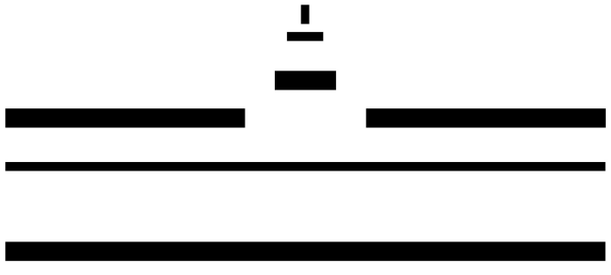

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Münster

SC19
Denver, CO | hpc is now.

Performance, Portability, and Productivity for Data-Parallel Applications on Multi- and Many-Core Architectures

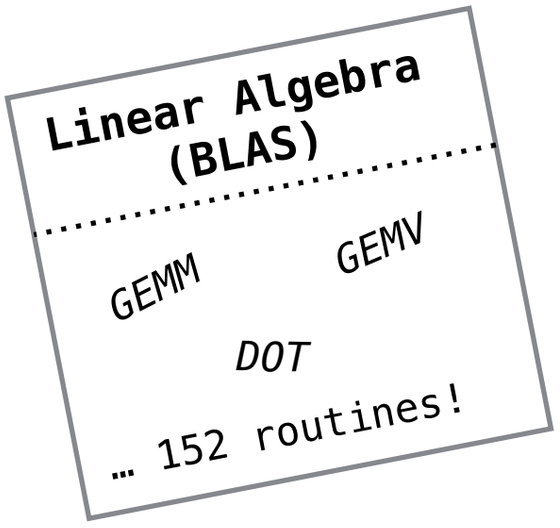
Ari Rasch and Sergei Gorlatch

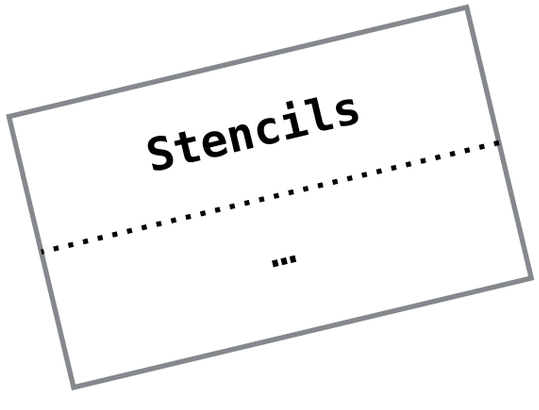
University of Münster, Germany

Motivation

Observation:

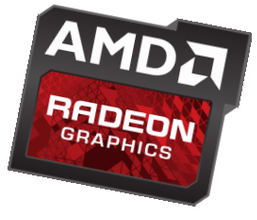
Applications

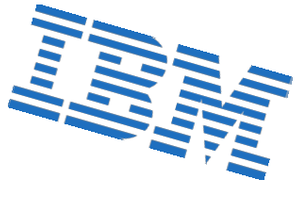




Architectures

X





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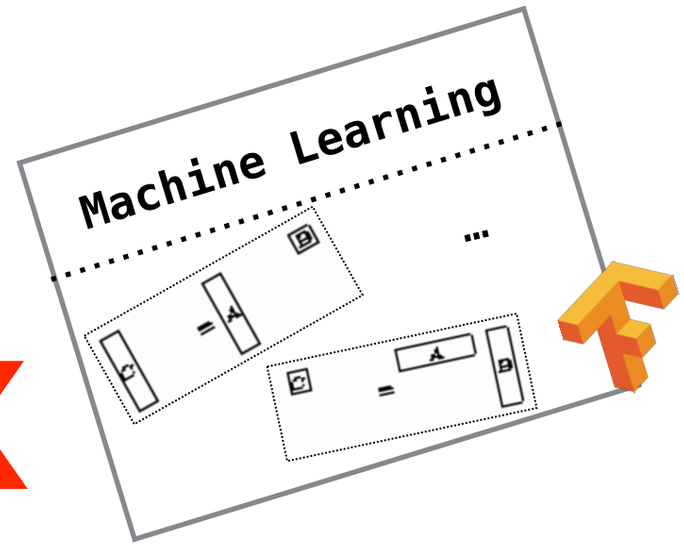
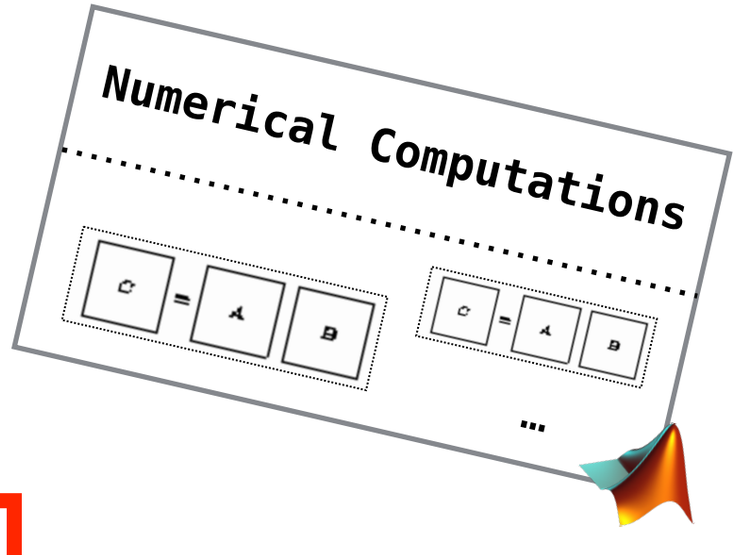
Input Sizes

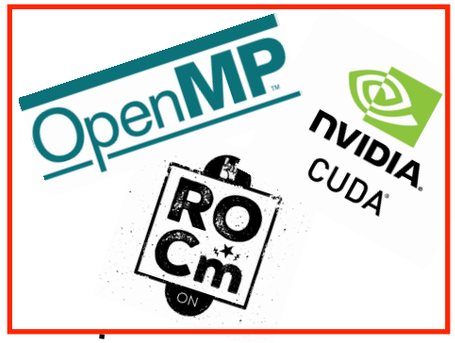


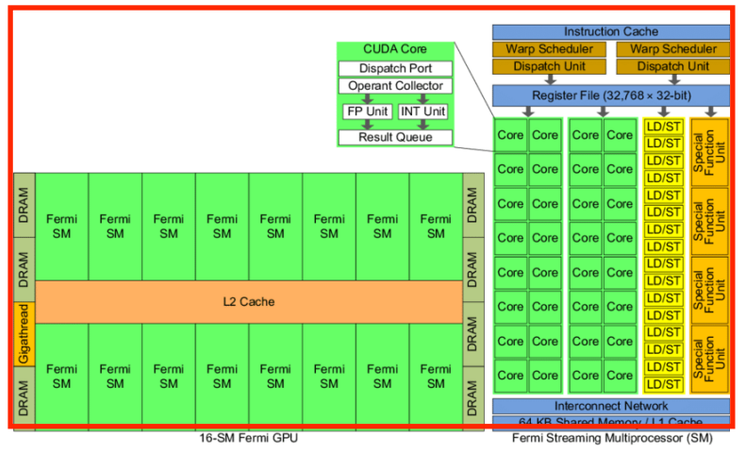


Combinatorial Explosion

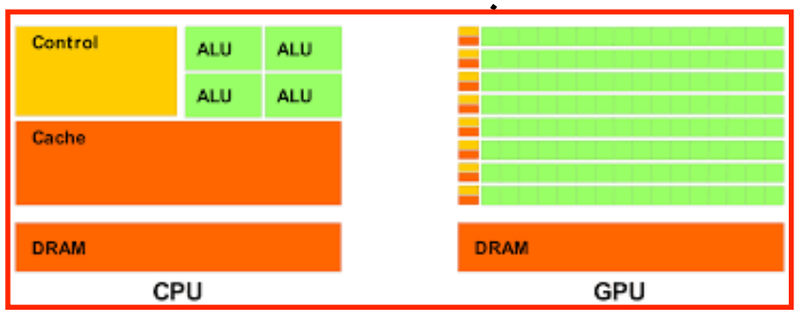
Motivation

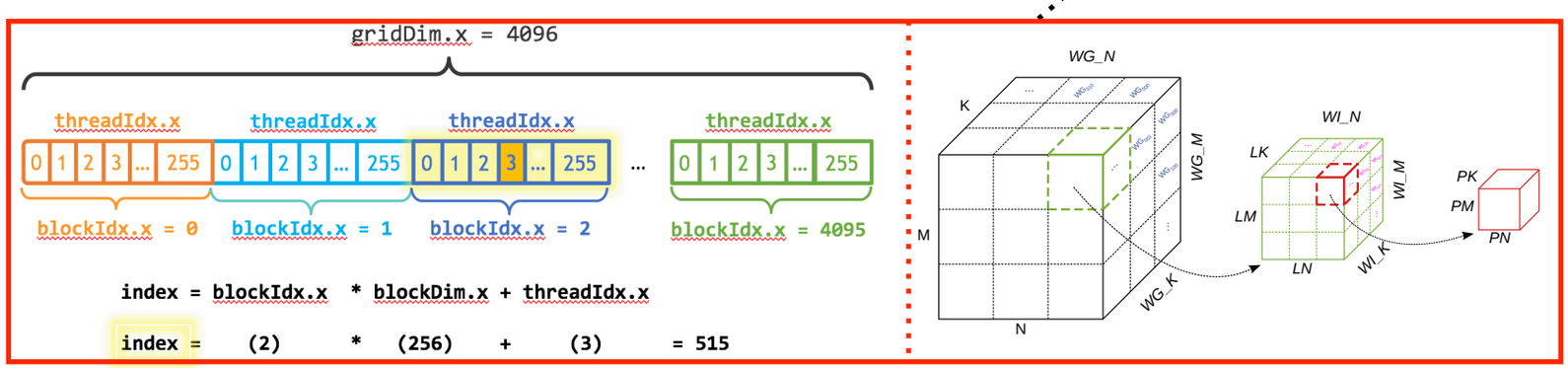
In a perfect world:





Write **one piece of code** for our application that provides **high performance**, is **performance-portable over different architectures** and **input sizes** and that is **easy to implement**.





dimensions			$C = AB$	$C = A^T B^T$	
m	n	k	Shape	Shape	small = 1
large	large	large			gemm
large	large	small			ger
large	small	large			gemv
large	small	small			axpy ($\beta = 1$)
small	large	large			gemv
small	large	small			axpy ($\beta = 1$)
small	small	large			dot ($\alpha = \beta = 1$)
small	small	small			scalar mult.

Our Approach

We provide a holistic code generation approach to address all aforementioned challenges for our algebraic class of *Multi-Dimensional Homomorphisms (MDHs)*:

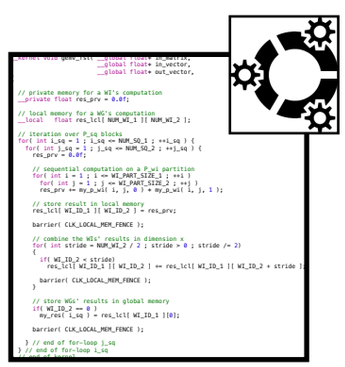
- **Multi-Dimensional Homomorphisms (MDHs)** provide a **formal notion of data parallelism** and thereby **cover important data-parallel computations**, e.g.: linear algebra (BLAS), stencils computations, …
- We enable **conveniently** and **uniformly implementing MDHs** by providing a **high-level DSL** for them.
- We provide a **DSL compiler** that **automatically generates OpenCL code** — the standard for uniformly programming different parallel architectures (e.g., CPU and GPU).
- Our OpenCL code is **fully automatically optimizable** (auto-tunable) — for each combination of a **target architecture**, and **input size** — by being generated as targeted to **OpenCL's abstract device models** and as **parametrized in these models' performance-critical parameters.**

Our approach consists of three major steps:

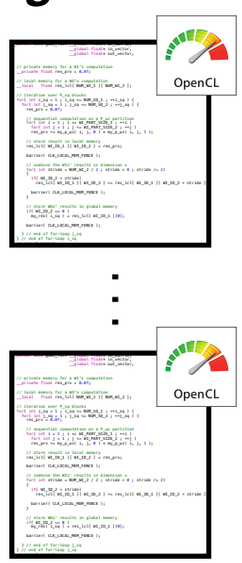
High-level parallel programming abstractions

$\texttt{md\_hom}(\, f,\, (\circledast_1, \ldots, \circledast_k)\,)$

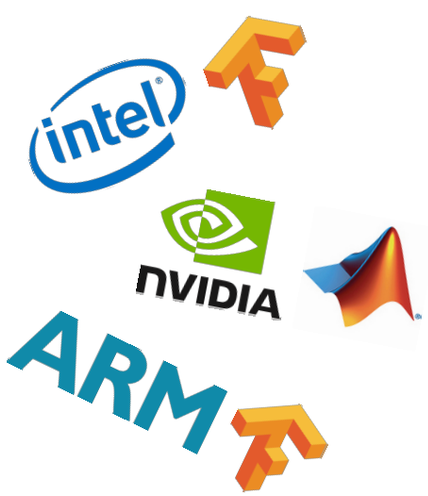
Generic program code



Executable program code



Different architectures and input sizes



(1) Generation *[PACT'19, IJPP'18]*

(2) Optimization *[CCPE'18, HPCC'17]*

(3) Execution *[JOS'19, ICPADS'18]*

Agenda

We discuss the three major steps of our approach:

1. **Generation**

2. **Optimization**

3. **Execution**

Afterwards:

4. **Experimental Results**

5. **Current/Future Work**

Multi-Dimensional Homomorphisms

Our class of targeted applications is formally specified as:

Definition: [*Multi-Dimensional Homomorphisms [1]*]

Let T and T' be two arbitrary types. A function $h : T[\,N_1\,]\ldots[\,N_d\,] \to T'$ on d-dimensional arrays is called a *Multi-Dimensional Homomorphism (MDH)* iff there exist *combine operators* $\circledast_1, \ldots, \circledast_d : T' \times T' \to T'$, such that for each $k \in [1, d]$ and arbitrary, concatenated input MDA $a +\!\!+_k b$:

$$h(\; a +\!\!+_k b \;) \;=\; h(a) \;\circledast_k\; h(b)$$

Definition: [`md_hom`]

We write

$$\texttt{md\_hom}(\; f,\, (\circledast_1, \ldots, \circledast_d)\;)$$

for the unique d-dimensional homomorphism with combine operators $\circledast_1, \ldots, \circledast_d$ and action f on singleton arrays.

[1] Rasch et al. "Multi-Dimensional Homomorphisms and Their Implementation in OpenCL.", *International Journal of Parallel Programming, 2018*

MDH — Examples

Important data-parallel functions are MDHs — we can express them conveniently in our DSL:

Linear Algebra

```
GEMM = md_hom( *, (++, ++, +) ) o view( A,B )( i,j,k )( A[i,k], B[k,j] )
```

```
for( int i = 0; i < M ; ++i )
  for( int j = 0; i < N ; ++j )
    for( int k = 0; i < K ; ++k )
      C[i][j] += A[i][k] * B[k][j];
```

GEMM in C

What's happening?

1. Prepare the domain-specific input uniformly for **`md_hom`**; for this, our DSL provides pattern **`view`**.
   - here: fuse matrices A and B to 3-dimensional array of pairs consisting of the elements in A and B to multiply: **`i,j,k ↦ (A[i,k],B[k,j])`**.
2. Apply multiplication (denoted as $*$) to each pair.
3. Combine results in dimension **`k`** by addition (**+**).
4. Combine results in dimensions **`i`** and **`j`** by concatenation (**++**).

MDH — Examples

Important data-parallel functions are MDHs — we can express them conveniently in our DSL:

Linear Algebra

```
GEMM = md_hom( ∗, (++, ++, +) ) o view( A,B )( i,j,k )( A[i,k], B[k,j] )
GEMV = md_hom( ∗, (++,     +) ) o view( A,B )( i,  k )( A[i,k], B[k]   )
DOT  = md_hom( ∗, (        +) ) o view( A,B )(     k )( A[k]  , B[k]   )
```

Stencil Computations

```
Gaussian_2D = md_hom( G_func, (++,++)     ) o view(…)
Jacobi_3D   = md_hom( J_func, (++,++, ++) ) o view(…)
```

