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Siemens Competition National Finals



Roadmap

- 1 The Problem

- 4 Key Findings



Autonomous Vehicles

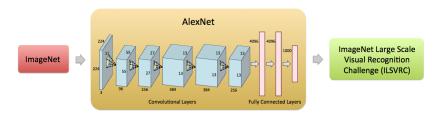
Revolutionizing transportation, reducing injuries, decreasing traffic congestion, and improving air quality



Google autonomous vehicle. Source: Michael Shick

AlexNet¹

ImageNet has sparked research innovation in visual object recognition through deep learning.

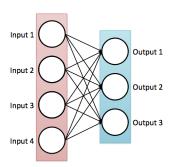


 $^{^{1} \}hbox{``Convolutional Neural Networks (CNNs/ConvNets).''} \ \textit{CS231n: Convolutional Neural Networks for Visual}$ Recognition. Stanford University, 2017. https://cs231n.github.io/convolutional-networks/

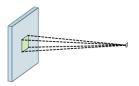


Deep Neural Networks

Convolutional neural networks (CNNs) utilize multiple layer types to achieve near-human accuracy in object recognition.



Fully Connected Layer



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Convolutional Layer



- Increased computational complexity
- Expensive customized hardware
- Complex configuration of associated software



- 1 The Problem
- 2 Existing Approaches
- 4 Key Findings



To Reduce Computational Complexity

- Use of binary weights
- Weight quantization: values restricted to powers of 2
- Replacement of multiplications with bit-shifts



Our Approach

Roadmap

- 3 Our Approach
- 4 Key Findings



Overview

1 Investigate how multiplication gates²(MGs) can be used in large neural networks

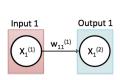
Our Approach

- Devise a set of no-multiplication architectures (NMAs) for:
 - Fully connected neural networks (FCNNs)
 - Convolutional neural networks (CNNs)
- 3 Derive mathematical expressions for the number of distinct products to compute in training these architectures in order to evaluate the extent to which NMAs decrease computation cost

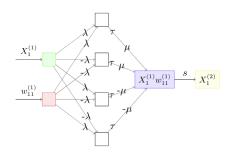
²Lin, Henry W., Max Tegmark, and David Rolnick. "Why does deep and cheap learning work so well?" *arXiv* preprint arXiv:1608.08225v4 [cond-mat.dis-nn], 2017. https://arxiv.org/pdf/1608.08225v4.pdf



NMA for the simplest case – forward propagation through an FCNN with L=1 layer, containing one neuron.



Original Architecture



Our Approach

No-Multiplication Architecture

Subsequent Methodology

- I Construct a generalized NMA for forward propagation through an FCNN with $L \ge 1$ layers.
- 2 Construct a generalized NMA for back propagation through an FCNN with $L \ge 1$ layers.
- 3 Similarly construct generalized NMAs for both forward and back propagation through a CNN with $L \ge 1$ convolutional layers.
- Derive mathematical expressions for the number of distinct products that must be computed using the NMAs.



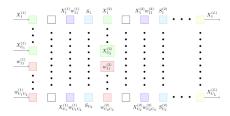
Roadmap

- 4 Key Findings

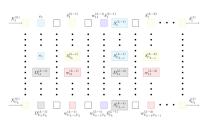


Generalized NMAs for FCNN with $L \ge 1$ layers

We constructed a set of architectures to implement FCNNs and fully connected layers without multiplication.



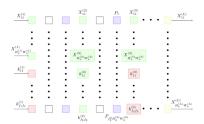
Forward Propagation



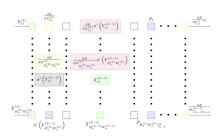
Back Propagation

Generalized NMAs for CNN with $L \ge 1$ layers

We constructed a set of architectures to implement convolutional layers without multiplication.



Forward Propagation



Back Propagation

Number of Distinct Products

We derived and proved theorems for three notable CNN cases:

- The number of distinct products to compute when an image containing repeated values is convolved with a kernel containing distinct weight values
- The number of distinct products to compute when an image containing distinct values is convolved with a kernel containing repeated weight values
- 3 The number of distinct products that must be computed for back propagation



 Our work on no-multiplication architectures has the potential to substantially expedite the training of neural networks on simple devices without custom hardware – a possible catalyst for the development of autonomous vehicles.

References



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