Neural Network Precision Tuning Using Stochastic Arithmetic

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Contributions

- Methodology for tuning the precision of an already trained neural network using stochastic arithmetic.
- Goal: obtain the lowest precision for each of its parameters, while keeping a certain accuracy on its results.

Floating-Point Arithmetic

IEEE754 Standard types

Format	Name	Length	Sign	Mantissa Length	Exponent Length
binary16	Half	16 bits	1 bit	11 bits	5 bits
binary32	Single	32 bits	1 bit	24 bits	8 bits
binary64	Double	64 bits	1 bit	53 bits	11 bits

Reduced precision:

- Shorter execution time ☺
- Less volume of results exchanged (less memory used) ☺
- Less energy consumption ☺
- Less accurate results - rounding errors ☹

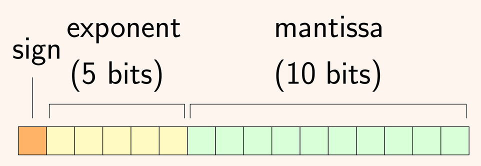
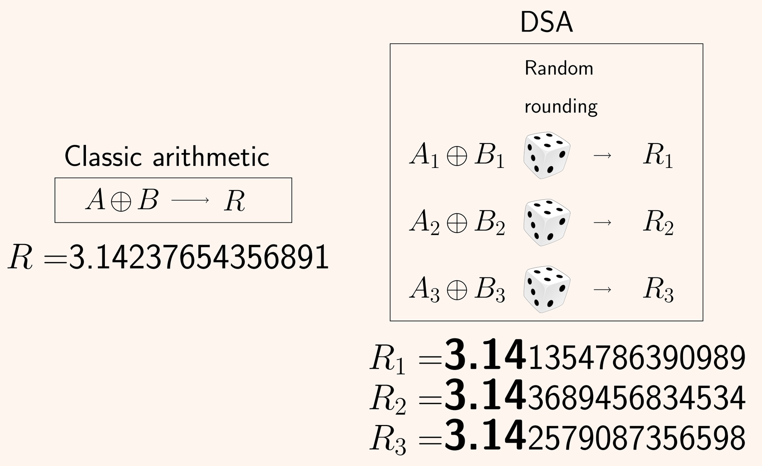


Figure 1. binary16 format

Discrete Stochastic Arithmetic (DSA)



- Allows round-off error estimation
- Based on random rounding
- For each operation, computes 3 samples of a result R
- Number of correct digits estimated thanks to Student's test with confidence level 95%

Numerical Validation Tools

CADNA Software (cadna.lip6.fr)

- Implements DSA for C/C++ or Fortran codes
- Provides stochastic types: 3 values of a variable + 1 integer being the estimated accuracy
- Displays values with their exact number of correct digits

PROMISE (promise.lip6.fr)

- Auto-tunes a C/C++ code to provide a mixed-precision version satisfying a given accuracy
- Uses CADNA to validate a configuration
- Uses the Delta-Debug algorithm to test the different configurations with mean complexity $O(n \log(n))$ for n variables [Zeller, 2019]