Data Mining

```
PRL = md_hom( weight, (++, Ⓧmax) ) o view(…)
```

Machine Learning

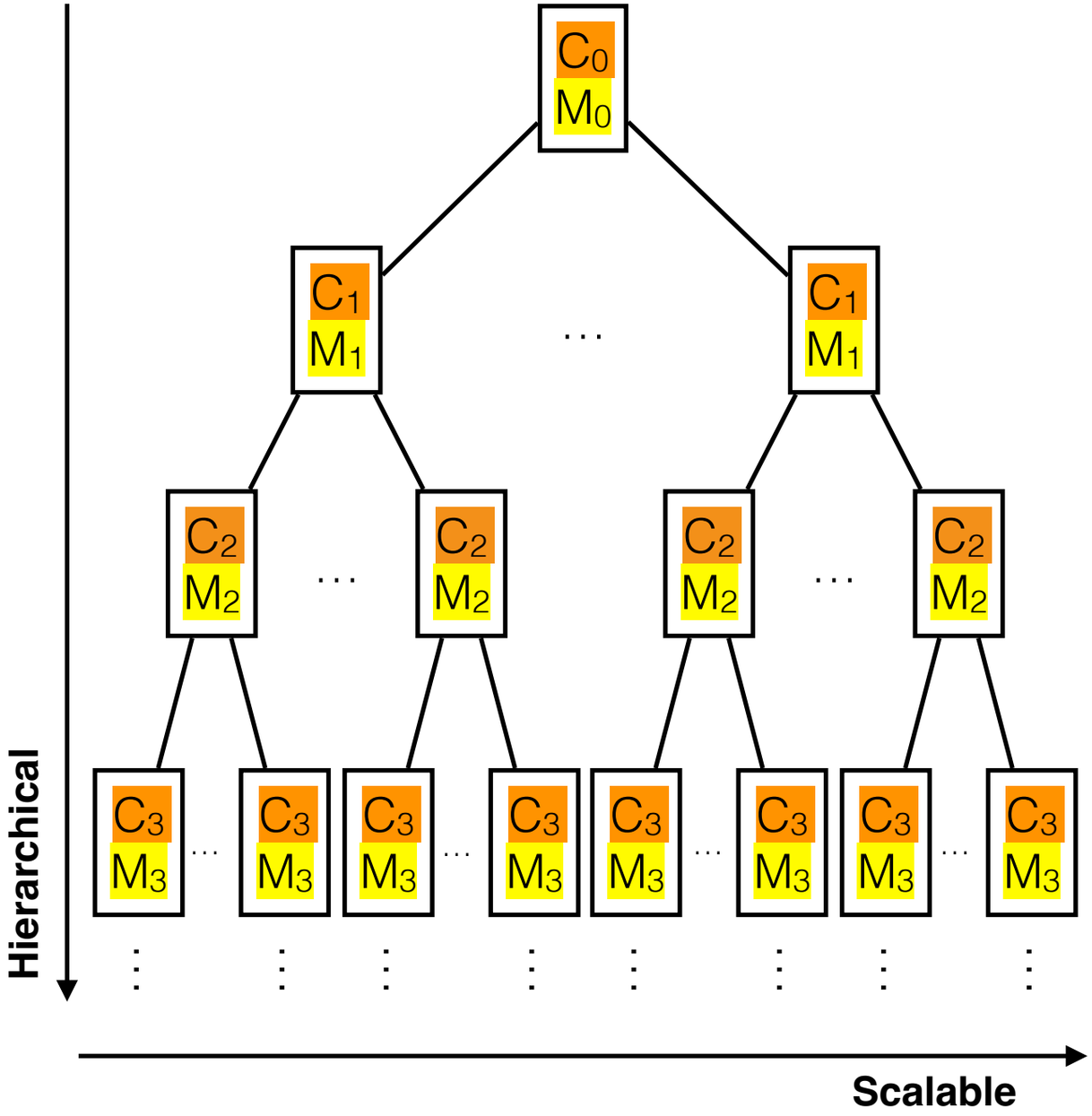
```
TC = md_hom( ∗, (++,…,++ , +,…,+) ) o view(…)
```

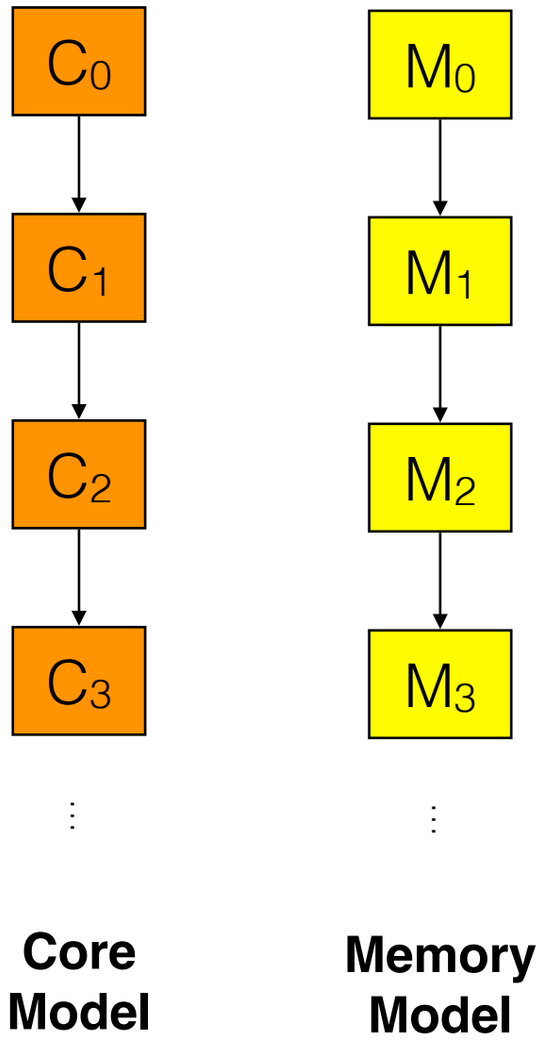
Further examples: MLP, SVM, ECC, …, Mandelbrot, Parallel Reduction, …

Our DSL needs only two patterns:
`md_hom(…)` and `view(…)`

MDH — Target Machine Model

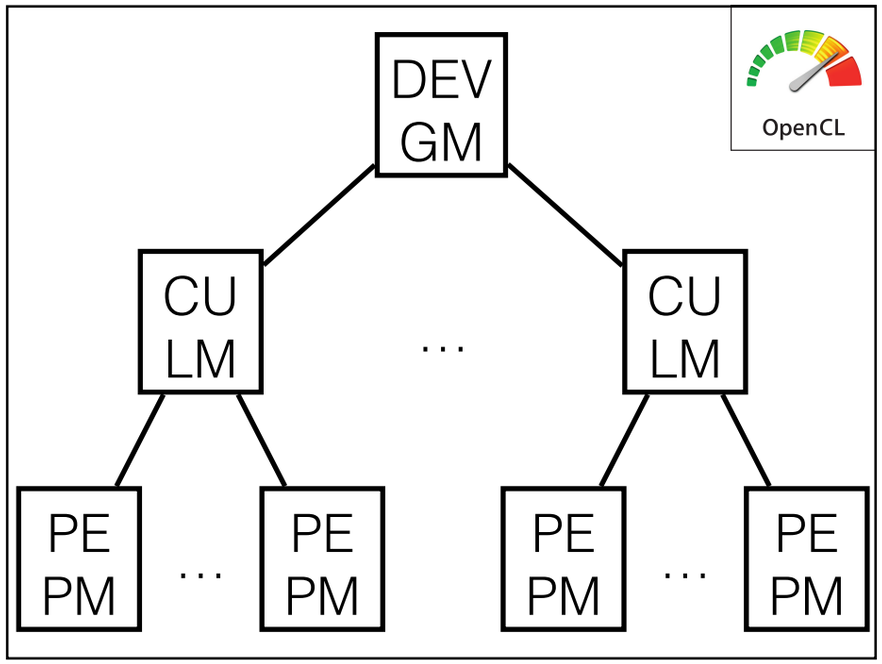
We target with MDHs arbitrary ***hierarchical***, ***scalable*** *machine models*:

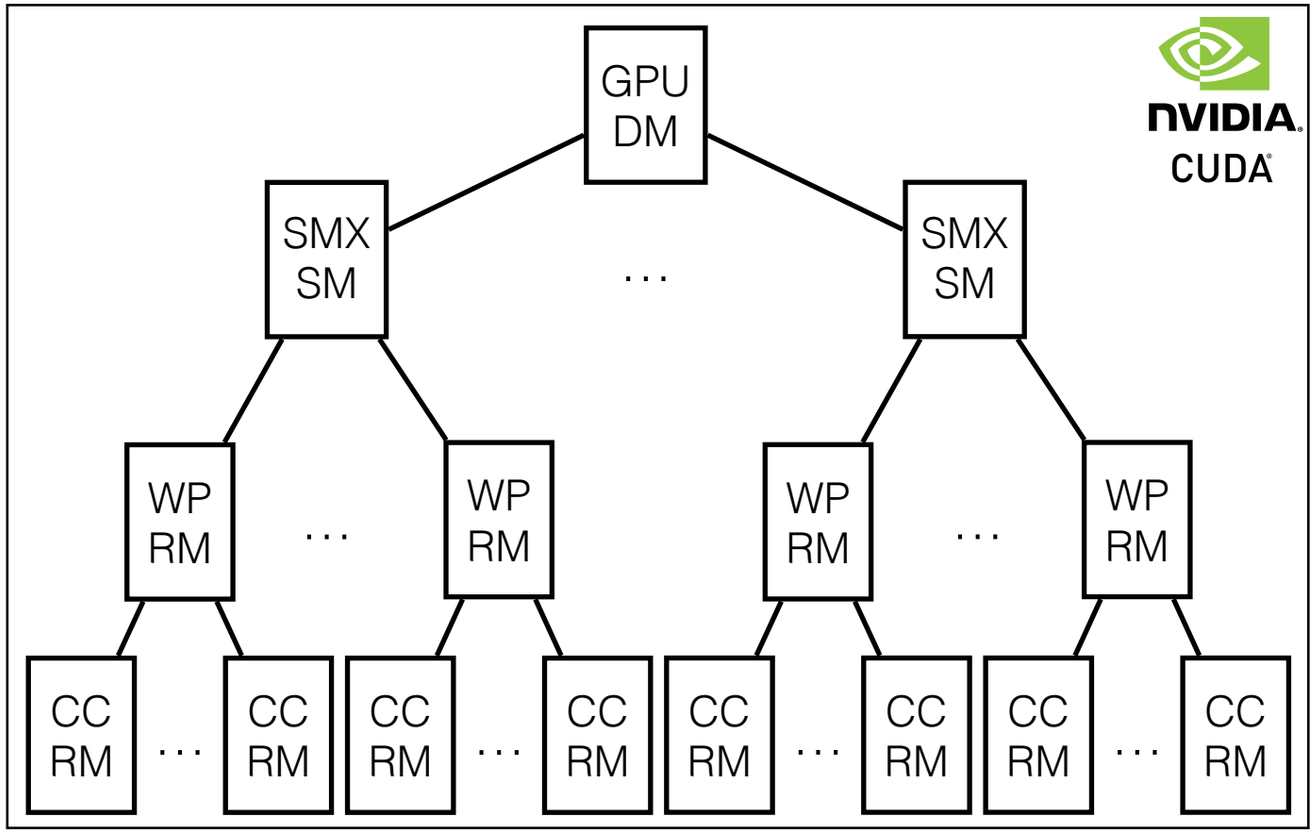


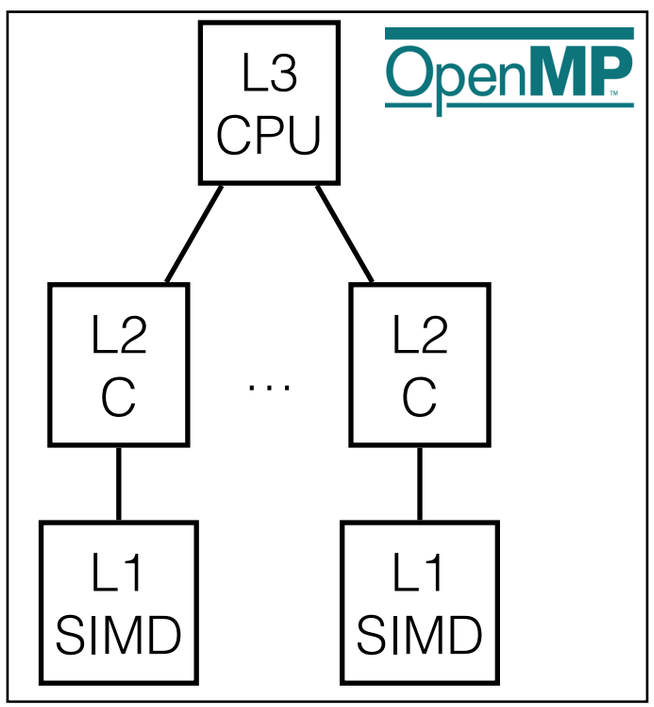


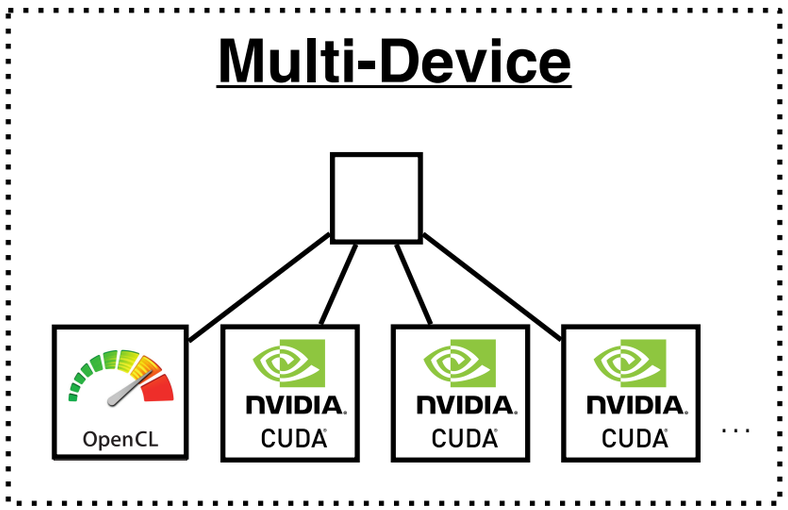
MDH — Target Machine Model

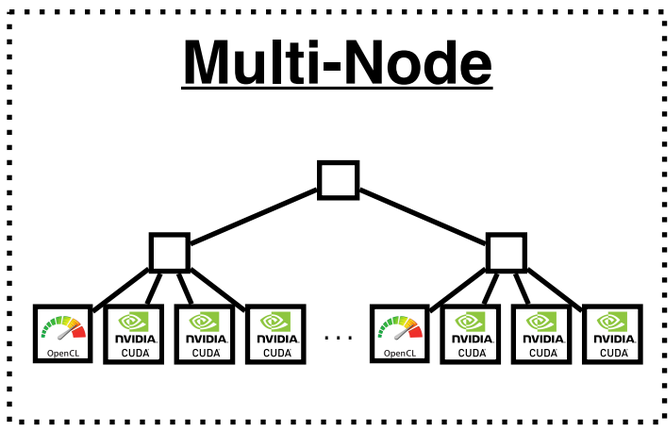
Examples of such *machine models*:





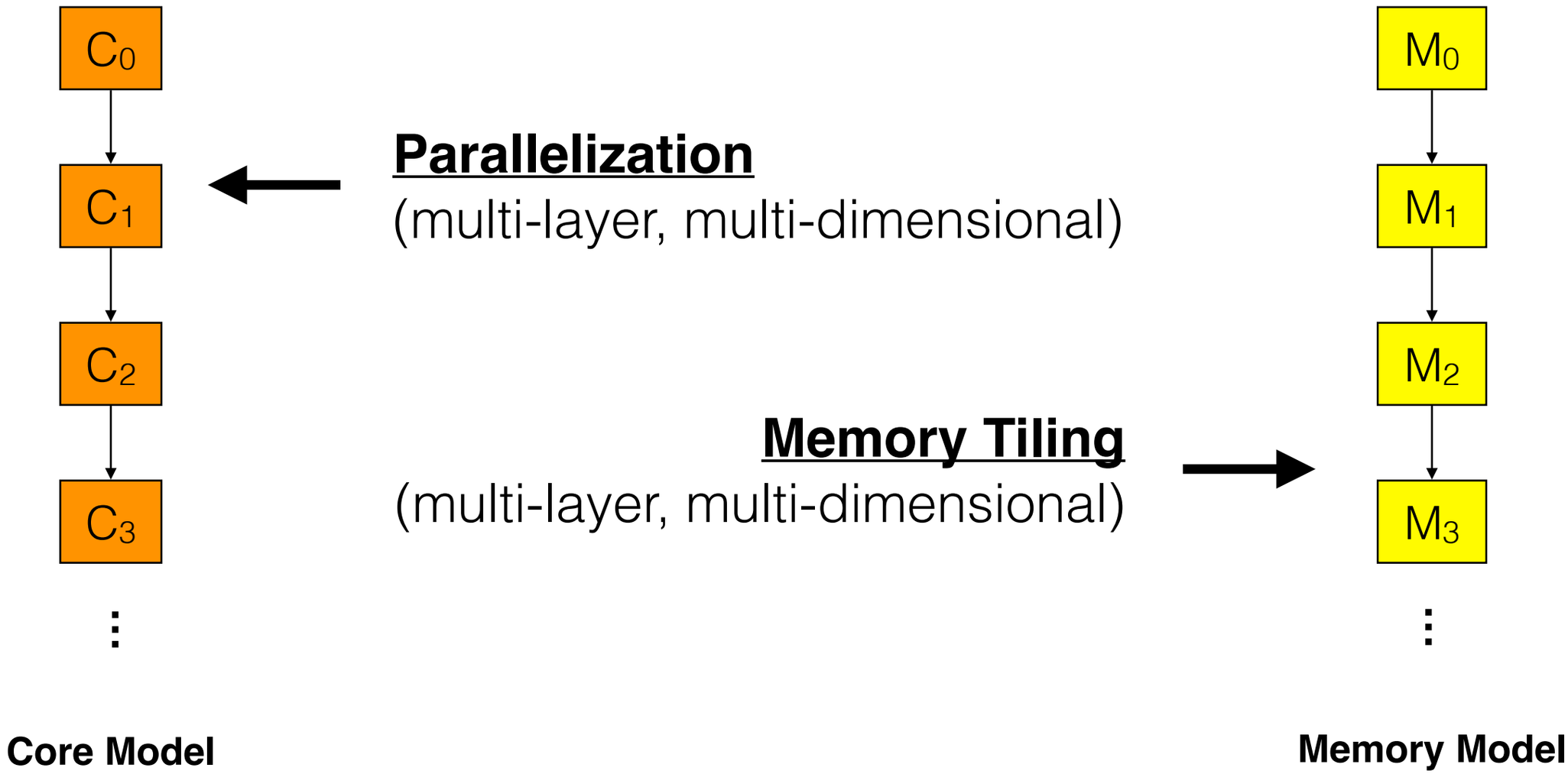






Code Generation for MDHs

Our **uniform `md_hom` representation** of MDHs enables **systematically generating code for such machine models** that can be **automatically optimized**:



In the following: Explain code generation at example of OpenCL.

