We start by testing the impact of different batch size.

We run this test with all default setting as the original paper except changing batchsize. We test larger batch sizes vs small batch sizes and since the code is tested based on CIFAR-10 dataset which has 50,000 training images(divisible by 10), we also include fully divisible batch size 200, 100 and 50 as options. From Table-1, we noticed that fully divisible batch size tends to have higher training time per epoch but less epoch to finish training. In addition to the training time, less batch size works better on CIFAR-10 dataset and when batch size is 100, resNet is able to reach 86.03% accuracy, which is higher than any other batch size by 1% to 2%.

| BatchSize(resNet18) | Accuracy | Time per epoch | Total Time Training |
|---------------------|----------|----------------|---------------------|
| 256 | 0.8478 | 41s | 1845s |
| 128 | 0.8482 | 55s | 2035s |
| 64 | 0.8593 | 92s | 4743s |
| 32 | 0.8409 | 155s | 5776s |
| 200 | 0.8480 | 41s | 1804s |
| 100 | 0.8603 | 67s | 3350s |
| 50 | 0.8517 | 105s | 4387s |

Table-1 resNet-18 with different batch size

The original author uses basic block in resNet18 and resNet34 but apply bottleneck block in the deeper resNet such as resNet152 because they states that bottleneck architecture could dramatically decrease the time complexity with deeper layers. Just like what author does from resNet34 to resNet50, we replaced basic block in resNet18 with bottleneck block leads to 8 more layers in the models(resNet26). ResNet26's time per epoch is only incremented by 2s.

| | Accuracy | Time per epoch | Total Time Training |
|---------------------|----------|----------------|---------------------|
| resNet18 | 0.8603 | 30s | 3350s |
| resNet18-bottleNeck | 0.8471 | 32s | 1472s |

Table-2 Basic Block vs BottleNeck Block

Based on Table-3, we verified that applying dropout after batch normalization leads to better accuracy than original bottleneck block with same training time per epoch.

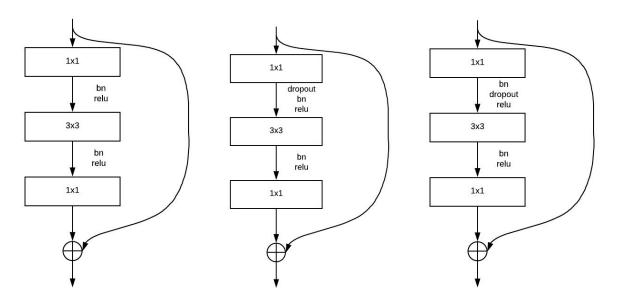


Image-1 Original bottleneck Block vs Dropout First Block vs Proposed Block

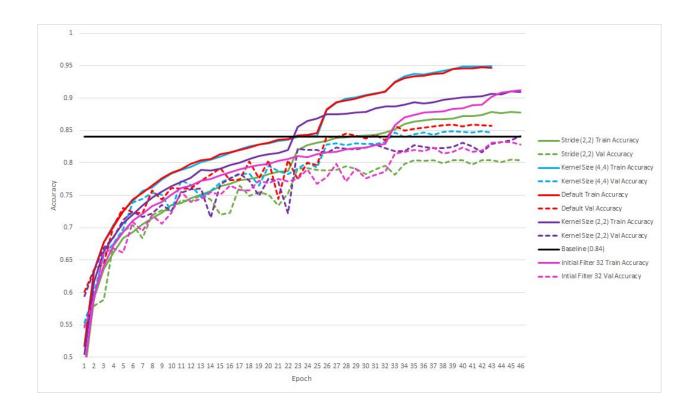
| | Accuracy | Time per epoch |
|---------------------------|----------|----------------|
| Original bottleneck Block | 0.8471 | 32s |
| Dropout First Block | 0.7812 | 36s |
| Proposed Block | 0.8505 | 32s |

Table-3 Original Block vs Dropout First Block vs Proposed Block

Figure 4 describes the results of a series of tests on ResNet18 (basic block version) where the default stride is set to (1,1). Note that for the initial layer of a block, the stride is always (2, 2). A test is then conducted where the stride is changed to (2,2) at all times, unchanged for first layer of block. The default kernel size for these blocks is (3,3) and these will be changed in 2 different tests: one test with a kernel size of (2,2) and the other with a kernel size of (4,4). The last test changes the initial filters from 64 to 32, in order to see its impact.

Observations:

- Kernel Size (3,3) and Kernel Size (4,4) have an identical training accuracy over the epoch however Kernel Size (4,4) is slower per epoch and also leads to a slightly lower final validation accuracy.
- Every other parameter change does not affect the epoch time, however they all performed worse, from 1.5% to 5% worse in accuracy by the final epoch.



Residual_block stride on ResNet18 (Basic Block)

| Change | Accuracy | Time per epoch |
|-----------------------------------|----------|----------------|
| Default | 0.8568 | 30s |
| Stride from (1,1) to (2,2) | 0.8042 | 30s |
| Kernel Size from (3,3) to (4,4) | 0.8469 | 37s |
| Kernel Size from (3,3) to (2,2) | 0.8416 | 29s |
| Filters start at 32 instead of 64 | 0.8283 | 28s |

Reference:

arXiv:1801.05134