When they go high we go low

Maksim Levental*
mlevental@uchicago.edu
University of Chicago

Elena Orlova
eorlova@uchicago.edu
University of Chicago

ABSTRACT

High level abstractions for implementing, training, and testing Deep Learning (DL) models abound. Such frameworks function primarily by abstracting away the implementation details of arbitrary neural architectures, thereby enabling researchers and engineers to focus on design. In principle, such frameworks could be "zero-cost abstractions"; in practice, they incur enormous translation and indirection overheads. We study at which points exactly in the engineering life-cycle of a DL model are the highest costs paid and whether they can be mitigated. We train, test, and evaluate a representative DL model using PyTorch, LibTorch, TorchScript, and cuDNN on representative datasets.

ACM Reference Format:
Maksim Levental and Elena Orlova. 2020. When they go high we go low. In *Proceedings of ACM Conference (Conference'17).* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Deep Learning (DL) frameworks represent neural network models as dataflow and computation graphs (where nodes correspond to functional units and edges correspond to composition). In recent years, there has been a proliferation of DL frameworks[1, 4, 7, 9] implemented as domain-specific languages (DSLs) embedded in "high-level" languages[1] such as Python, Java, and C#. These DSLs serve as *abstractions* that aim to map the DL graphs onto hardware pipelines. That is to say, they hide (or *encapsulate*) details of DL models that are judged to be either irrelevant or too onerous to consider. By virtue of these design decisions the frameworks trade-off ease-of-use for execution performance; quoting the architects of PyTorch:

> *To be useful, PyTorch needs to deliver compelling performance, although not at the expense of simplicity and ease of use. Trading 10% of speed for a significantly simpler to use model is acceptable; 100% is not.*

Trading off ergonomics for performance is manifestly reasonable[2], especially during the early phases of the DL engineering/research process (i.e. during the hypothesis generation and experimentation phases). Ultimately though, if one is in industry and taking for granted a research direction bears fruit, one needs to put the DL model into production. It is at this phase of the DL engineering process that every percentage point of execution performance becomes critical. Alternatively, there are many areas of academic DL where the research community strives to incrementally improve performance[2, 5, 8]. For example, in the area of super-resolution a deliberate goal is to be able to "super-resolve" in real-time[10]. Similarly, in natural language processing, where enormous language models are becoming the norm[3], memory efficiency of DL models is of the utmost concern. In such instances it's natural to wonder whether ease-of-use trade-offs that sacrifice execution performance, or memory efficiency, are worthwhile and whether their costs can be mitigated.

Thus, our aim here is to investigate the costs of some of the abstractions employed by framework developers. In particular we focus on the PyTorch framework and ecosystem (chosen for its popularity amongst academic researchers). To that end, we implement a popular and fairly representative[3] DL model at four levels of abstraction: conventional Python/PyTorch, C++/LibTorch, C++/cuDNN, and C++/TorchScript. We argue that in the forthcoming that these four implementations do in fact span considerable breadth in the abstraction spectrum. Furthermore we train, test, evaluate each of the implementations on four object detection datasets and tabulate performance and accuracy metrics.

The rest of this article is organizing as follows: section2 covers quickly reviews the germaine background material on graph compilers and GPUs, section3 describes the implementations and our profiling methodology, section4 presents our results and a comparative discussion thereof, section5 discusses broad lessons learned, section6 proposes future work, and section7 speculates wildly about the future of DL systems more generally.

2 BACKGROUND

What are the design choices made by DL framework architects and what are their costs? That is to say, what are the costs of the abstractions

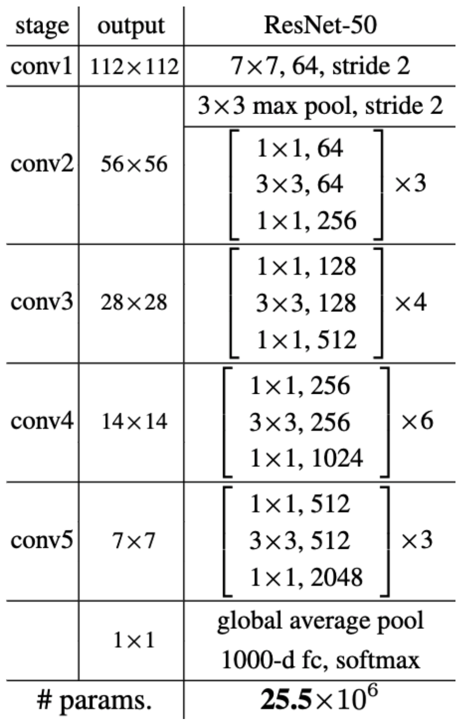
These frameworks encapsulate and "abstract away" many of the implementation details of DL, such as

- building the dataflow graph between units/layers (and the corresponding gradient-flow graph)
- tensor manipulation and memory layout

*Both authors contributed equally to this research.
[1]For the purposes of this article, we take "high-level" to mean garbage collected and agnostic with respect to hardware from *from the perspective of the user.*

[2]"The real problem is that programmers have spent far too much time worrying about efficiency in the wrong places and at the wrong times; premature optimization is the root of all evil (or at least most of it) in programming." [6]
[3]In the sense that the functional units constituting the model are widely used in various other models.