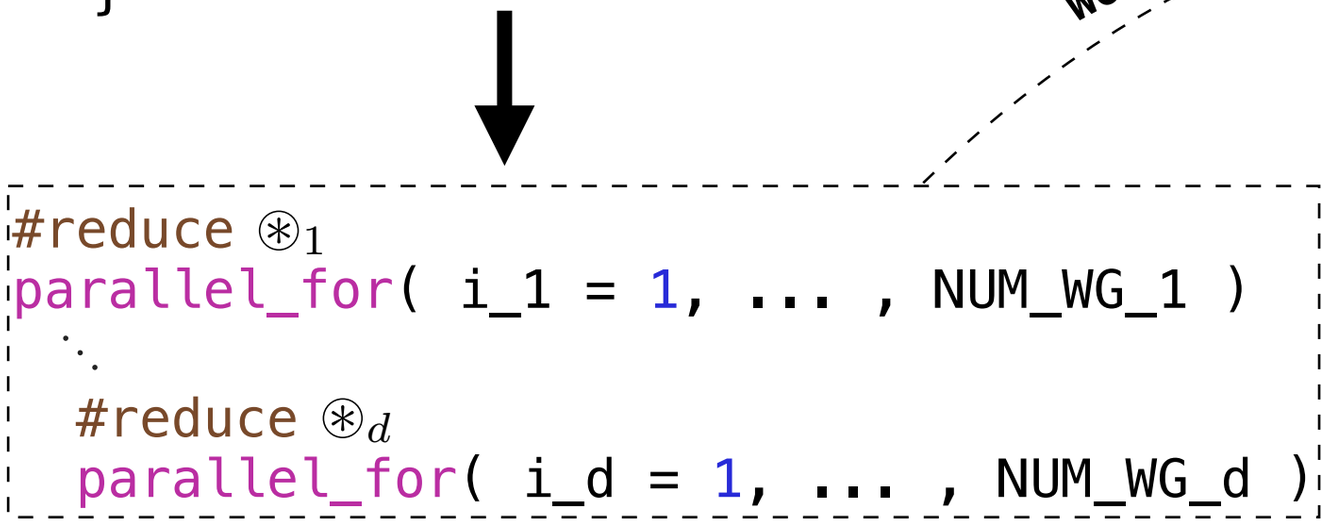
Code Generation for MDHs

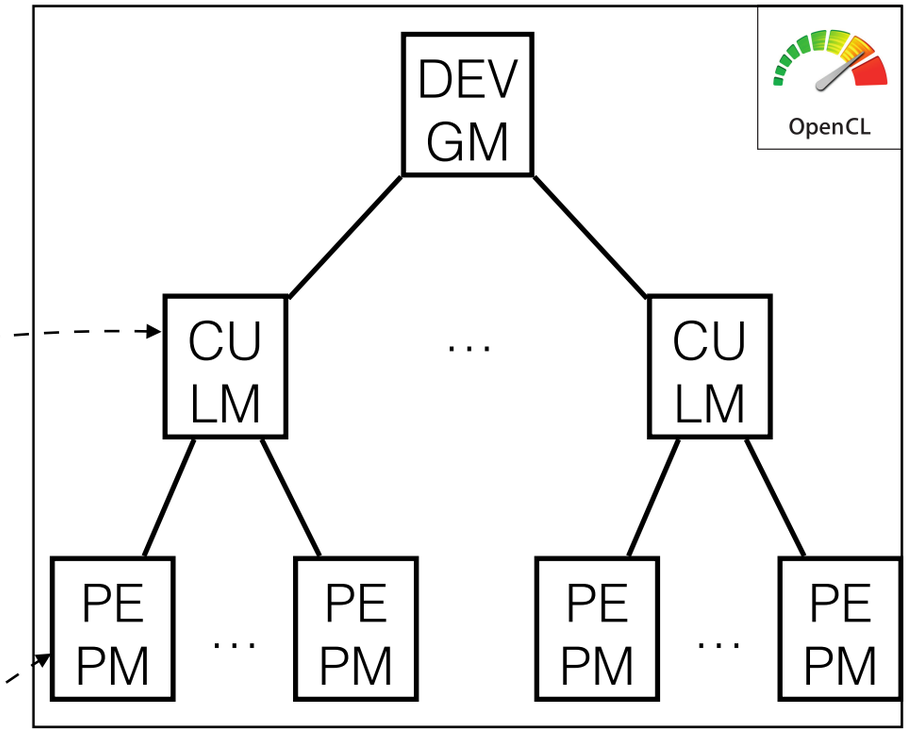
1. Parallelization (multi-layer, multi-dimensional):

```
#reduce ⊛1
for( i_1 = 1, ... , N_1 )
  ⋱
   #reduce ⊛d
   for( i_d = 1, ... , N_d )
   {
     f( a[i_1]...[i_d] )
   }
```

MDH pseudocode for

$\texttt{md\_hom}(\, f,\ (\circledast_1, \ldots, \circledast_d)\ )$





- We parallelize for each of OpenCL's **two parallel layers.**
- We parallelize **on each layer** in **all *d* dimensions** of the MDH.
- We **auto-tune** the number of threads **on each layer** and **in each dimension**.

Code Generation for MDHs

2. Memory Tiling (multiple layers, multiple dimensions):

```
#reduce ⊛1
parallel_for( i_1 = 1, ... , NUM_WG_1 )
  ⋱
  #reduce ⊛d
  parallel_for( i_d = 1, ... , NUM_WG_d )
```

Work-Groups

```
#reduce ⊛1
parallel_for( ii_1 = 1, ... , NUM_WI_1 )
  ⋱
  #reduce ⊛d
  parallel_for( ii_d = 1, ... , NUM_WI_d)
```

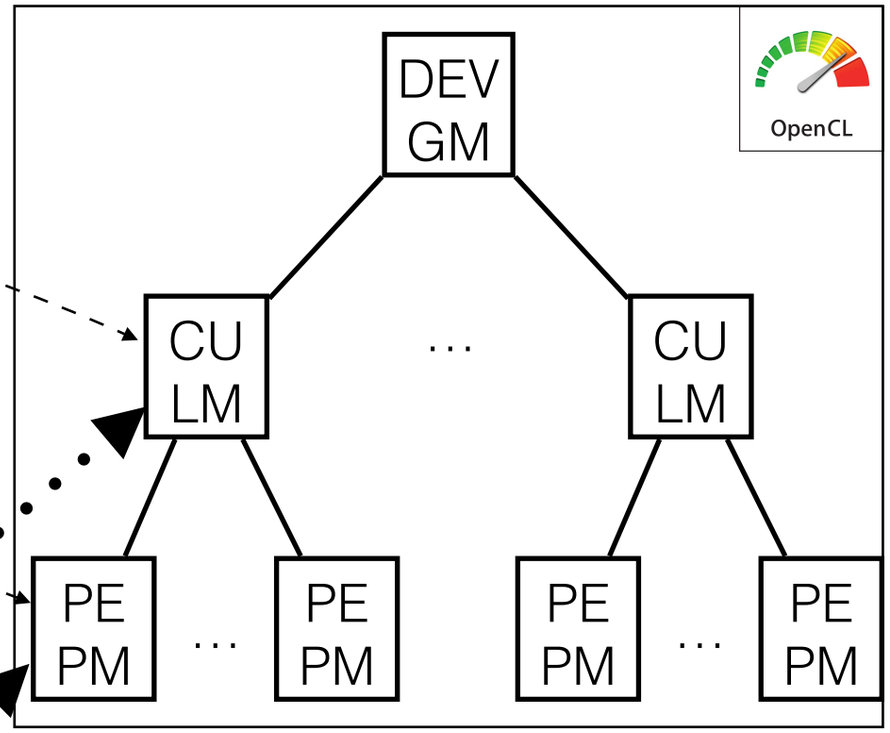
Work-Items

```
for( j_1 = 1, ... , NUM_LM_TL_1 )
  ⋱
  for( j_d = 1, ... , NUM_LM_TL_d )
```

LM-Tiles

```
for( j_1 = 1, ... , NUM_PM_TL_1 )
  ⋱
   for( j_d = 1, ... , NUM_PM_TL_d )
    {
      f( ...)
    }
```

PM-Tiles



- We tile for each of OpenCL's **two memory layers.**
- We tile **on each layer** in **all dimensions** of the MDH.
- We **auto-tune** the sizes of tiles **on each layer** and **in each dimension**.

Code Generation for MDHs

Our OpenCL implementation is generated as **parametrized in performance-critical parameters** (a.k.a. tuning parameters):

No.	Name	Description
1	$\texttt{NUM\_WG}^{\texttt{<i>}}$	number of Work-Groups
2	$\texttt{NUM\_WI}^{\texttt{<i>}}$	number of Work-Items
3	$\texttt{LT\_SIZE}^{\texttt{<i>}}$	local tile size
4	$\texttt{PT\_SIZE}^{\texttt{<i>}}$	private tile size
5	$\texttt{MEM\_INP}^{\texttt{<LYR,b,i>}}$	memory regions for caching input
6	$\texttt{MEM\_RES}^{\texttt{<LYR,b,i>}}$	memory regions for comp. results
7	$\sigma^{\texttt{<LYR>}}_{\texttt{arr}\rightarrow\texttt{ocl}}$	mapping array to OpenCL dimensions
8	$\sigma^{\texttt{<LYR,b>}}_{\texttt{buff-do}}$	buffer dimension order
9	$\sigma^{\texttt{<LYR>}}_{\texttt{mdh-do}}$	MDH dimension order
10	CMB_RES	layer to combine results on

All parameters are chosen as optimized for:

i) OpenCL's abstract device models;
ii) arbitrary MDH;
iii) arbitrary input size.

Automatic Performance Tuning

We use our ***Auto-Tuning Framework (ATF)*** to automatically choose optimized values of our performance-critical parameters.

	Domain-specific auto-tuning	OpenTuner	CLTune	ATF
Arbitrary Programming Language		✓		✓
Arbitrary Application Domain		✓	✓	✓
Arbitrary Tuning Objective	✓	✓		✓
Arbitrary Search Technique	✓	✓	✓	✓
Interdependent Parameters	✓		✓	✓
Large Parameter Ranges	✓	✓		✓
Directive-Based Auto-Tuning				✓
Automatic Cost Function Generation	✓		✓	✓

ATF combines major advantages over state-of-the-art auto-tuning approaches

Experimental Results

We evaluate or **automatically-generated and auto-tuned code** using:

Applications

1. Linear Algebra Routines: GEMM, GEMV
2. Stencils: Gaussian Convolution 2D, Jacobi 3D
3. Data Mining: Probabilistic Record Linkage
4. Machine Learning: Tensor Contractions

Competitors

- Performance-Portable approaches:
  - Lift: *BLAS*, *Stencils* ***[CGO'17, CGO'18 — Best Paper]***
- Domain- and hardware-specific, hand-optimized approaches:
  - Intel MKL, NVIDIA cuBLAS: *BLAS*
  - Intel MKL-DNN, NVIDIA cuDNN: *Stencils*
  - EKR: *Probabilistic Record Linkage* ***[HFSL'13]***
  - COGENT, Facebook Tensor Comprehensions: *Tensor Contractions* ***[CGO'19, arXiv'18]***

Architectures

- Intel Xeon multi-core CPU (E5-2640)
- NVIDIA Tesla V100 GPU (SMX2-16GB)

Data Sets

- RW: Real-world sizes, e.g., from deep learning
- PC: Sizes that are preferable for our competitors

Experimental Results

Linear Algebra

CPU	GEMM		GEMV	
	RW	PC	RW	PC
Lift [1]	fails	3.04	1.51	1.99
MKL	4.22	0.74	1.05	0.87

GPU	GEMM		GEMV	
	RW	PC	RW	PC
Lift [1]	4.33	1.17	3.52	2.98
cuBLAS	2.91	0.83	1.03	1.00

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

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**.

Our MDH approach achieves in most cases better performance than our competitors

Tensor Contractions

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. "Tensor Comprehensions: Framework-Agnostic High-Performance Machine Learning Abstractions.", ***arXiv,* 2018**.

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)**.

Experimental Results

Summary:

- **Lift:** Speedups of up to
  - **1.02x - 5.96x**, including own **Stencil** samples presented at **[CGO'18 — Best Paper]**;
  - **1.17x - 4.33x**, including own **BLAS** samples presented at **[CGO'17]**.

- **COGENT / Facebook Tensor Comprehensions:** Speedups of
  - **1.19x - 2.89x** on own **Tensor Contraction** samples **[CGO'19, arXiv'18]**.

- **Intel MKL / NVIDIA cuBLAS:** Speedups of
  - **0.74x-1.00x** for **BLAS** on **their preferable sizes**;
  - **1.03x-4.22x** for **BLAS** on **real-world input sizes**.

Experimental Results

Our better results are because:

We generate an OpenCL implementation that is auto-tunable for each particular combination of a device and input size.

Lift

Relies on transformation rules which require hand pruning (infinitely-large) optimization space for exploration

Fair Competitor for us

Intel MKL/MKL-DNN & NVIDIA cuBLAS/cuDNN

Rely on hand-optimized kernels which are available for only some designated input sizes.

EKR Java

Not auto-tunable for input size & inefficient memory usage.

Tensor Comprehensions & COGENT

No parallelization in summation dimensions; use smaller optimizations spaces

Unfair Competitors for us: Architecture and Domain Specific

Conclusion

We provide a holistic code generation approach to **performance**, **portability**, and **productivity** for data-parallel applications:

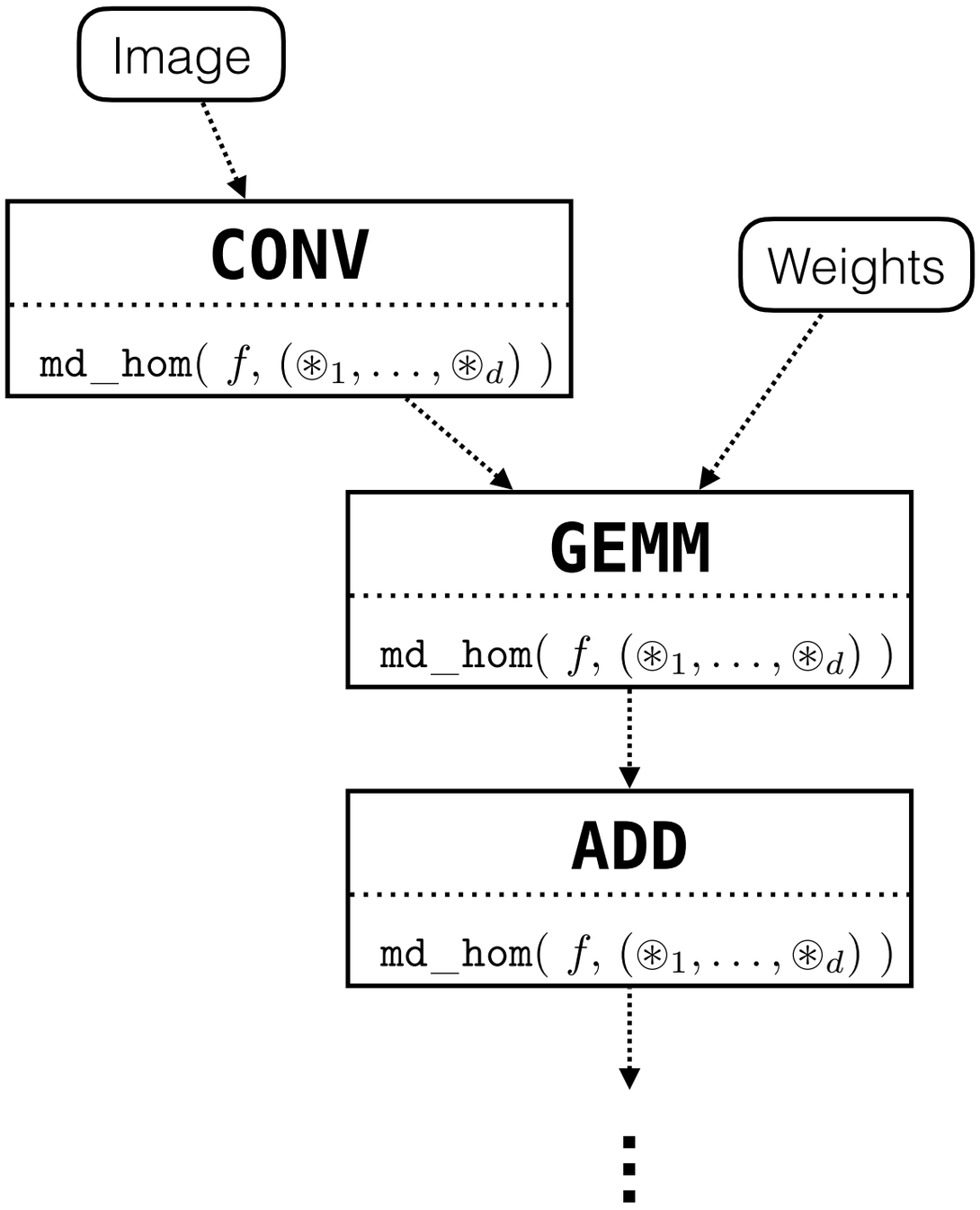
1. MDHs **uniformly cover data-parallel computations** (BLAS, Stencil, PRL, TC, …).
2. MDHs can be computed with **high performance** (speedups up to >4).
3. MDHs are functionally and performance **portable over architectures and input sizes**.
4. MDHs can be **conveniently implemented** using our DSL for MDHs.

Moreover:

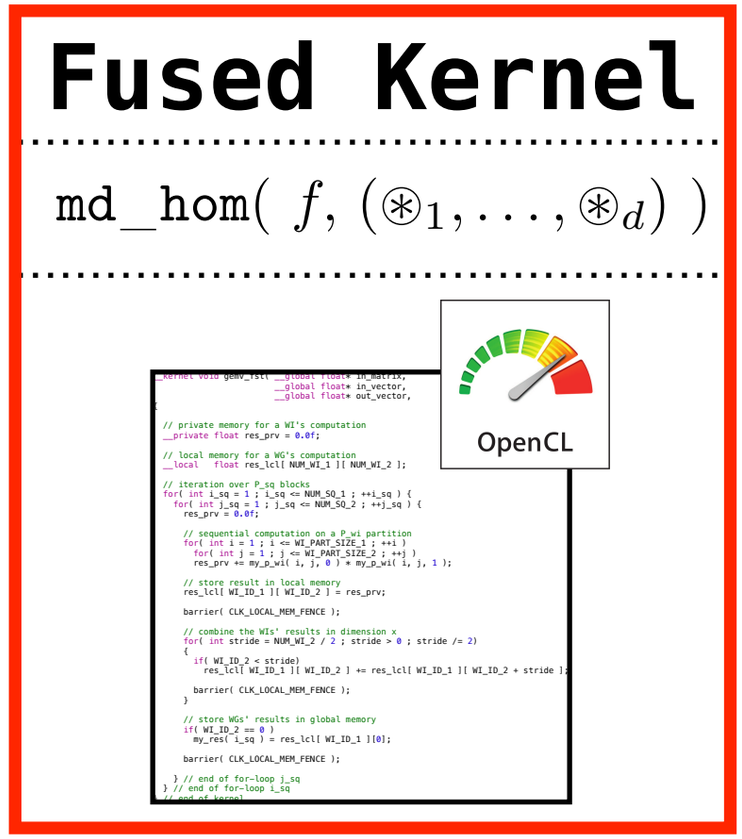
- Our **Auto-Tuning Framework (ATF)** is a **general-purpose approach** that **supports auto-tuning of interdependent tuning parameters.**
- We provide our **dOCAL** framework for **conveniently executing OpenCL kernels on multi-device/multi-node systems**, and it automatically provides **host code optimizations** (e.g., overlapping data transfers with computations).

Current/Future Work

Code generation for **composed `md_hom` expression** (e.g. as in deep learning graphs):

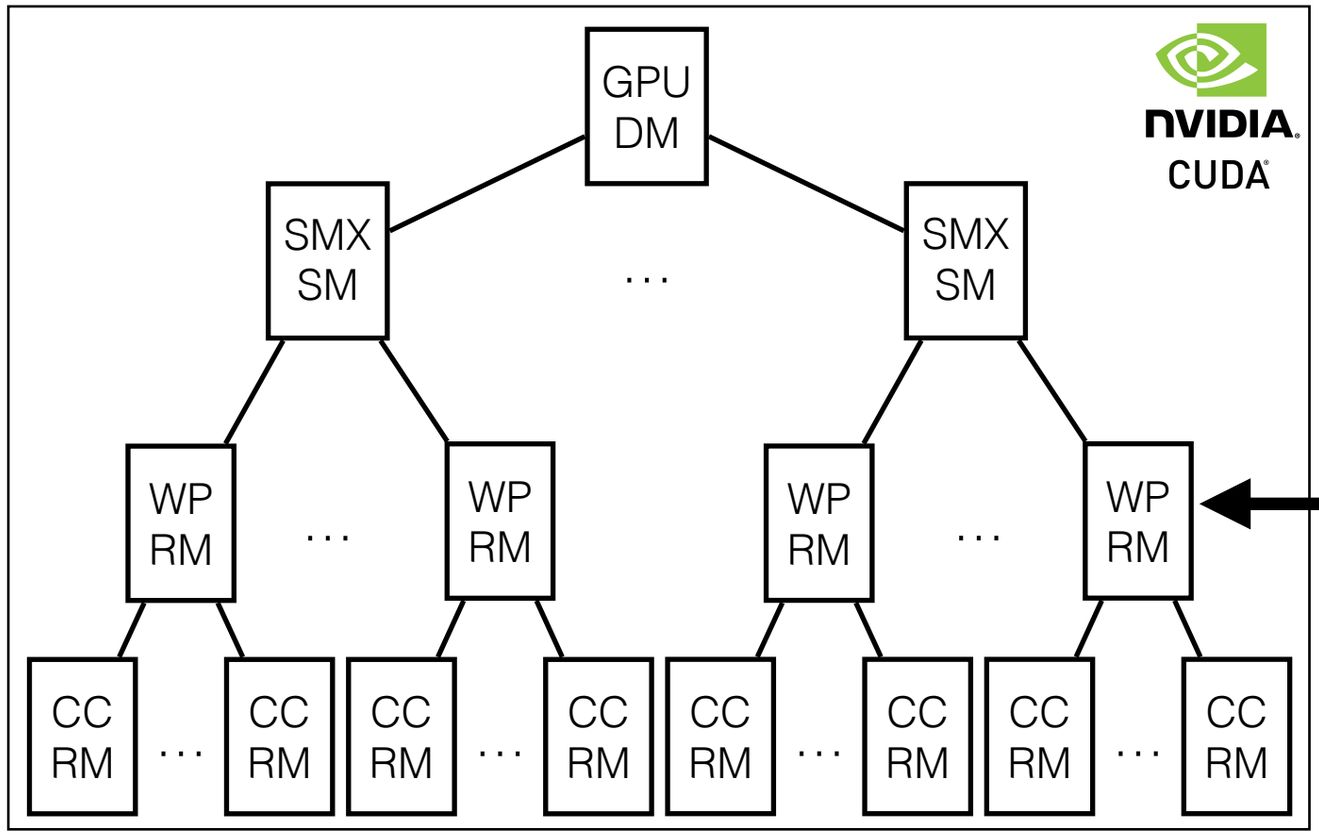


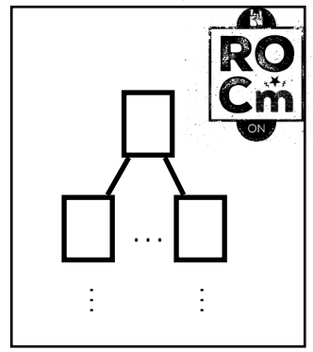
Exploiting **`md_hom`** representation for fusing (better locality)



Current/Future Work

Further backends:

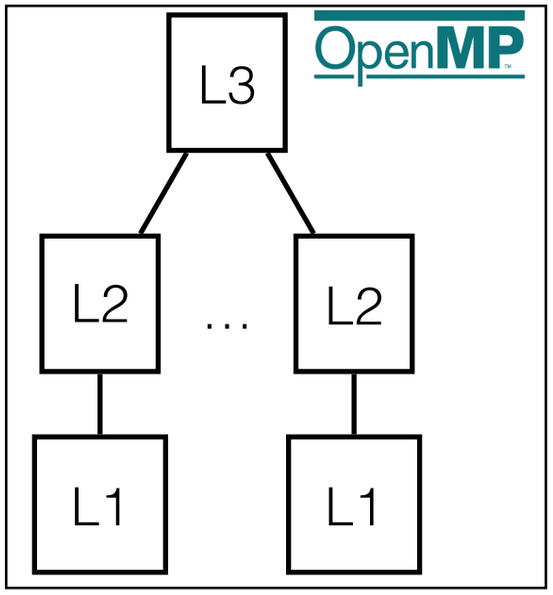




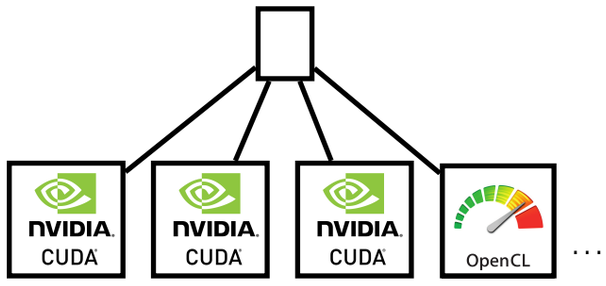
- **Tensor Cores**
- **Shuffle Operations**

