Approximate Computation using Neuralized FPU

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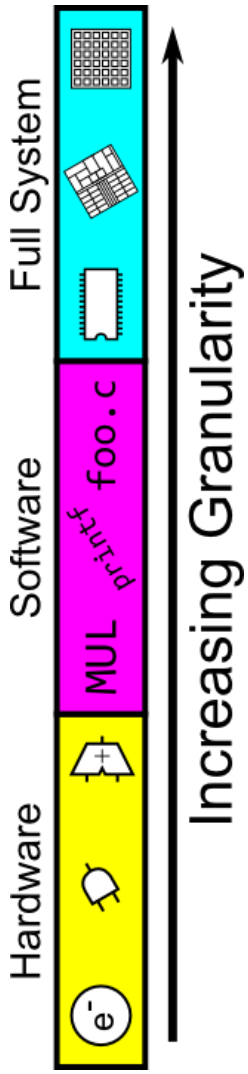
Granularities of Computation

- Within the realm of computing, there exists many computational granularities encompassing:
  - Hardware
  - Software
  - Full Systems
- Power, performance, and area benefits can be achieved by approximating granularities of computation
- One approach towards approximating computation uses neural networks as function approximators



NNs as Approximators – Gen. Purpose

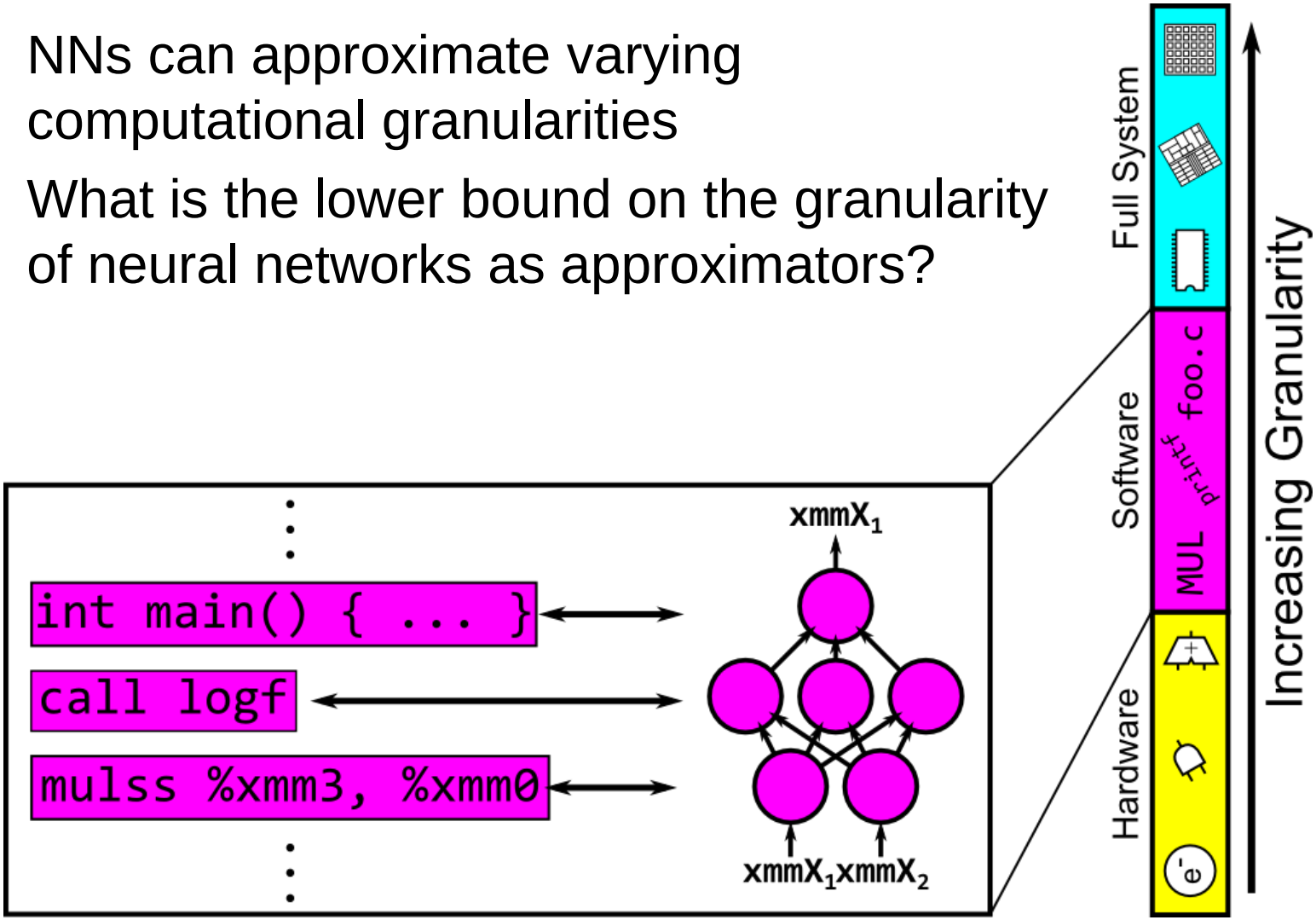
- Neural Networks can be general purpose function approximators
  - NNs can approximate regions of code [1]
  - NNs can approximate dominant functions in PARSEC [2]
  - Hardware implementations of NNs impart performance benefits
  - Accuracy impacts are acceptable
- Approximating large regions of code is best
  - Maximal performance benefits are imparted by large code regions
  - This can be achieved via compiler assisted user annotations [1]
  - This can be achieved via explicit user modifications [2]
  - User involvement is expensive and difficult

