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

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Code Artifact and Video Narration.

Introduction

We present our work-in-progress **code generation and optimization approach** for **DL computations**:

- based on the formalism of **Multi-Dimensional Homomorphisms (MDH)** [1]
- achieves **high-performance** for popular DL computations by exploiting the already existing MDH GPU code generation and optimization approach
- **more expressive** than the state-of-the-art DL abstractions (e.g., as provided by TensorFlow): we are capable of expressing multiple DL computations as a single MDH expression

[1] Rasch, Gorlatch, "Multi-Dimensional Homomorphisms and Their Implementation in OpenCL", IJPP'18

The MDH Formalism

$$\texttt{MatMul}^{<T\in\texttt{Type}\,|\,\texttt{M,N,K}\in\mathbb{N}>} := \texttt{out\_view}^{<\dots>}(\dots)\circ \quad \textbf{(c)}$$
$$\texttt{md\_hom}^{<\dots>}(\dots)\circ \quad \textbf{(b)}$$
$$\texttt{inp\_view}^{<\dots>}(\dots) \quad \textbf{(a)}$$

(a) $\texttt{inp\_view}^{<\texttt{T,T}>}(\ \texttt{A}:(\texttt{i,j,k})\mapsto(\texttt{i,k})\ ,\ \texttt{B}:(\texttt{i,j,k})\mapsto(\texttt{k,j})\ )$

scalar types of input matrices

input matrices

indices for input matrices

data accesses

(b) $\texttt{md\_hom}^{<\texttt{M,N,K}>}(\ *,\ (+\!\!+_1,\ +\!\!+_2,\ +)\ )$

dimension sizes

multiply elements in A and B

concatenate in dimensions i & j

sum in dimension k

(c) $\texttt{out\_view}^{<\texttt{T}>}(\ \texttt{C}:(\texttt{i,j,k})\mapsto(\texttt{i,j})\ )$

scalar types of output matrix

output matrix

indices for output matrix

data accesses

MDH allows us conveniently expressing data-parallel computations and automatically generate CUDA code for them [2, 3].

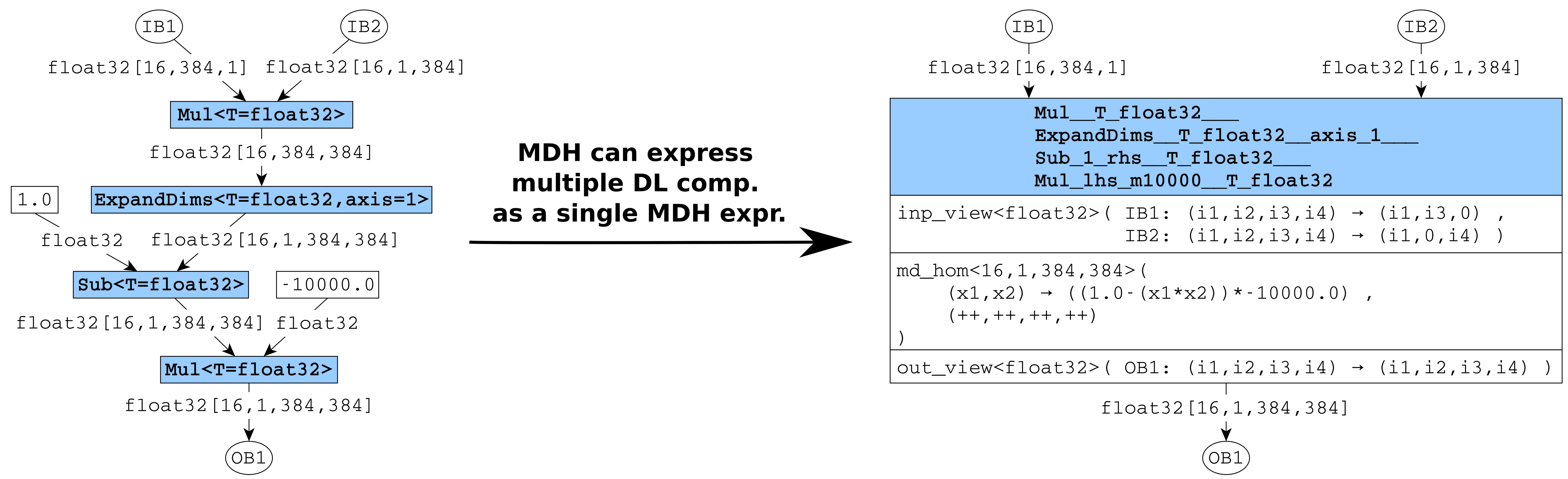
[2] Rasch, Schulze, Gorlatch, "Generating Portable High-Performance Code via Multi-Dimensional Homomorphisms", PACT'19

[3] Rasch, Schulze, Steuwer, Gorlatch, "Efficient Auto-Tuning of Parallel Programs with Interdependent Tuning Parameters via Auto-Tuning Framework (ATF)", TACO'21

DL Computations Expressed in the MDH Formalism

Operator	out_view<…>	md_hom<…>	inp_view<…>
$\texttt{Mul}^{<\dots>}$	$\texttt{OB1:(i,j)}\mapsto\texttt{(i,j)}$	$*\ ,\ (+\!\!+_1,+\!\!+_2)$	$\texttt{IB1:(i,j)}\mapsto\texttt{(i,j)}$, $\texttt{IB2:(i,j)}\mapsto\texttt{(i,j)}$
$\texttt{Sub}^{<\dots>}$	$\texttt{OB1:(i,j)}\mapsto\texttt{(i,j)}$	$-\ ,\ (+\!\!+_1,+\!\!+_2)$	$\texttt{IB1:(i,j)}\mapsto\texttt{(i,j)}$, $\texttt{IB2:(i,j)}\mapsto\texttt{(i,j)}$
$\texttt{ExpandDims}^{<\texttt{axis,D}\in\mathbb{N}\,|\,\dots>}$	$\texttt{OB1:}(\texttt{i}_1,\dots,\texttt{i}_D)\mapsto(\dots,\texttt{i}_{\texttt{axis}-1},0,\texttt{i}_{\texttt{axis}},\dots)$	$id\ ,\ (+\!\!+_1,\dots+\!\!+_D)$	$\texttt{IB1:}(\texttt{i}_1,\dots,\texttt{i}_D)\mapsto(\texttt{i}_1,\dots,\texttt{i}_D)$
$\texttt{BiasAddGrad}^{<\texttt{NHWC}\,|\,\dots>}$	$\texttt{OB1:(i,j)}\mapsto\texttt{(j)}$	$id\ ,\ (+,+\!\!+_2)$	$\texttt{IB1:(i,j)}\mapsto\texttt{(i,j)}$
$\texttt{BatchMatMul}^{<\texttt{N,N}\,|\,\dots>}$	$\texttt{OB1:(b1,b2,i,j,k)}\mapsto\texttt{(b1,b2,i,j)}$	$*\ ,\ (+\!\!+_1,\dots,+\!\!+_4,+)$	$\texttt{IB1:(b1,b2,i,j,k)}\mapsto\texttt{(b1,b2,i,k)}$, $\texttt{IB2:(b1,b2,i,j,k)}\mapsto\texttt{(b1,b2,k,j)}$

Popular DL computations¹ are conveniently expressed in the MDH formalism.



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

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** competitors on real-world data sizes.

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

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

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

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