Neural network retraining for overlapping weights encoded in a transpose pattern

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Project Description

Over the last decade, neural networks have been applied to a wide range of applications with great success. However, the weights they store result in a large memory overhead at all levels of the memory hierarchy [1]. Much work has been done to mitigate the drawbacks of this characteristic of neural networks.

The goal of this project is to utilize a new transposable access RRAM memory to increase the storage capacity allocated to weights, reducing the necessity for memory movement.

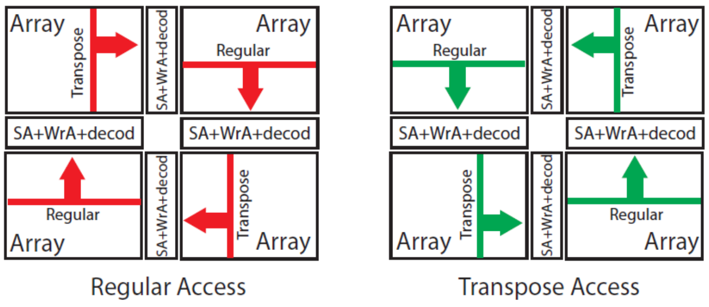
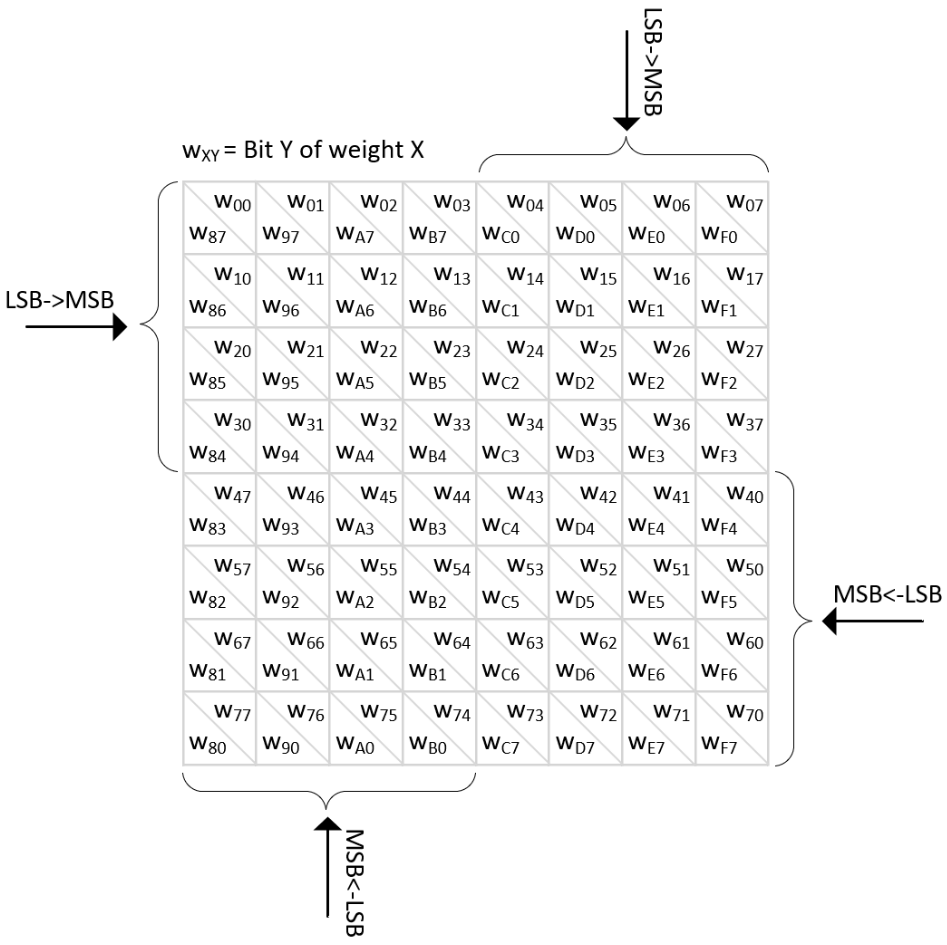


Figure 1: Transposable access memory

Figure 1 presents a high-level view of the functionality of the transpose access memory array. At each memory access, each subarray can be accessed in either a regular or transposed manner, enabling new data access patterns that can accelerate application runtime.