Conference'17, July 2017, Washington, DC, USA
© 2020 Association for Computing Machinery.
ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn



stage	output	ResNet-50
conv1	112×112	7×7, 64, stride 2
conv2	56×56	3×3 max pool, stride 2
		$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3	28×28	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$
conv4	14×14	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$
conv5	7×7	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	global average pool 1000-d fc, softmax
# params.		**25.5**$\times10^6$

- hardware specific optimizations

2.1 GPUs

2.2 Graph compilers

2.2.1 Static.

2.2.2 Dynamic.

3 METHODOLOGY

We implement ResNet-50 at four levels of abstraction: PyTorch, TorchScript, LibTorch, and cuDNN. The reason for staying within the same ecosystem (PyTorch)is, in theory, we keep as many of the pieces of functionality orthogonal to our concerns as possible. We'll see that that reasoning doesn't quite bear out (see5).

3.1 Implementations

3.2 Profiling

4 RESULTS

4.1 Training and evaluation

4.2 Memory and utilization

5 DISCUSSION

6 FUTURE WORK

7 SPECULATION

REFERENCES

[1] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mane, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viegas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. 2016. TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems. arXiv:cs.DC/1603.04467

[2] Abdelrahman Abdelhamed, Mahmoud Afifi, Radu Timofte, Michael S. Brown, Yue Cao, Zhilu Zhang, Wangmeng Zuo, Xiaoling Zhang, Jiye Liu, Wendong Chen, Changyuan Wen, Meng Liu, Shuailin Lv, Yunchao Zhang, Zhihong Pan, Baopu Li, Teng Xi, Yanwen Fan, Xiyu Yu, Gang Zhang, Jingtuo Liu, Junyu Han, Errui Ding, Songhyun Yu, Bumjun Park, Jechang Jeong, Shuai Liu, Ziyao Zong, Nan Nan, Chenghua Li, Zengli Yang, Long Bao, Shuangquan Wang, Dongwoon Bai, Jungwon Lee, Youngjung Kim, Kyeongha Rho, Changyeop Shin, Sungho Kim, Pengliang Tang, Yiyun Zhao, Yuqian Zhou, Yuchen Fan, Thomas Huang, Zhihao Li, Nisarg A. Shah, Wei Liu, Qiong Yan, Yuzhi Zhao, Marcin Możejko, Tomasz Latkowski, Lukasz Treszczotko, Michał Szafraniuk, Krzysztof Trojanowski, Yanhong Wu, Pablo Navarrete Michelini, Fengshuo Hu, Yunhua Lu, Sujin Kim, Wonjin Kim, Jaayeon Lee, Jang-Hwan Choi, Magauiya Zhussip, Azamat Khassenov, Jong Hyun Kim, Hwechul Cho, Priya Kansal, Sabari Nathan, Zhangyu Ye, Xiwen Lu, Yaqi Wu, Jiangxin Yang, Yanlong Cao, Siliang Tang, Yanpeng Cao, Matteo Maggioni, Ioannis Marras, Thomas Tanay, Gregory Slabaugh, Youliang Yan, Myungjoo Kang, Han-Soo Choi, Kyungmin Song, Shusong Xu, Xiaomu Lu, Tingniao Wang, Chunxia Lei, Bin Liu, Rajat Gupta, and Vineet Kumar. 2020. NTIRE 2020 Challenge on Real Image Denoising: Dataset, Methods and Results. arXiv:cs.CV/2005.04117

[3] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. arXiv:cs.CL/2005.14165

[4] Tianqi Chen, Mu Li, Yutian Li, Min Lin, Naiyan Wang, Minjie Wang, Tianjun Xiao, Bing Xu, Chiyuan Zhang, and Zheng Zhang. 2015. MXNet: A Flexible and Efficient Machine Learning Library for Heterogeneous Distributed Systems. arXiv:cs.DC/1512.01274

[5] David Hall, Feras Dayoub, John Skinner, Haoyang Zhang, Dimity Miller, Peter Corke, Gustavo Carneiro, Anelia Angelova, and Niko Sünderhauf. 2020. Probabilistic Object Detection: Definition and Evaluation. In *IEEE Winter Conference on Applications of Computer Vision (WACV)*.

[6] Donald E. Knuth. 1974. Computer Programming as an Art. *Commun. ACM* 17, 12 (Dec. 1974), 667–673. https://doi.org/10.1145/361604.361612

[7] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. arXiv:cs.LG/1912.01703

[8] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. 2015. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)* 115, 3 (2015), 211–252. https://doi.org/10.1007/s11263-015-0816-y

[9] Frank Seide and Amit Agarwal. 2016. CNTK: Microsoft's Open-Source Deep-Learning Toolkit. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16)*. Association for Computing Machinery, New York, NY, USA, 2135. https://doi.org/10.1145/2939672.2945397

[10] W. Shi, J. Caballero, F. Huszár, J. Totz, A. P. Aitken, R. Bishop, D. Rueckert, and Z. Wang. 2016. Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 1874–1883. https://doi.org/10.1109/CVPR.2016.207

Appendices

A APPENDIX