









### HOLIGRAIL

HOLlistic approaches to GReener model Architectures for Inference and Learning

Olivier Sentieys (Université de Rennes, Inria, IRISA)

Olivier Bichler (CEA List/LIAE, Saclay)

Mohamed Tamaazousti (CEA List/LVML, Saclay)

Florent De Dinechin (INSA Lyon, CITI)

Fabrice Rastello (Inria Grenoble)

Adrien Prost-Boucle (Grenoble-INP, CNRS)



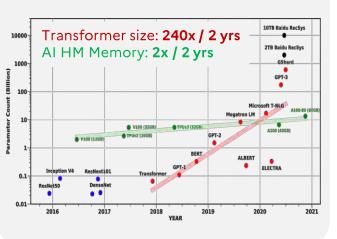


### **Motivation**

Deployment, from cloud to edge, a necessity: Application maturity Scale-up Cost reduction Quantum limit of Unsustainable Al cloud Moore's law1 Physical world interaction Cloud Al: development Computing power (TOPS) (large-scale learning, circuit, Era of "wired" circuits IBM ASCI White 7.23 TFLOPS Apple A16 17 TOPS Cray-1 Edge IA: 160 MFLOPS ARM Cortex-M4 deployment 250 MOPS (inference & adaptation) 1985 2000 2010 2022 ~2036

## Al's "Moore law" is **two order of magnitude** faster than silicon's

Evolution of the number of parameters is **much higher** than available on-chip memory

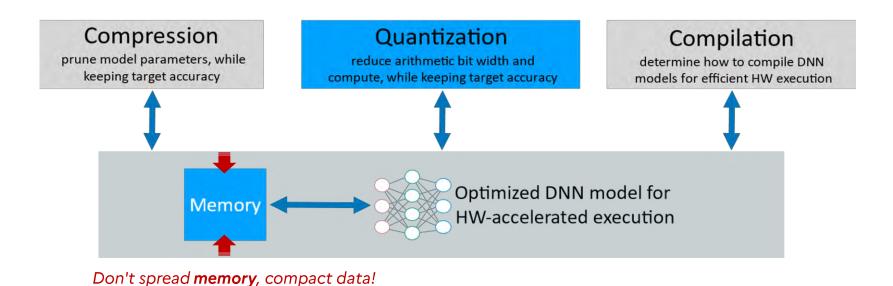


→ Holigrail targets breakthroughs in algorithms coding compactness, arithmetic operators efficiency and related compiler optimizations for both training and inference



## **Need for DNN Compression**

From Sensors to Clouds, for both Inference and Training

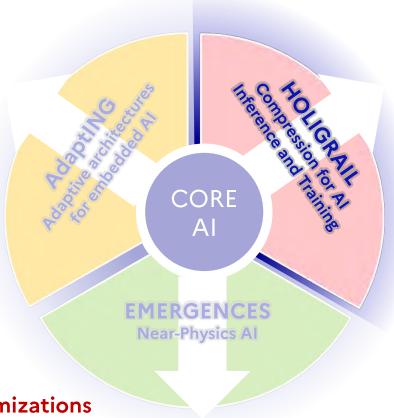




## From Cloud to Edge

### **Research Challenges**

- Extreme quantization
- Structured sparsity
- Maximum entropy coding
- Tensor methods
- Low-precision training
- Compiler and architectural support



All are related to Hardware-Aware Optimizations



### Challenges: Quantization

### Quantization effects: the good

- Reduced memory usage, reduced energy, faster execution
- Less silicon area, more parallelism and performance

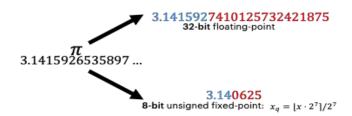
### Quantization effects: the bad

Less precision results in lower accuracy

### Need for new methods for extreme quantization

- Below 8 bits, ternary/binary
- Quantize weights and activations
- Non-standard number representation formats
- Complex DNN models (e.g., transformers, LLM)