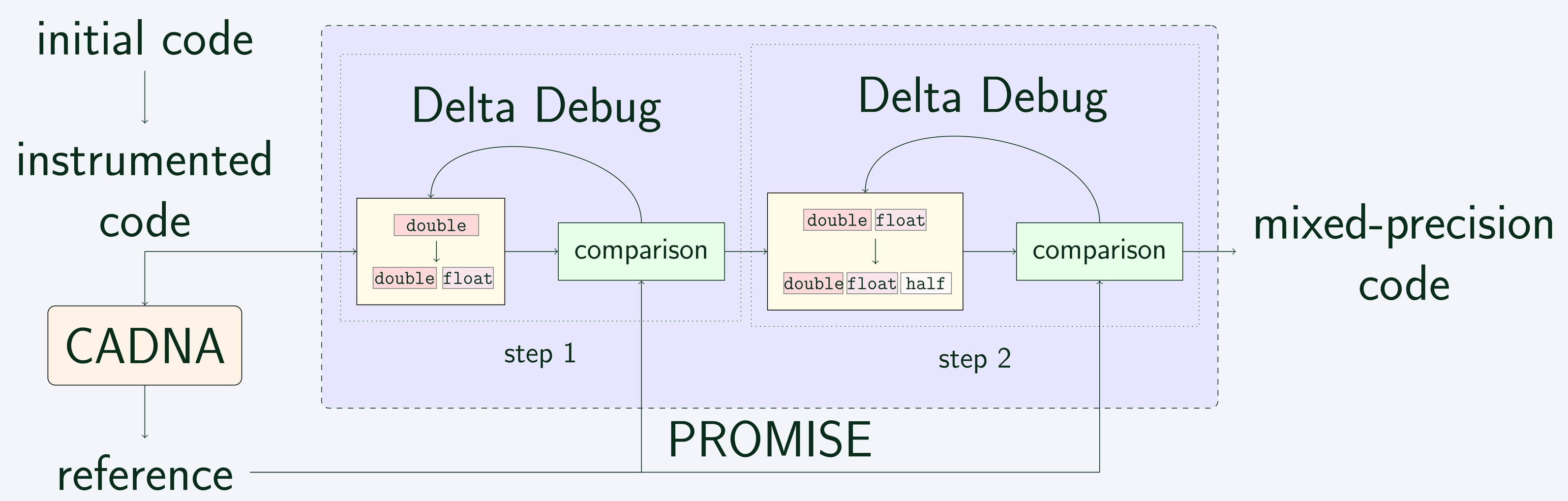


Figure 2. PROMISE Dataflow

Methodology

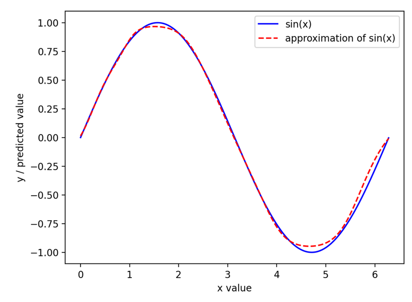
Neural network Python file → Model saved in HDF file → Model parameters in CSV files → C++ file with PROMISE variables

Application of PROMISE with two approaches:

- Considering one type per neuron (weight vector and bias of one neuron have the same precision).
- Considering one type per layer (weights and bias of one layer have the same precision).

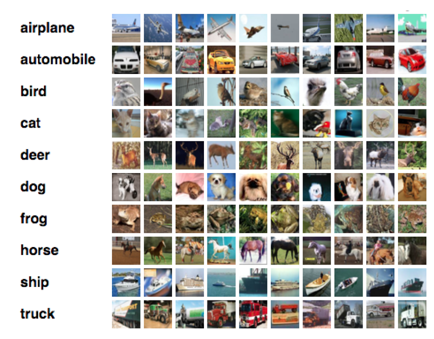
Considered Neural Networks

- Sine NN: dense neural network, approximation of sine function

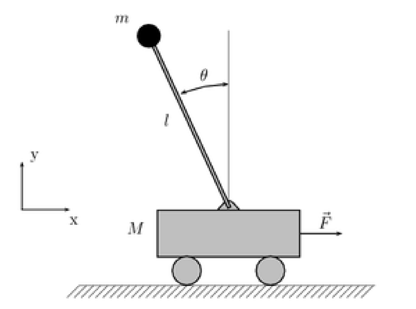


- MNIST NN: dense neural network, classification of handwritten digits

- CIFAR NN: convolutional neural network, classification of pictures among 10 classes



- Inverted Pendulum: dense neural network, computation of a Lyapunov function [Chang et al. 2020]



