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# Code Generation & Optimization for Deep-Learning Computations on GPUs via Multi-Dimensional Homomorphisms

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*Best Poster Finalist*

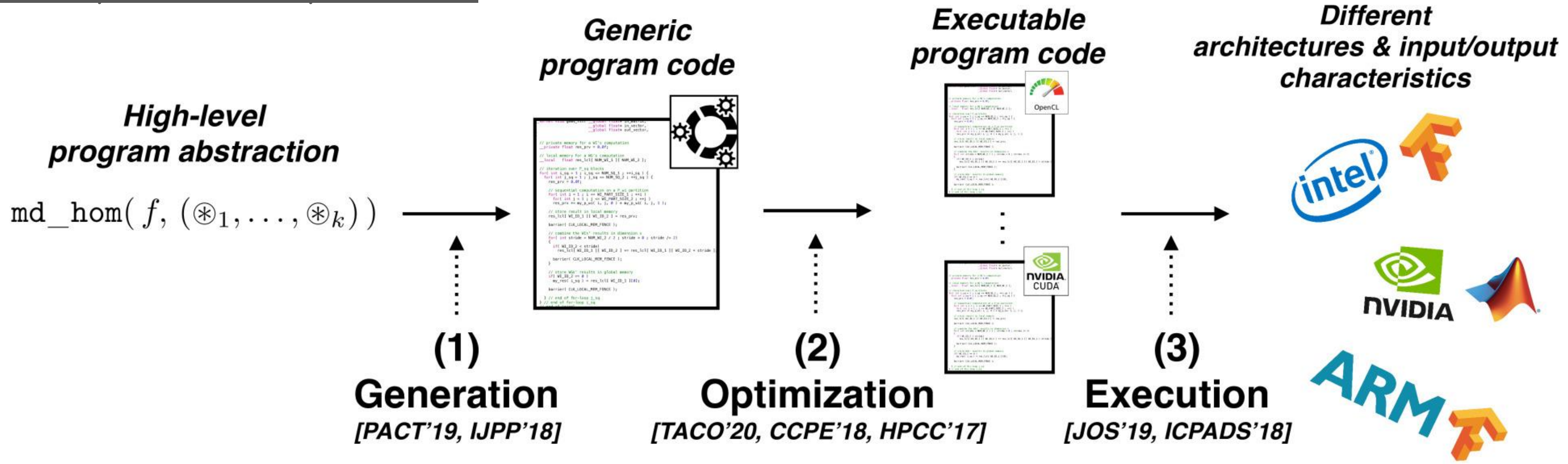
# Introduction

We present our work-in-progress code generation and optimization approach for Deep Learning (DL) computations:

- based on our approach of **Multi-Dimensional Homomorphisms (MDH)** *[IJPP'18]*
- achieves **high performance** for popular DL computations by exploiting the already existing MDH GPU code generation *[PACT'19]* & optimization *[TACO'20]* & execution *[JOS'19]* approach
- **more expressive** than the state-of-the-art DL abstractions (e.g., as provided by TensorFlow): we show that MDH can express multiple DL computations as a single MDH expression, enabling optimization across computations (parallelization, tiling, etc.)

# Excursion: MDH in a Nutshell

A holistic approach toward automatic code *generation* & *optimization* & *execution* for *data-parallel computations*:




- We **formally define data-parallel computations** (linear algebra routines (BLAS), convolutions, ...) as **Multi-Dimensional Homomorphisms (MDHs)**.
- We enable **conveniently** implementing MDHs by providing a **high-level DSL** for them.
- We provide a **DSL compiler** for automatically **generating executable low-level code** (CUDA, etc) -- the code is **fully automatically optimized** (auto-tuned) for the target device and data characteristics (size, layout, etc).