[1] H. Esmaeilzadeh et al., “Neural acceleration for general-purpose approximate programs,” in IEEE MICRO, 2012.

[2] T. Chen et al., “Benchnn: On the broad potential application scope of hardware neural network accelerators,” in IISWC. IEEE, 2012, pp. 36–45.

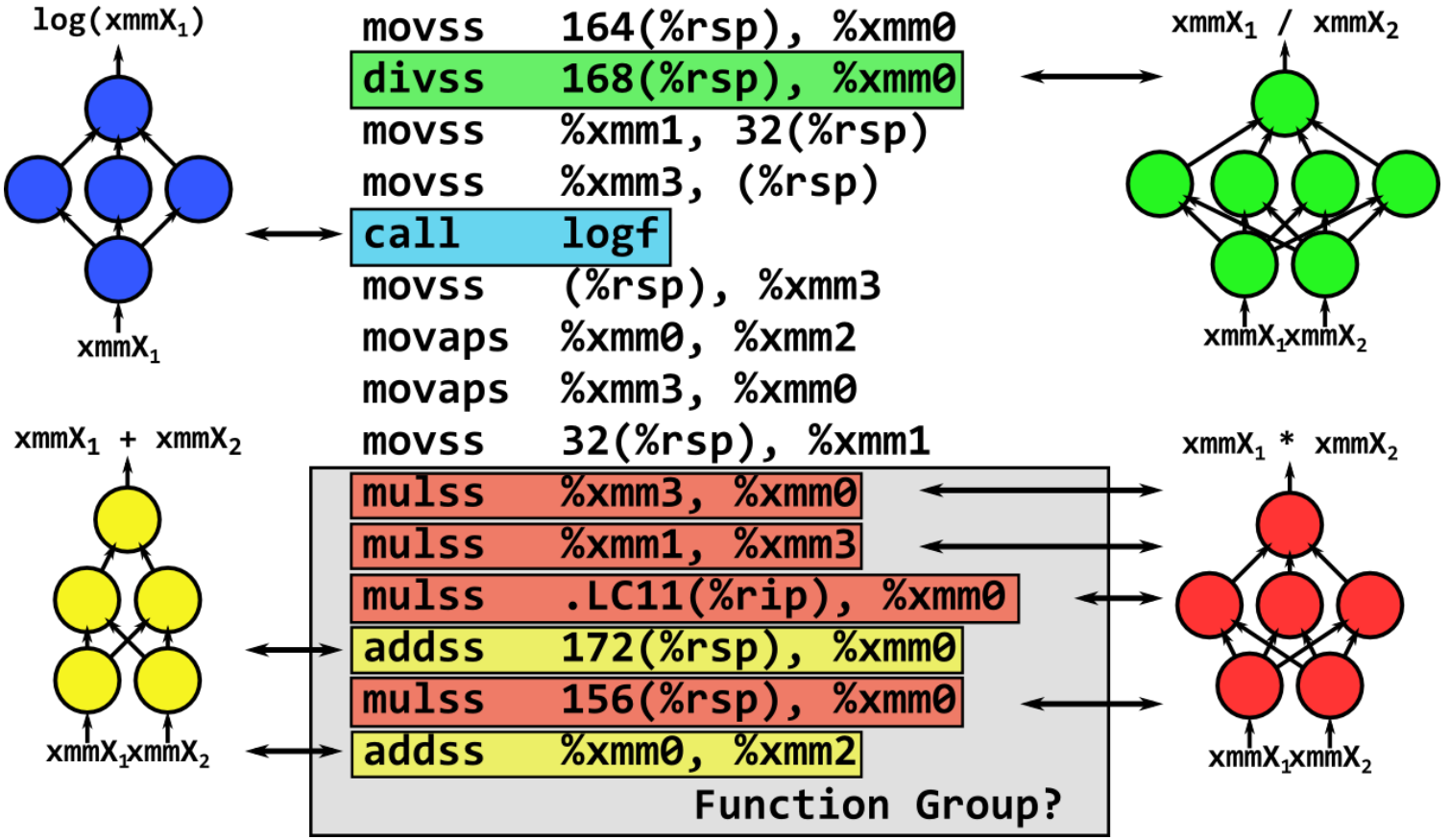
NNs as Approximators - Granularity

- NNs can approximate varying computational granularities
- What is the lower bound on the granularity of neural networks as approximators?



NNs as Approximators – Example

- NNs can approximate different instructions
- Approximation occurs in general purpose code



Neuralized FPMul – Details

- Can all instructions be approximated?
  - Instructions can be conditionally or generally approximated
- We explore approximating floating point multiplications
- As a case study, all floating point multiplications in three PARSEC [3] benchmarks (`blackscholes`, `bodytrack`, `swaptions`) are replaced with neuralized versions

[3] Bienia, C. et al., "The parsec benchmark suite: Characterization and architectural implications," in 17th International Conference on Parallel Architectures and Compliance Techniques. ACM, 2008, pp. 72-81.