In order to take advantage of such an architecture for the acceleration of neural networks, we propose to encode neural network weights such that they overlap in a regular/transpose manner, effectively doubling the capacity of the memory array at the cost of a loss of weight accuracy (not necessarily neural network accuracy however). Weights will be stored such that the MSBs of weights stored in regular fashion overlap with the LSBs of weights stored in transpose fashion. Such a configuration reduces the error induced by bit sharing. Individual bit values can then be modified to minimize the error of the final weights with respect to their original values. It has already been demonstrated empirically that it is possible to reduce weight error to an average of 0.6% and a max of 1.44% for an overlapping array of 32 16-bit random integer values arranged in such a configuration. This adjustment of weight values, combined with network retraining, for example through incremental retraining[2], may enable more compact weight storage at little to no loss of neural network accuracy. Figure 2 illustrates the storage strategy.



w_XY = Bit Y of weight X
LSB->MSB
LSB->MSB
MSB<-LSB
MSB<-LSB
w00 w87 w01 w97 w02 wA7 w03 wB7 w04 wC0 w05 wD0 w06 wE0 w07 wF0
w10 w86 w11 w96 w12 wA6 w13 wB6 w14 wC1 w15 wD1 w16 wE1 w17 wF1
w20 w85 w21 w95 w22 wA5 w23 wB5 w24 wC2 w25 wD2 w26 wE2 w27 wF2
w30 w84 w31 w94 w32 wA4 w33 wB4 w34 wC3 w35 wD3 w36 wE3 w37 wF3
w47 w83 w46 w93 w45 wA3 w44 wB3 w43 wC4 w42 wD4 w41 wE4 w40 wF4
w57 w82 w56 w92 w55 wA2 w54 wB2 w53 wC5 w52 wD5 w51 wE5 w50 wF5
w67 w81 w66 w91 w65 wA1 w64 wB1 w63 wC6 w62 wD6 w61 wE6 w60 wF6
w77 w80 w76 w90 w75 wA0 w74 wB0 w73 wC7 w72 wD7 w71 wE7 w70 wF7

Figure 2: Overlapping weight storage for 8-bit weights.

The concept presented here can be expanded upon in multiple directions. The primary objective will be implementing an algorithm for adjusting weight values to minimize individual weight error while retraining the network to maintain accuracy. Network retraining can be performed in a variety of ways, with the suggested starting point being the strategy outlined in [2]. Other objectives may include an upper bound on weight error, introducing the ability to shift weight values to provide another degree of freedom when encoding, and considering the expansion of the concept into the 3rd dimension (aka a 3d memory stack) to further increase capacity.

Tasks of the Student:

1. Exploration of current quantization methods.
2. Develop encoding/quantization strategy for storing weights at minimal error within Matlab.
3. Implement algorithm for modifying weights and retraining network within a neural network framework. (Tensorflow, Caffe, etc.)
4. If previous objectives are fulfilled, this work will be a part of a submission in a peer-reviewed conference or journal.

Requirements:

- Understanding of neural network theory, both training and inference.
- Previous work with Matlab, Python or C++.

Appreciated Skills:

- Previous work with Tensorflow or equivalent neural network framework.
- Motivation to learn new skills.
- Autonomous work ability.

References:

[1] S. Bianco, R. Cadene et al., “Benchmark analysis of representative deep neural network architectures,” IEEE Access, vol. 6, 2018.
[2] Incremental Network Quantization: Towards Lossless CNNs with Low-Precision Weights