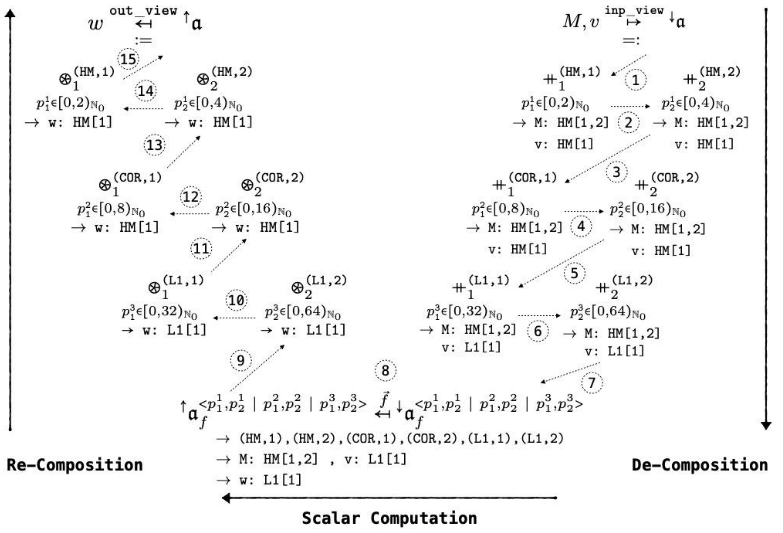
# Excursion: MDH in a Nutshell

Behind the scenes:

```
MatVec<T∈TYPE | I,K∈ℕ> :=

out_view<T>( w:(i,k)↦(i) ) ∘
md_hom<I,K>( *, (++,+) ) ∘
inp_view<T,T>( M:(i,k)↦(i,k) , v:(i,k)↦(k) )
```

*formally sound, auto-tunable lowering process*




## High-Level MDH Representation

- Expresses *what* to compute, via algebraic higher-order functions
- Agnostic from hardware and optimization details

## Low-Level MDH Representation

- Expresses *how* to compute, by explicitly expressing (de-)composition of computations
- straightforwardly transformable to executable program code

# Excursion: MDH in a Nutshell

The MDH high-level representation at example *Matrix Multiplication (MatMul)*:

**MDH needs exactly three higher-order functions (patterns) to express data-parallel computations:**

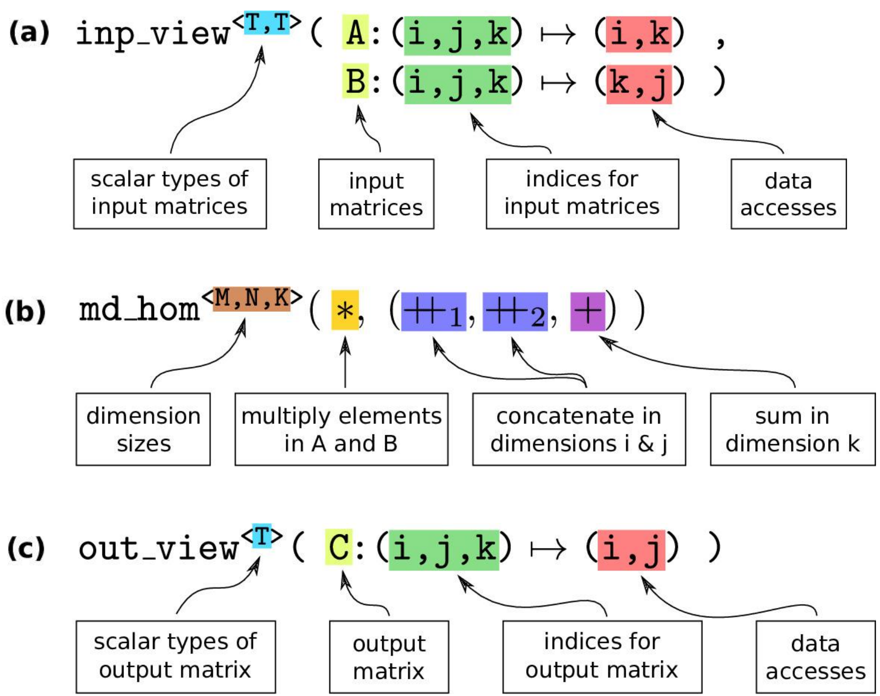
$$\mathtt{MatMul}^{<T\in\mathtt{Type}\,|\,M,N,K\in\mathbb{N}>} :=$$

$$\mathtt{out\_view}^{<\dots>}(\dots)\circ \qquad \textbf{(c)}$$

$$\mathtt{md\_hom}^{<\dots>}(\dots)\circ \qquad \textbf{(b)}$$

$$\mathtt{inp\_view}^{<\dots>}(\dots) \qquad \textbf{(a)}$$

**MDH pattern instances for MatMul:**



# Excursion: MDH in a Nutshell

Important functions can naturally be expressed as MDHs:

### Linear Algebra

```
MatMul<...> = out_view<...>( ... ) o md_hom<...>( *, (++, ++, +) ) o inp_view<...>( ... )
MatVec<...> = out_view<...>( ... ) o md_hom<...>( *, (++, +)     ) o inp_view<...>( ... )
DOT<...>    = out_view<...>( ... ) o md_hom<...>( *, (+)         ) o inp_view<...>( ... )
```

Access neighboring elements within their input buffer

### Stencil Computations

```
Gaussian_2D<...> = out_view<...>( ... ) o md_hom( f_G, (++, ++)     ) o inp_view<...>( ... )
Jacobi_3D<...>   = out_view<...>( ... ) o md_hom( f_J, (++, ++, ++) ) o inp_view<...>( ... )
```

### Data Mining

```
PRL<...> = out_view<...>( ... ) o md_hom( weight, (++, Ⓧmax) ) o inp_view<...>( ... )
```

Access user-defined combine operator that operates on user-defined data type

Often very high dimensional (e.g., 7 dims)

### Quantum Chemistry

```
TC<...> = out_view<...>( ... ) o md_hom( *, (++,…,++ , +,…,+) ) o inp_view<...>( ... )
```

Further examples: MLP, SVM, ECC, …, Mandelbrot, Parallel Reduction, ...

# Excursion: MDH in a Nutshell

## Stencils

| CPU | Gaussian (2D) | | Jacobi (3D) | |
|---|---|---|---|---|
| | RW | PC | RW | PC |
| Lift [2] | 4.90 | 5.96 | 1.94 | 2.49 |
| MKL-DNN | 6.99 | 14.31 | N/A | N/A |

| GPU | Gaussian (2D) | | Jacobi (3D) | |
|---|---|---|---|---|
| | RW | PC | RW | PC |
| Lift [2] | 2.33 | 1.09 | 1.14 | 1.02 |
| cuDNN | 3.78 | 19.11 | N/A | N/A |

[2] Hagedorn et. al, "High Performance Stencil Code Generation with LIFT.", **CGO'18 (Best Paper Award)**.

**MDH proved in previous work to achieve high performance on CPUs & GPUs [1]**

[1] Rasch, Schulze, Gorlatch. "Generating Portable High-Performance Code via Multi-Dimensional Homomorphisms.", PACT'19

## Linear Algebra

| CPU | GEMM | | GEMV | |
|---|---|---|---|---|
| | RW | PC | RW | PC |
| Lift [6] | fails | 3.04 | 1.51 | 1.99 |
| MKL | 4.22 | 0.74 | 1.05 | 0.87 |

| GPU | GEMM | | GEMV | |
|---|---|---|---|---|
| | RW | PC | RW | PC |
| Lift [6] | 4.33 | 1.17 | 3.52 | 2.98 |
| cuBLAS | 2.91 | 0.83 | 1.03 | 1.00 |

[6] Steuwer et. al, "Lift: A Functional Data-Parallel IR for High-Performance GPU Code Generation", **CGO'17**.

## Quantum Chemistry

| GPU | Tensor Contractions | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | RW 1 | RW 2 | RW 3 | RW 4 | RW 5 | RW 6 | RW 7 | RW 8 | RW 9 |
| COGENT [3] | 1.26 | 1.16 | 2.12 | 1.24 | 1.18 | 1.36 | 1.48 | 1.44 | 1.85 |
| F-TC [4] | 1.19 | 2.00 | 1.43 | 2.89 | 1.35 | 1.54 | 1.25 | 2.02 | 1.49 |

[3] Kim et. al. "A Code Generator for High-Performance Tensor Contractions on GPUs.", **CGO'19**.