ADD energy (pJ)				Memory access	
INT8	INT32	FP16	FP32	energy (pJ)	
0.03	0.1	0.4	0.9	Cache (64-bit)	
20%				8KB	10
30x energy reduction				32KB	20
MULT energy (pJ)				1MB	100
INT8	INT32	FP16	FP32	External Mem.	
0.2	3.1	1.1	3.7	DRAM	1300-
18.5x energy reduction					2600







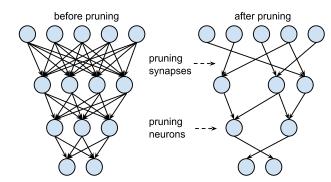
## **Challenges: Sparsity**

Sparsity is intrinsically present in DL models
But naturally unstructured and thus difficult to
exploit by data-parallel hardware

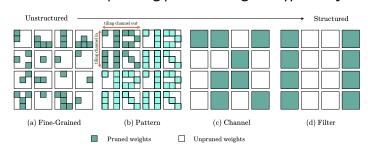
### Propose methods for structured sparsity

- More direct and efficient parallel implementations
- Combined with extreme quantization
- Explore learned data-dependent structured sparsity
- Explore automaton schemes

### Network Pruning



#### Structured pruning provides higher efficiency



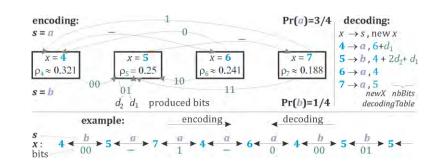


## Challenges: Maximum entropy coding

In information theory, entropy measure the quantity of information, in fractional bits A coding that maximizes entropy per bit should be efficient (no useless bit) Inversely, minimizing entropy regardless of coding allows efficient compression!

Propose training objectives that enable entropy-based compression:

- Minimize the entropy, not the bit-width
- Exploit arithmetic compression
- Trade memory for (little) computation







### Challenges: Low-precision training

### Carbon footprint of DNN training

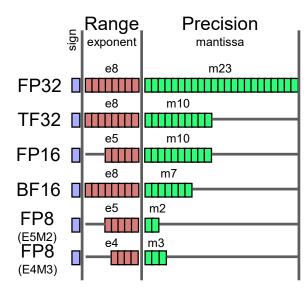
Analyzing the carbon footprint of current natural-language processing models shows an alarming trend: training one huge model for machine translation emits the same amount of CO2 as five cars in their lifetimes (fuel included)

[Strubell et al., ACL 2019]

 Many more operations than inference, more pressure on memory access, much more difficult to accelerate



- Mixed-precision, run-time adaptation, analytical models
- Low-precision floating-point and variable-precision variants
- New models or training algorithms



FP8 (8-bit floating-point) currently under standardization by IEEE P3109 working group

3/20/2024



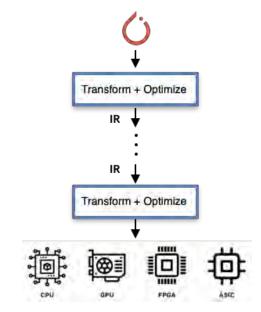
# Challenges: Compiler and architectural support

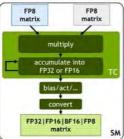
Compiling and generating code from a DNN framework is still an unsolved problem Current runtime and compiler rely on:

- Optimized DNN specific libraries
- Pattern specific (for tensors) compiler optimization

Need for new compiler techniques and frameworks

- Reduce amount of computation and memory footprint
- Exploit current context (sparsity, extreme quantization)
- Revisiting pattern-specific optimization strategies
- Analytical and statistical performance models (high-level)
- Co-design compiler / optimization / hardware





Nvidia Hopper GH100 GPU

FP8 support in tensor cores provides up to 4x speedup





### **HOLIGRAIL** Partners

### Complementary skills in

- machine learning, optimization,
- computer arithmetic,
- hardware architecture,
- hardware acceleration,
- compiler optimizations,
- coding theory







