## **ALGORITHM-HARDWARE CO-DESIGN OF DISTRIBUTION-AWARE LOGARITHMIC-POSIT ENCODINGS FOR EFFICIENT DNN INFERENCE**

Akshat Ramachandran<sup>1</sup>, Zishen Wan<sup>1</sup>, Geonhwa Jeong<sup>1</sup>, John Gustafson<sup>2</sup>, Tushar Krishna<sup>1</sup> <sup>1</sup>Georgia Institute of Technology, <sup>2</sup>Arizona State University



## (3) Algorithm: Genetic-Algorithm Based LP Quantization (LPQ) (1) Motivation P<6,2,3,0> LP<6,2,5,0> Precision LP<6,2,2,0> Step 1: Candidate Initizalization AF<6.3> DNN Model Transformer Layer ResNet Layer Maximize inner product daptive flat )LN-1 1.0De-L5 FFN L1 Conv $C_1(n es rs sf n es rs sf \cdot \cdot \cdot \cdot$ $ullet n \; es \; rs \;$ sf $\;$ , $L_{F1}$ ) En-L1 FFN L2 Conv $\frac{10^{10}}{10^{3}}$ 0.5Concatenate IR Population LN-1 ediate Representations (IR) En-L1 MHSA L3 Conv $C_P($ $n \ es \ rs \ sf \ n \ es \ rs \ sf \ \cdot \cdot \cdot \cdot \cdot n \ es \ rs \ sf \ , L_{F2})$ 0.0Minimize inner product Different Layers have . Batch $\bullet \bullet \circ \circ \circ$ between similar classes Relative -0.5 -1.0ferent weight distribut Quantized Corresponding FP Bate Step 2: Regeneration Model's Outpu Quantized DNN Model Select top 2 Perform Mutation & $L_{N-1}$ -1.5candidates from Choose Block for rossover to produce population with best regeneration child $(C_N)$ -22-2.0Step 4: Evaluation and Population Update -2040-4020 Model Weight Distribution Log2(|x|)Add $C_N$ and best Evaluate all generated > Uniform Quantization: Substantial distributional variance and orders Obtain $L_F$ for each of ( $C_{N1}$ , $C_{N2}$ ....) to children on the candidate population as ( $\Delta_C, L_F$ ) of **magnitude difference** in DNN parameters causing significant calibration data **Step 3: Diversity Prompting Selection**

- > Floating-Point Techniques: Fail to adapt to the tapered distribution of DNN parameters and use **flat accuracy**, have increased hardware complexity.
- > Why Posits?: Posit-based representations outperform floats in DNN inference, offering **improved dynamic range**, **higher accuracy**, **simpler** exception handling and tapered accuracy. But still have complex hardware.
- > Logarithmic Posits: A composite data type that blends the adaptability of posits with the hardware efficiency of LNS.

(2) Logarithmic Posits (LP)

quantization errors.

- Express standard fraction and exponent in the logarithmic domain as a unified fixed-point exponent of the power of two as  $2^{ulfx}$ , where ulfx=e+f.

## > Fitness Function:

Generate multiple

random parents

Mutate with  $C_N$ 

- $\checkmark$  A novel global-local contrastive loss, combats overfitting to calibration data and prevents premature convergence by minimizing representational divergence of intermediate layers.
- $\checkmark$  Also includes a compression loss that drives the optimization to identify lower bit widths.

Generate diverse

children ( $C_{N1}$ ,  $C_{N2}$ ..

 $\checkmark$  This combination of fitness function drives the genetic algorithm for layer-wise quantization.

## (4) Hardware: Logarithmic-Posit Accelerator (LPA)