[4] Vasilache et al. "The Next 700 Accelerated Layers: From Mathematical Expressions of Network Computation Graphs to Accelerated GPU Kernels, Automatically.", ***TACO'19***.

## Data Mining

| CPU | Probabilistic Record Linkage | | | | | |
|---|---|---|---|---|---|---|
| | $2^{15}$ | $2^{16}$ | $2^{17}$ | $2^{18}$ | $2^{19}$ | $2^{20}$ |
| EKR [5] | 1.87 | 2.06 | 4.98 | 13.86 | 28.34 | 39.36 |

[5] Forchhammer et al. "Duplicate Detection on GPUs.", **HFSL'13**.

# Goal of this Work

Can MDH also

*express* DL computations and achieve

*high performance* for them?

→ **Our WIP results look encouraging**

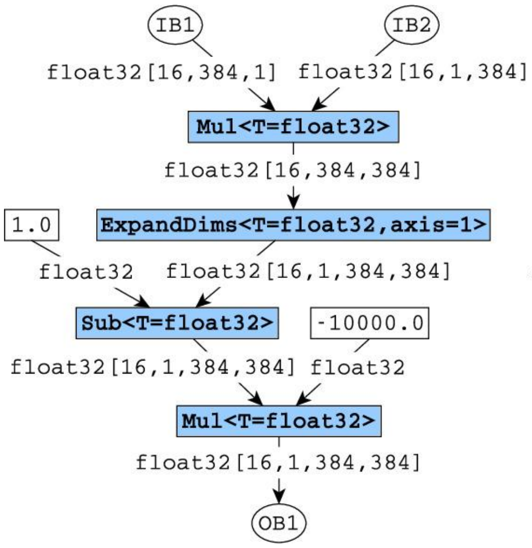
# DL Computations Expressed in the MDH Formalism

| Operator | $\mathtt{out\_view}^{<\ldots>}$ | $\mathtt{md\_hom}^{<\ldots>}$ | | $\mathtt{inp\_view}^{<\ldots>}$ |
|---|---|---|---|---|
| $\mathtt{Mul}^{<\ldots>}$ | $\mathtt{OB1:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{i},\mathtt{j})$ | $*$ | $+\!\!+ , +\!\!+$ | $\mathtt{IB1:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{i},\mathtt{j})$ ,<br>$\mathtt{IB2:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{i},\mathtt{j})$ |
| $\mathtt{Sub}^{<\ldots>}$ | $\mathtt{OB1:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{i},\mathtt{j})$ | $-$ | $+\!\!+ , +\!\!+$ | $\mathtt{IB1:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{i},\mathtt{j})$ ,<br>$\mathtt{IB2:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{i},\mathtt{j})$ |
| $\mathtt{ExpandDims}^{<\mathtt{axis},\mathtt{D}\in\mathbb{N} \mid \ldots>}$ | $\mathtt{OB1:}(\mathtt{i}_1,\ldots,\mathtt{i}_D) \mapsto (\ldots,\mathtt{i}_{\mathtt{axis}-1},0,\mathtt{i}_{\mathtt{axis}},\ldots)$ | id | $+\!\!+ ,\ldots, +\!\!+$ | $\mathtt{IB1:}(\mathtt{i}_1,\ldots,\mathtt{i}_D) \mapsto (\mathtt{i}_1,\ldots,\mathtt{i}_D)$ |
| $\mathtt{BiasAddGrad}^{<\mathtt{NHWC} \mid \ldots>}$ | $\mathtt{OB1:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{j})$ | id | $+ , +\!\!+$ | $\mathtt{IB1:}(\mathtt{i},\mathtt{j}) \mapsto (\mathtt{i},\mathtt{j})$ |
| $\mathtt{BatchMatMul}^{<\mathtt{N},\mathtt{N} \mid \ldots>}$ | $\mathtt{OB1:}(\mathtt{b1},\mathtt{b2},\mathtt{i},\mathtt{j},\mathtt{k}) \mapsto (\mathtt{b1},\mathtt{b2},\mathtt{i},\mathtt{j})$ | $*$ | $+\!\!+ ,\ldots, +\!\!+ , +$ | $\mathtt{IB1:}(\mathtt{b1},\mathtt{b2},\mathtt{i},\mathtt{j},\mathtt{k}) \mapsto (\mathtt{b1},\mathtt{b2},\mathtt{i},\mathtt{k})$ ,<br>$\mathtt{IB2:}(\mathtt{b1},\mathtt{b2},\mathtt{i},\mathtt{j},\mathtt{k}) \mapsto (\mathtt{b1},\mathtt{b2},\mathtt{k},\mathtt{j})$ |

**Popular DL computations[1] are conveniently expressed in the MDH formalism.**

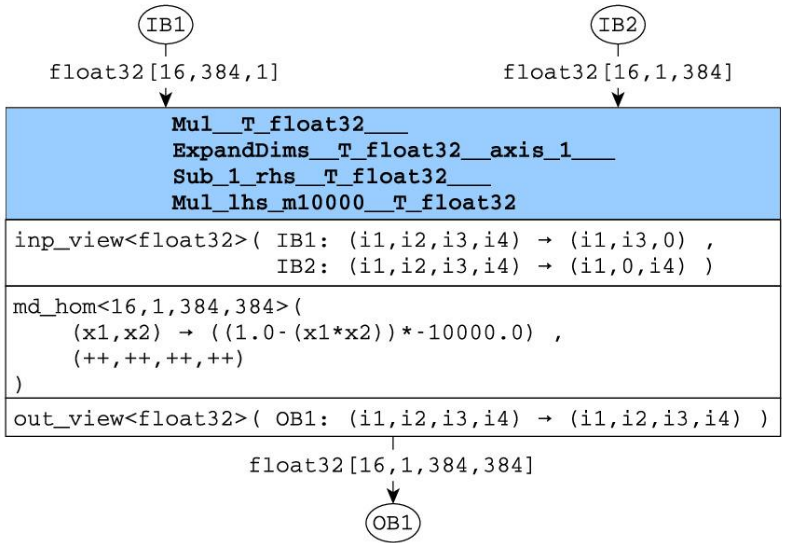
[1] Taken from the TensorFlow implementation of the real-world BERT neural network.

# DL Computations Expressed in the MDH Formalism




BERT Subgraph
in **TensorFlow**

**MDH can express multiple DL comp. as a single MDH expr.**




BERT Subgraph
in **MDH**

# Experimental Results

**2.9x** faster than **TVM** for **BiasAddGrad**

**1.5x** faster than **TensorFlow** for **BiasAddGrad**

**1.1x** faster than **TVM** for **BatchMatMul**

**3.8x** faster than **TVM** for a **subgraph of BERT**

Our preliminary experimental results on NVIDIA V100 GPU show that we can achieve **better performance** than well-performing **machine-** and **hand-optimized** approaches on real-world data sizes taken from the BERT neural network.

**1.9x** faster than **TC** for **BatchMatMul**

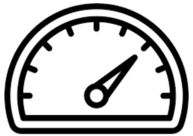
**1.7x** faster than **TC** for a **subgraph of BERT**

**1.7x** faster than **TC** for **BiasAddGrad**

**4.9x** faster than **TensorFlow** for a **subgraph of BERT**

# Conclusion

<u>MDH for DL— advantages we see:</u>



***Performance***

*encouraging WIP results*

***Portability***

*MDH targets also CPUs, etc.*

***Productivity***

*encouraging WIP results*

<u>Future Work:</u>

- Automatizing **“DL-subgraph-to-MDH-node” process**, by exploiting MDHs’ formal properties;
- Targeting **sparse computations**;
- Analyzing MDH for DL on **further architectures** (CPU, etc);
- …

# Thank you for listening!

- 3-year funded by DFG:

  ***P**erformance, **P**ortability, and **P**roductivity for*
  ***D**eep **L**earning Applications on*
  *Multi- and Many-Core Architectures (**PPP-DL**)*

- Code artifact available:

  https://gitlab.com/mdh-project/sc21_poster

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