### Consortium members

#### Université de Rennes, Inria, IRISA

Project coordinator
Olivier Sentieys, Silviu Filip





## Commissariat à l'énergie atomique et aux énergies alternatives (CEA)



Olivier Bichler, Mohamed Tamaazousti

#### Previous works in the field

- Computer arithmetic and architecture for embedded systems
- Energy-efficient hardware accelerators, for machine learning and data mining
- Approximate computing: reduced-precision arithmetic, numerical accuracy analysis
- Low-precision training
- Quantization-aware training

#### Previous works in the field

- Architectures based on resistive memory technology and neuromorphic computing
- Development of the N2D2 deep learning quantization and deployment framework



- Computer vision applications
- Deep neural networks representation and compression
- Random tensor theories for machine learning models





### Consortium members

Université Grenoble Alpes, Inria Corse

<u>Fabrice Rastello</u>, Christophe Guillon





Previous works in the field

- Automatic parallelization and compiler backend optimization
- Pattern-specific compiler optimization for hardware accelerators
- Performance debugging based on binary instrumentation
- Compiler design

Université Grenoble Alpes, Grenoble-INP, CNRS, TIMA





<u>Adrien Prost-Boucle</u>, Olivier Muller, Frédéric Pétrot

TiMA

Previous works in the field

- High-level synthesis
- Optimized implementations for FPGA
- Digital circuit accelerators for AI inference
- Focus on resources and energy usage





### Consortium members

INSA Lyon, CITI Lab, Inria



Florent De Dinechin, Anastasia Volkova



Previous works in the field

- Hardware and software computer arithmetic
- FPGA arithmetic and computing
- Formal proof for arithmetic algorithms
- Low-level implementations of artificial neural networks
- FloPoCo arithmetic cores generator software project







WPO: Management, Dissemination, and Valorization

## WP1: Model Compression and Optimization

Compression framework at the algorithm level: unified formulation including pruning, quantization and decomposition:

- Tensor decomposition
- Quantization-aware training
- Mixed-precision quantization
- Maximum entropy coding



## WP2: Optimizing Sparse Computation and Quantization

Enhance efficiency and speed of sparse computations in deep neural networks, taking into account quantization:

- Generation of optimized codelets
- Fast heuristics for compressibility
- Quantization-aware sparsity



## WP3: Arithmetic Operators and Code Generation

Optimize neural networks at the micro-architecture level, down to compiler back-end techniques:

- Small formats arithmetic units
- Memory access optimizations
- Resource-constrained execution



#### From algorithm optimization to hardware mapping

#### WP4: Tool Development and Validation

Integration and interoperability with existing reference frameworks. Develop hardware librairies, prototypes or demonstrators to showcase HOLIGRAIL results, fully synchronized with the outcomes of ADAPTING and DEEPGREEN.





#### WPO: Management, Dissemination, and Valorization

## WP1: Model Compression and Optimization

PhD wist (+) )
PhD wist
PostDoc wist
PostDoc wist
PhD withvertiff
PhD wist
PhD

## WP2: Optimizing Sparse Computation and Quantization



## WP3: Arithmetic Operators and Code Generation



### From algorithm optimization to hardware mapping

#### WP4: Tool Development and Validation

5 research engineers and 3 PostDoc, partially shared with WP1, WP2 and WP3



### Project expected outcomes

- Breakthroughs in efficiency for inference and training algorithms on specialized hardware:
  - o Algorithms coding compactness
  - o Arithmetic operators efficiency
  - o Compiler optimizations
- Dissemination in high-quality publications in journals and conferences with high impact
- Open-source software (e.g., MPTorch, FloPoCo, MLIR/LLVM) and hardware specifications
- Integration in embedded system solutions, in particular the DeepGreen framework ( aidge )

#### Manpower

14 PhD students, 7 post-doctoral fellows (16.5 p.y), 4 research eng. (10.5 p.y)

p.y: person year















### Relation with other projects from the PEPR