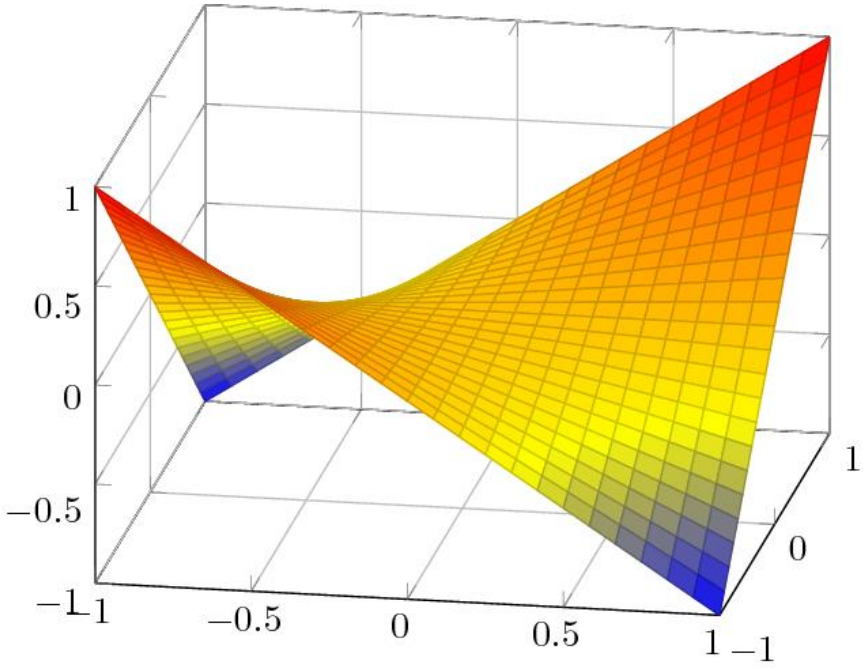
Neuralized FPMul – Implementation

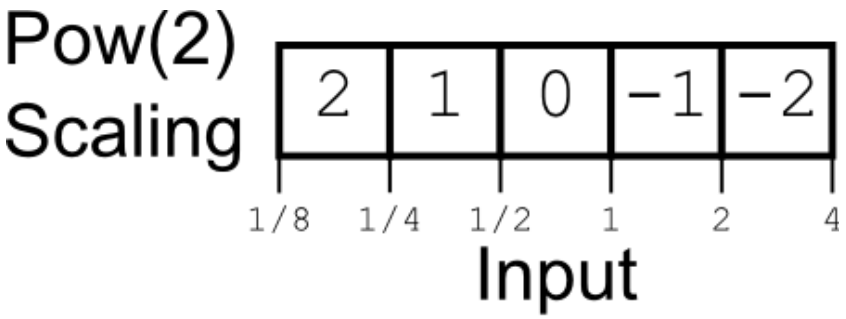
- Floating point multiplications are approximated with MLP networks
- MLPs are implemented using the Fast Artificial Neural Network Library (FANN) [4]
- The range of floating point numbers is problematic
  - Floating point range is large
  - Floating point numbers require accuracy for both large and small numbers
  - An MLP cannot approximate this range well for all values

[4] “Implementation of a fast artificial neural network library (fann),” Department of Computer Science University of Copenhagen (DIKU), Tech. Rep., 2003, http://fann.sf.net.

Neuralized FPMul - Scaling

- Multiplication are approximated on range: `[-1, 1]`
- Inputs are scaled by powers of 2 onto the disjoint range: `[-1, -0.5], [0.5, 1]`
- Different scalings are suitable for other functions