Assembler Backends

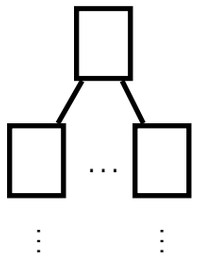
(e.g., NVIDIA PTX, Intel x86-64, …)



Multi-Device



Multi-Node



Current/Future Work

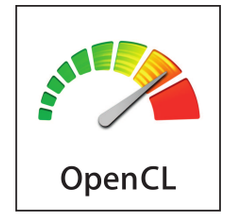
Simplifying code generation via *Directives*:

```
int main()
{
  // ...

  #pragma mdh ( ,, +:C[i][j] )
  for( int i = 0 ; i < M ; ++i )
    for( int j = 0 ; j < N ; ++j )
      for( int k = 0 ; k < K ; ++k )
      {
        C[ i ][ j ] += A[ i ][ k ] * B[ k ][ j ];
      }

  // ...
}
```

MDH
Compiler



NVIDIA
CUDA

. . .

md_hom expression and **view** are automatically generated by MDH compiler:

```
md_hom( loop_body, (++, ++, +:C[i][j]) )
 view( A,B )( i,j,k )( A[i][k], B[k][j])
```

Annotating sequential C-Code with simple *MDH directives* *(similarly as in OpenMP/OpenACC).*

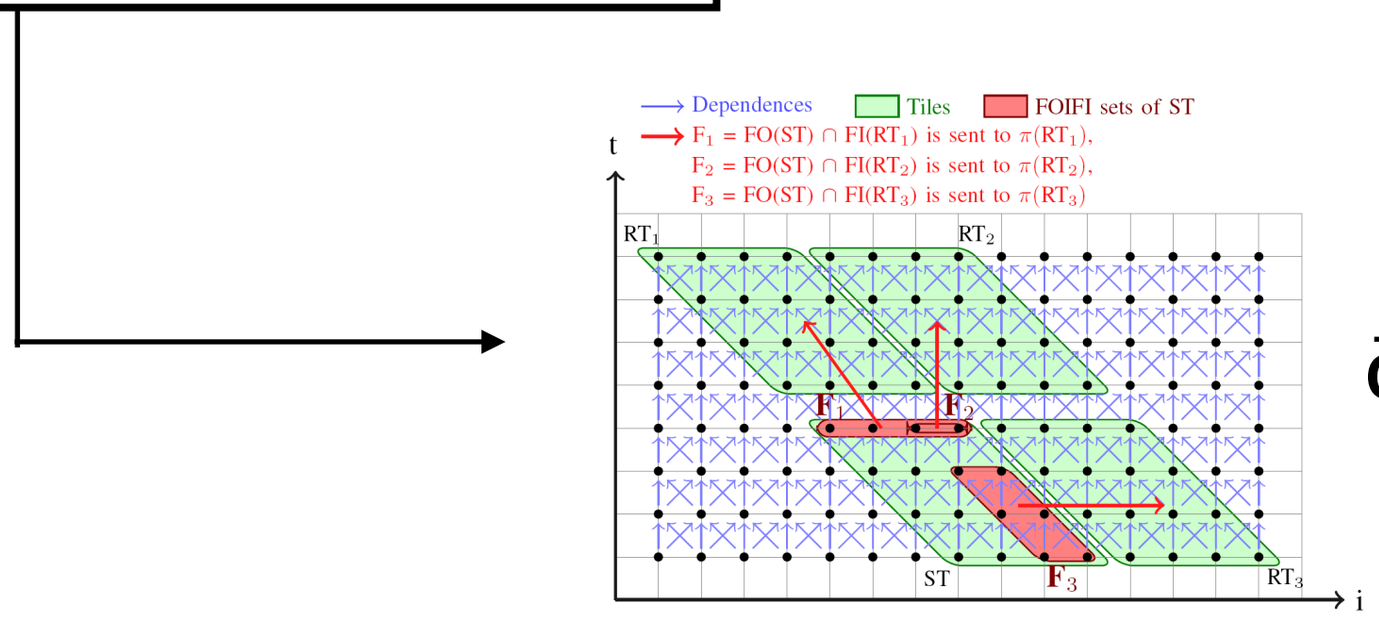
Current/Future Work

Automatic parallelization of sequential C programs:

```
int main()
{
  // ...

   for( int i = 0 ; i < M ; ++i )
    for( int j = 0 ; j < N ; ++j )
      for( int k = 0 ; k < K ; ++k )
      {
        C[ i ][ j ] += A[ i ][ k ] * B[ k ][ j ];
      }

  // ...
}
```



Polyhedral Model

MDH
Code Generation

. . .

Automatic MDH code generation via *Polyhedral Model*

Current/Future Work

Analyze efficiency of our *MDH+ATF+dOACL* approach's for more use cases:

Benchmark	Typical Bottleneck of an Unoptimized Implementation	Optimizations Applied	Optimized Implementation Bottleneck	Potential Improvements
cutcp	Contention, Locality	Scatter-to-Gather, Binning, Regularization, Coarsening	Instruction Throughput	Minimizing Reads/Checks of Irrelevant Bin Data
mri-q	Poor Locality	Data Layout Transformation, Tiling, Coarsening	Instruction Throughput	
gridding	Contention, Load Imbalance	Scatter-to-Gather, Binning, Compaction, Regularization, Coarsening	Instruction Throughput	Minimizing Reads/Checks of Irrelevant Bin Data
sad	Locality	Tiling, Coarsening	Memory Bandwidth/Latency	Target Devices with Higher Register Capacities
stencil	Locality	Coarsening, Tiling	Bandwidth	
tpacf	Locality, Contention	Tiling, Privatization, Coarsening	Instruction Throughput	
lbm	Bandwidth	Data Layout Transformation	Bandwidth	
sgemm	Bandwidth	Coarsening, Tiling	Instruction Throughput	
spmv	Bandwidth	Data Layout Transformation	Bandwidth	
bfs	Contention, Load Imbalance	Privatization, Compaction, Regularization	Bandwidth	Avoiding Global Barriers / Better Kernels for Midsized Frontiers
histogram	Contention, Bandwidth	Privatization, Scatter-to-Gather	Bandwidth	Reducing Reads of Irrelevant Input (alleviated by cache)

Parboil

TABLE I
RODINIA APPLICATIONS AND KERNELS (*DENOTES KERNEL).

Application / Kernel	Dwarf	Domain
K-means	Dense Linear Algebra	Data Mining
Needleman-Wunsch	Dynamic Programming	Bioinformatics
HotSpot*	Structured Grid	Physics Simulation
Back Propagation*	Unstructured Grid	Pattern Recognition
SRAD	Structured Grid	Image Processing
Leukocyte Tracking	Structured Grid	Medical Imaging
Breadth-First Search*	Graph Traversal	Graph Algorithms
Stream Cluster*	Dense Linear Algebra	Data Mining
Similarity Scores*	MapReduce	Web Mining

Rodinia

Benchmark	Description
`2mm`	2 Matrix Multiplications (D=A.B; E=C.D)
`3mm`	3 Matrix Multiplications (E=A.B; F=C.D; G=E.F)
`adi`	Alternating Direction Implicit solver
`atax`	Matrix Transpose and Vector Multiplication
`bicg`	BiCG Sub Kernel of BiCGStab Linear Solver
`cholesky`	Cholesky Decomposition
`correlation`	Correlation Computation
`covariance`	Covariance Computation
`doitgen`	Multiresolution analysis kernel (MADNESS)
`durbin`	Toeplitz system solver
`dynprog`	Dynamic programming (2D)
`fdtd-2d`	2-D Finite Different Time Domain Kernel
`fdtd-apml`	FDTD using Anisotropic Perfectly Matched Layer
`gauss-filter`	Gaussian Filter
`gemm`	Matrix-multiply C=alpha.A.B+beta.C
`gemver`	Vector Multiplication and Matrix Addition
`gesummv`	Scalar, Vector and Matrix Multiplication
`gramschmidt`	Gram-Schmidt decomposition
`jacobi-1D`	1-D Jacobi stencil computation
`jacobi-2D`	2-D Jacobi stencil computation
`lu`	LU decomposition
`ludcmp`	LU decomposition
`mvt`	Matrix Vector Product and Transpose
`reg-detect`	2-D Image processing
`seidel`	2-D Seidel stencil computation
`symm`	Symmetric matrix-multiply
`syr2k`	Symmetric rank-2k operations
`syrk`	Symmetric rank-k operations
`trisolv`	Triangular solver
`trmm`	Triangular matrix-multiply

PolyBench

Questions?