Precision Auto-tuning Applied to CIFAR NN

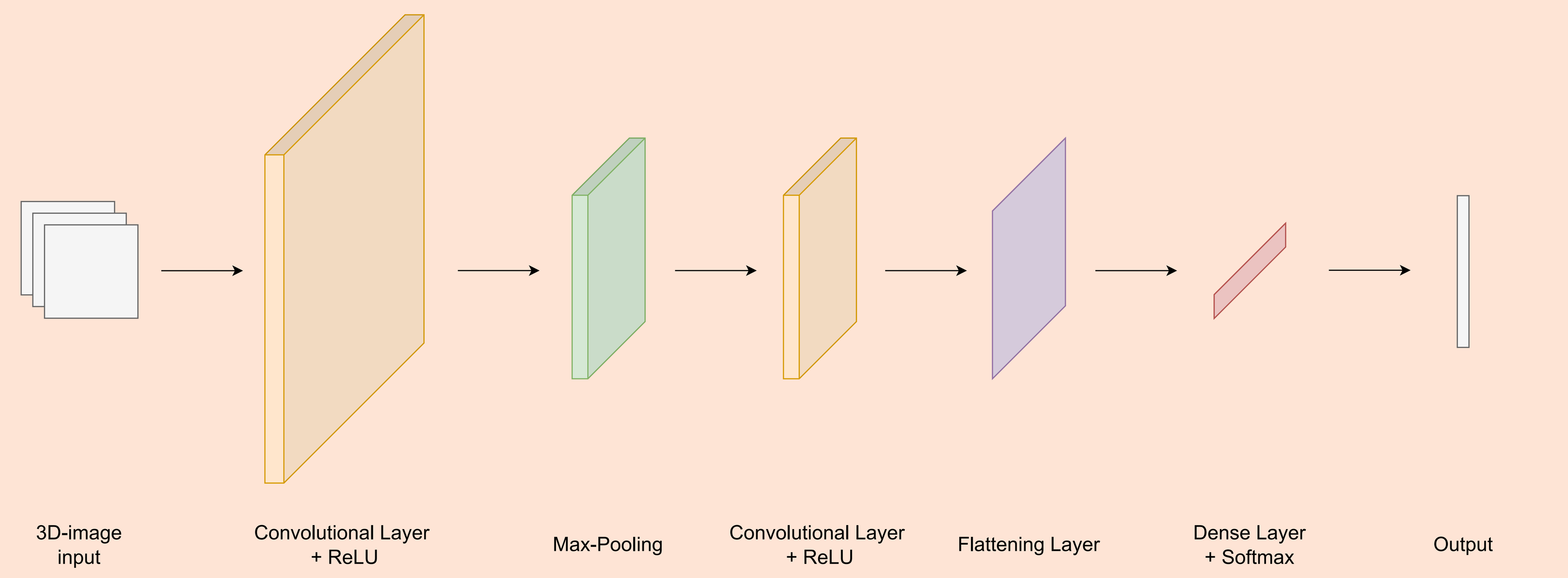


Figure 3. CIFAR NN architecture

Type distribution and PROMISE execution time:

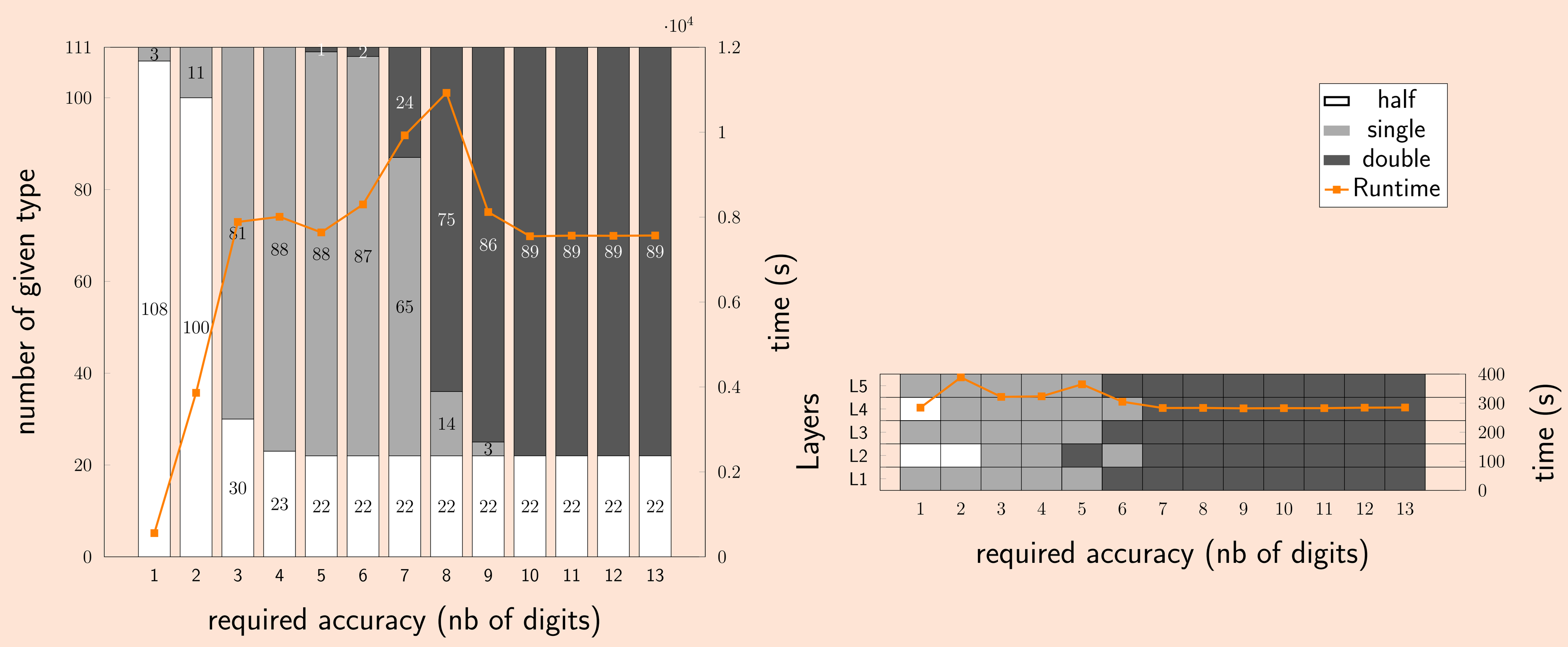


Figure 4. Type distribution per neuron (left) and per layer (right) with image test data[386]

- Mixed precision programs taking into account the required accuracy.
- One type per layer: PROMISE execution time is reduced, but often leads to uniform precision programs.
- Input values have actually a low impact on the type configurations obtained.

Future Works

- Analyse actual gain in time and memory
- Consider the parallelization of the Delta-Debug Algorithm and PROMISE
- Extend PROMISE to GPUs and to arbitrary precision on FPGAs
- Extend PROMISE to other types such as bfloat16

Related works

Precision tuning tools with static approach ([Chiang et al. 2017], etc.) or dynamic approach ([Lam et al. 2013], etc.).

Auto-tuning of neural networks in [Ioualalen and Martel 2019], with a different approach, not using stochastic arithmetic.

References

- Chang, Y.-C. et al. (Dec. 2020). "Neural Lyapunov Control". In: *33rd Conference on Neural Information Processing Systems (NeurIPS 2019)*.
- Ioualalen, A. and M. Martel (2019). "Neural Network Precision Tuning". In: *Quantitative Evaluation of Systems*. Ed. by D. Parker and V. Wolf. Cham: Springer International Publishing.
- Chiang, W.-F. et al. (2017). "Rigorous Floating-Point Mixed-Precision Tuning". In: *Proceedings of the 44th ACM SIGPLAN Symposium on Principles of Programming Languages*. POPL 2017. Paris, France: ACM.
- Lam, M. O. et al. (2013). "Automatically Adapting Programs for Mixed-Precision Floating-Point Computation". In: *Proceedings of the 27th International ACM Conference on International Conference on Supercomputing*. ICS '13. Eugene, Oregon, USA: ACM.

Further information: