EML10EX02 - Leandro Borzyk, Niels Kissner, Kenneth Styppa, Florian Schrittwieser

2.1 Reading

Primary Contribution: The primary contribution of the paper lies in the successful integration of cuDNN, a library of efficient deep learning primitives, into the Caffe deep learning framework. This integration resulted in a substantial performance improvement of 36% during training iterations, showcasing the effectiveness of leveraging optimized computational primitives for convolutional neural networks. By seamlessly incorporating cuDNN into Caffe, the paper demonstrates how deep learning frameworks can benefit from specialized libraries to enhance training efficiency without the need for extensive modifications.

Key Insight: The key insight of this contribution is the emphasis on maintaining the core structure of the Caffe framework while leveraging the computational power of cuDNN. By providing low-level computational primitives and a modular design, cuDNN enables deep learning frameworks to access optimized routines for convolutional operations without requiring significant changes to the framework architecture. This insight highlights the importance of integrating specialized libraries to streamline deep learning model development and improve training performance.

Opinion/Relevance: In my opinion, this paper represents a significant advancement in the field of deep learning optimization by showcasing the tangible benefits of integrating cuDNN into established frameworks like Caffe. The demonstrated performance improvements and streamlined integration process underscore the relevance of this contribution in today's rapidly evolving deep learning landscape. As deep learning models grow in complexity and scale, the efficient utilization of specialized libraries like cuDNN remains crucial for achieving optimal training efficiency and model performance.

Acceptance to Journal: I strongly believe that this paper warrants acceptance in a scientific journal due to its clear presentation of the integration process, performance enhancements, and implications for the deep learning community. The detailed description of integrating cuDNN with Caffe, coupled with the substantial performance gains observed, makes it a valuable contribution to the field of deep learning optimization. The paper's relevance, practical insights, and potential impact on improving training efficiency in deep learning frameworks support its acceptance for publication in a reputable scientific journal.