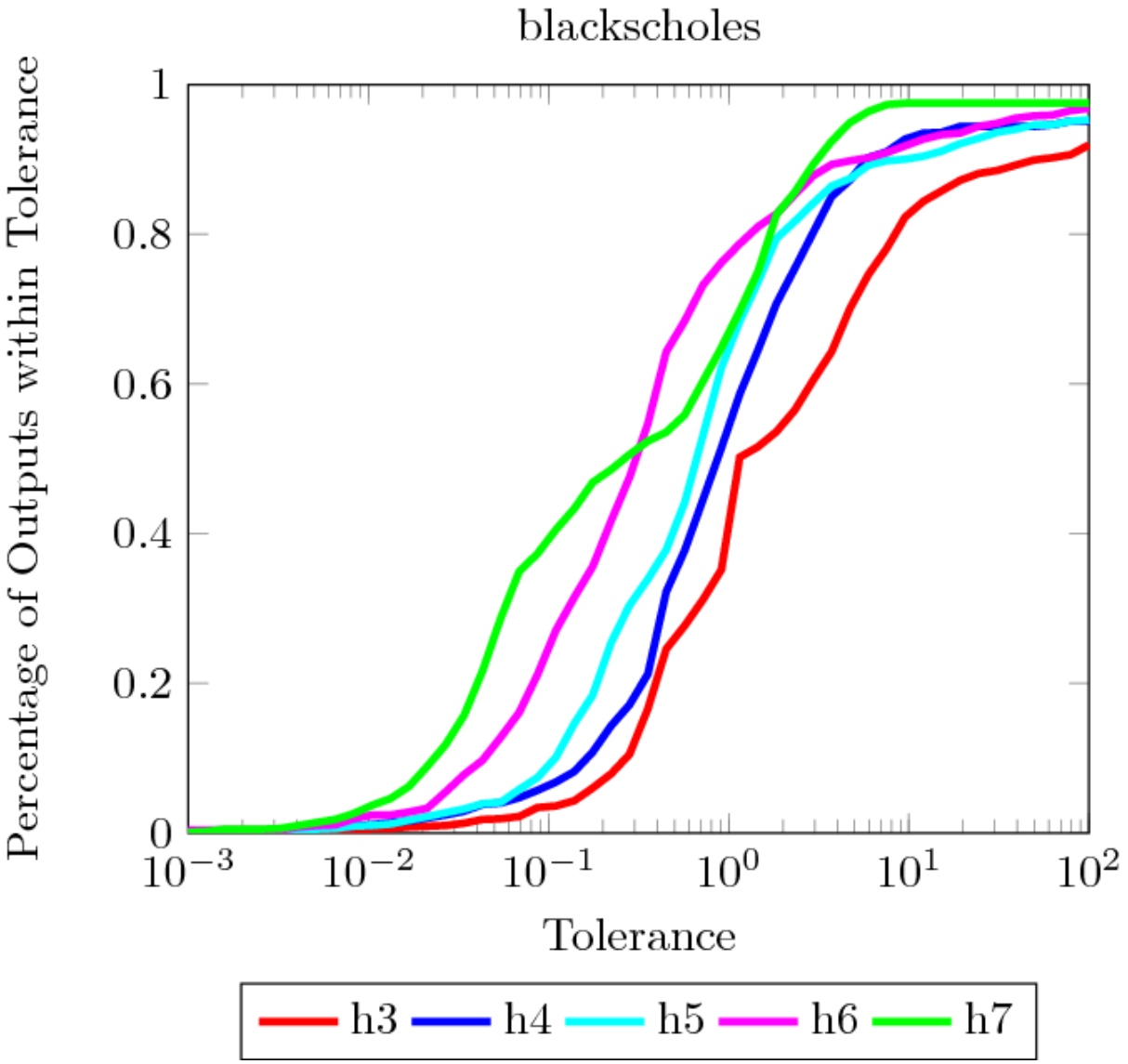


Neuralized FPMul – Training/Testing

- Multiplication MLPs are trained with resilient backpropagation using training and validation datasets
- Mean Squared Error (MSE) minimization was the goal of training
- The design space is explored from between 3 to 7 hidden nodes
- `Blackscholes`, `bodytrack`, and `swaptions` are executed using this Neuralized FPMul
- Output accuracy is measured
- An accurate output is defined as being within a percent tolerance of a correct output

