Norm Pruning



L2 Norm Pruning

Conclusion

Conclusion



Convolution Optimazition
GEMM
Winograd
Runtime [Milliseconds]
340
335
330
325
320
315
310
305
300
32
64
128
256
512
1024
2048
4096
Matrix Size

Vielen Dank
für Ihre Aufmerksamkeit!