2.2 Neural network from scratch

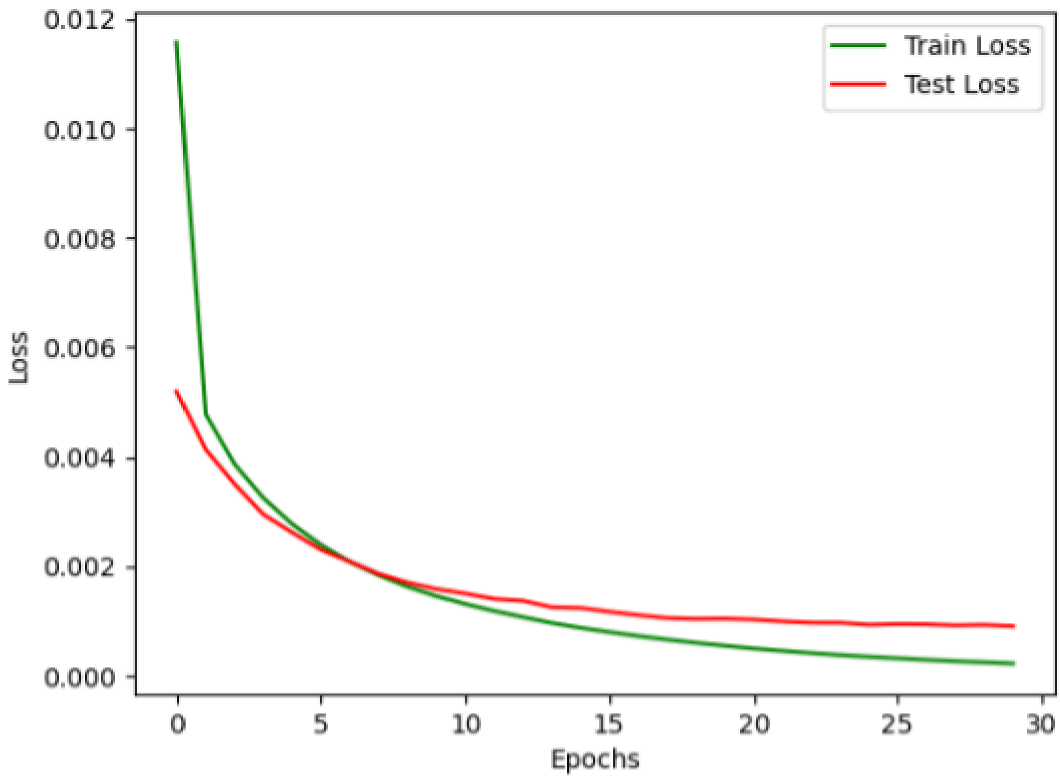

Fig. 1

Figure 1 shows a decrease in Train & Test Loss with increasing epochs. It can be observed that over increasing epoch sizes the model is more specialized on the training data indicated by a lower train loss than test loss. Resulting from this, test loss is a better indicator for network performance than train loss. The sweet spot between train loss and test loss is found when test loss reaches a minimum before increasing again.

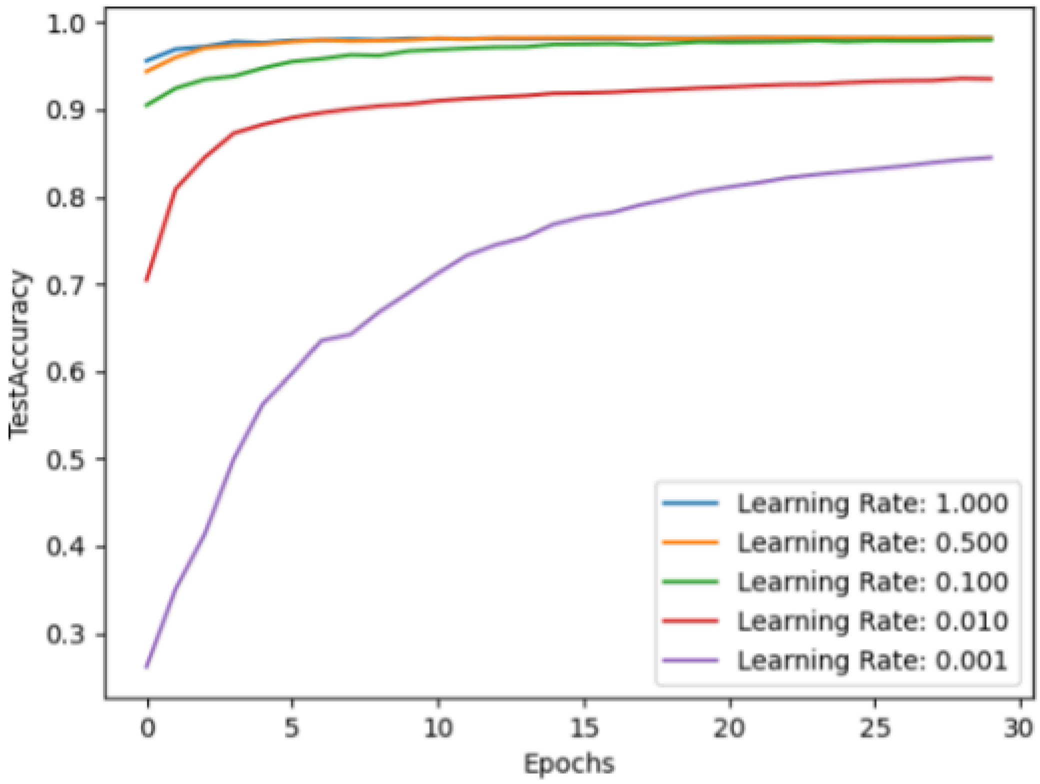

Fig. 2

Figure 2 shows different settings for learning rates. As a result it can be seen that higher learning rates result in a faster evolution of the network. With lower learning rates the adaptation to training results is much lower, resulting in much more needed epochs for reaching the same result as with higher learning rates.

Hypothesis: a possible speedup could be generated by starting with a high learning rate and decreasing it over increasing epochs.

2.3 Willingness to Present:

Willing to present 2.1 and 2.2.