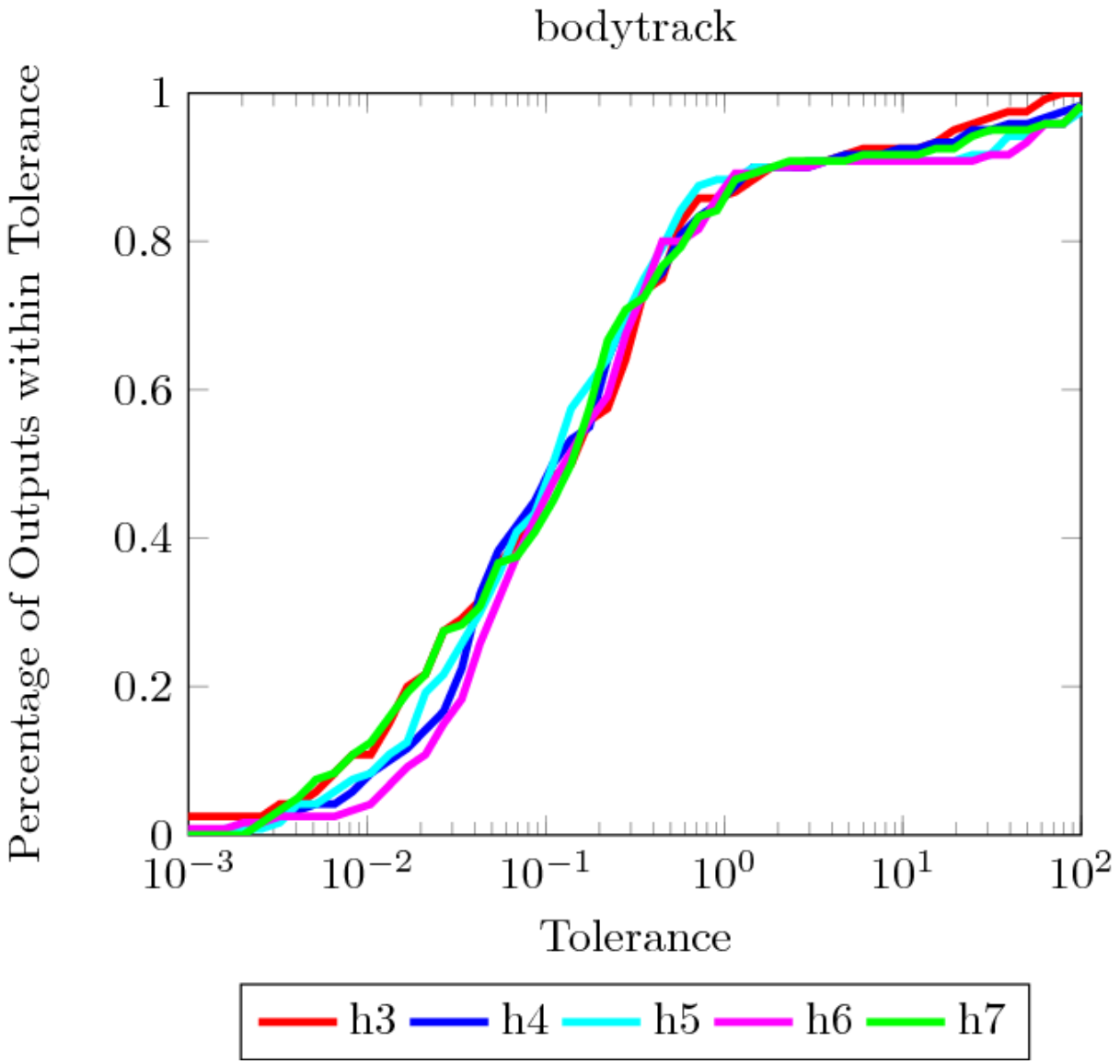
Results - `blackscholes`

- `Blackscholes` is dependent on the accuracy of the network approximating multiplication
- Networks with more nodes and lower MSE outperform networks with less nodes



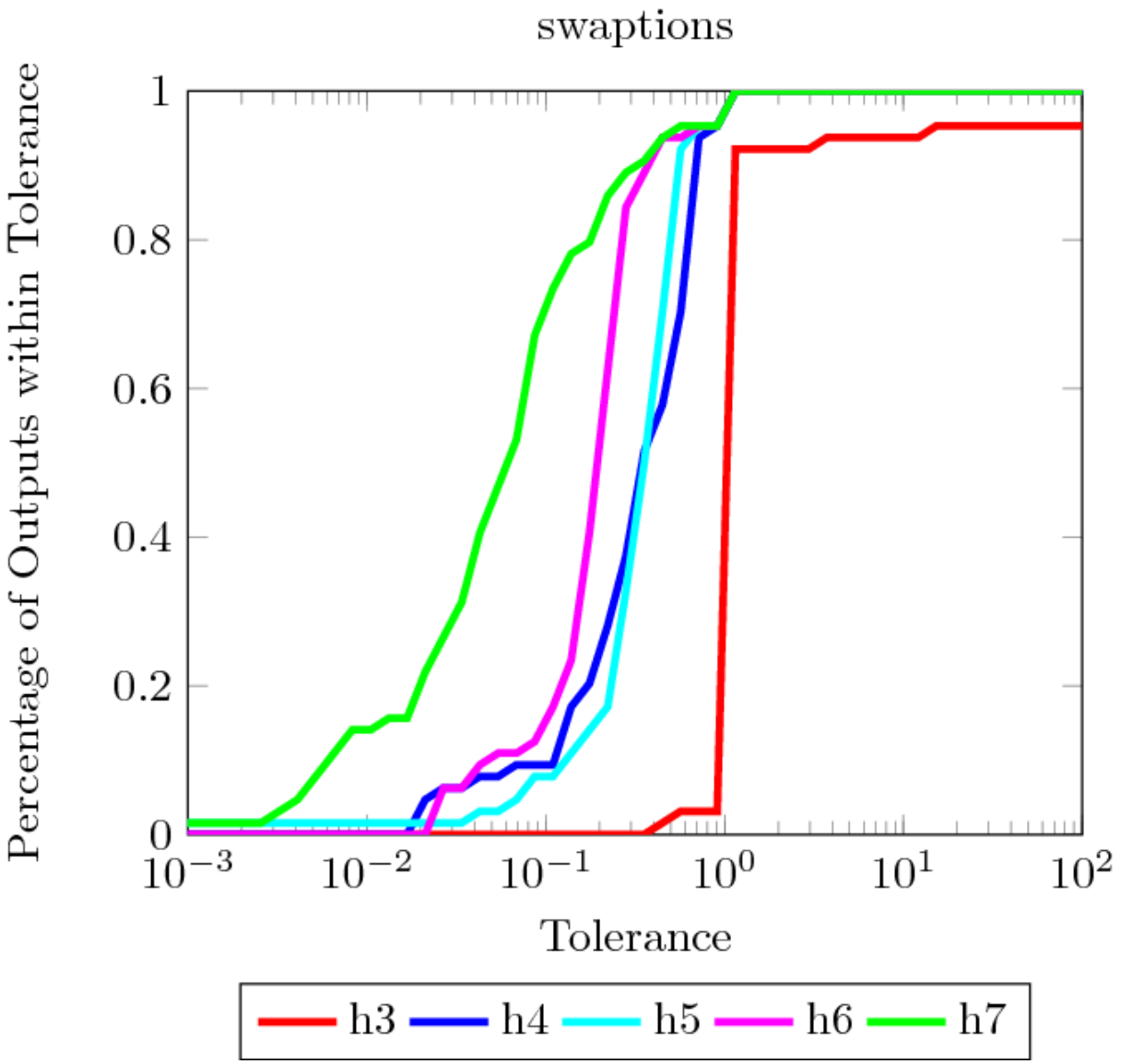
Results - bodytrack

- The accuracy of `bodytrack` is independent of approximation
- `Bodytrack` is a particle filter application
- Percent tolerance may not be the best metric
- More complex networks provide no benefits



Results - swaptions

- Swaptions shows a dependency on network accuracy
- A 7 hidden node network greatly outperforms a 6 hidden node network
- For high tolerances, network topology is less important



Discussion - Approximation

- One caveat: Not all floating point multiplications can be approximated
  - `Bodytrack` requires one variable to be on an exact range
  - Floating point multiplications in `glibc exp` cannot be approximated
- Coding styles affect the required precision
- Two examples found in PARSEC are:
  - Errors occur when function outputs are out of bounds
  - Errors occur when table lookups are derived from floating point computations
- A contrived example is:
  - Errors occur when control flow is dependent on the result of a floating point multiplication

Discussion – Impracticalities

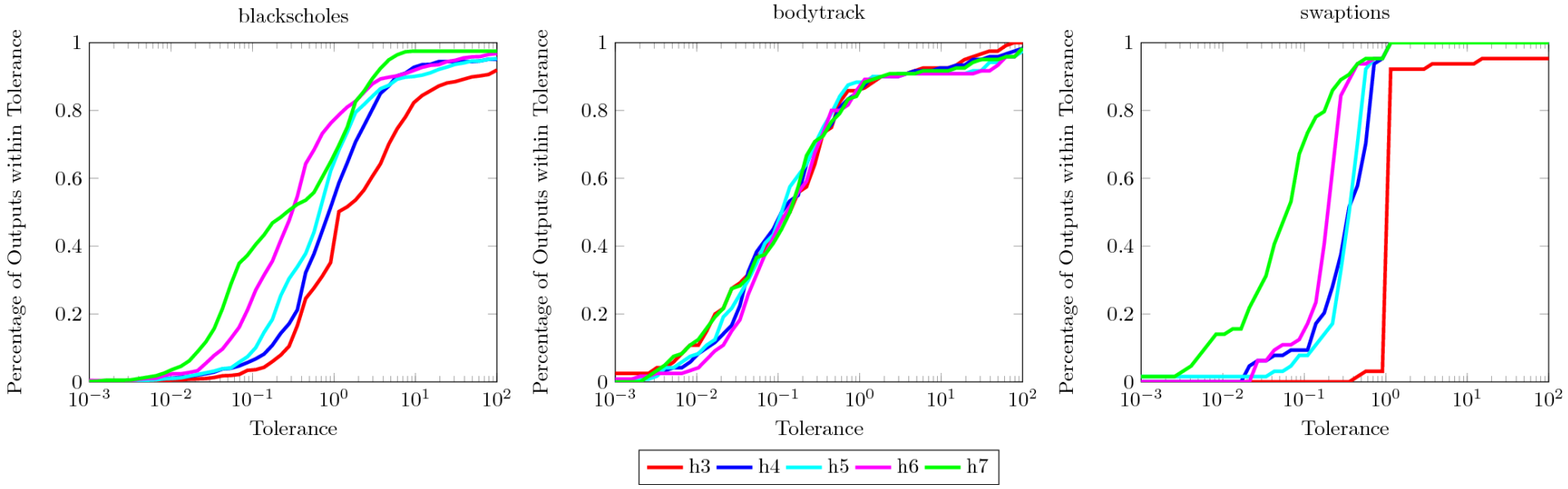
- Using current hardware neural networks are expensive
  - The total complexity of the approximation network should be less than the complexity of the approximated function
- Implementing neural network approximators using more operations than the instruction being approximated is a poor design choice
- Efficient implementations and emerging technologies may make small granularity practical
- Nevertheless, probing the lower bounds of approximating computational granularities is the goal of this research

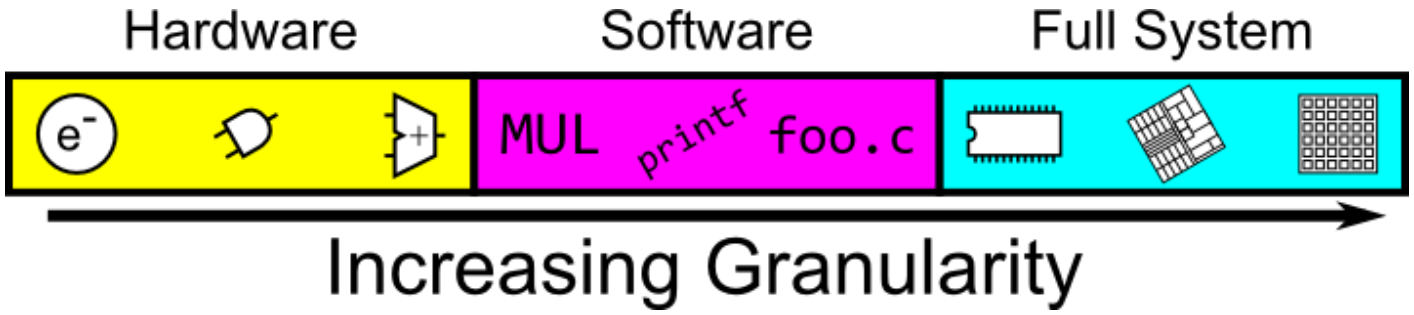
Discussion - Fault Tolerance

- An ignored benefit of neural network approximators is fault tolerance
- Fault tolerant training / retraining could be beneficial
- Examples include the following:
  - NNs can train/retrain with CMOS-specific faults [5]
  - Approximators with large granularity are robust in time and space
  - NNs can provide graceful performance degradation
- The best method to leverage fault tolerance remains an open question

[5] O. Temam, “A defect-tolerant accelerator for emerging highperformance applications,” in 39th ISCA, June 2012, pp. 356 –367

Questions


blackscholes
bodytrack
swaptions
Percentage of Outputs within Tolerance
Tolerance
h3
h4
h5
h6
h7


Hardware
Software
Full System
MUL
printf
foo.c
Increasing Granularity