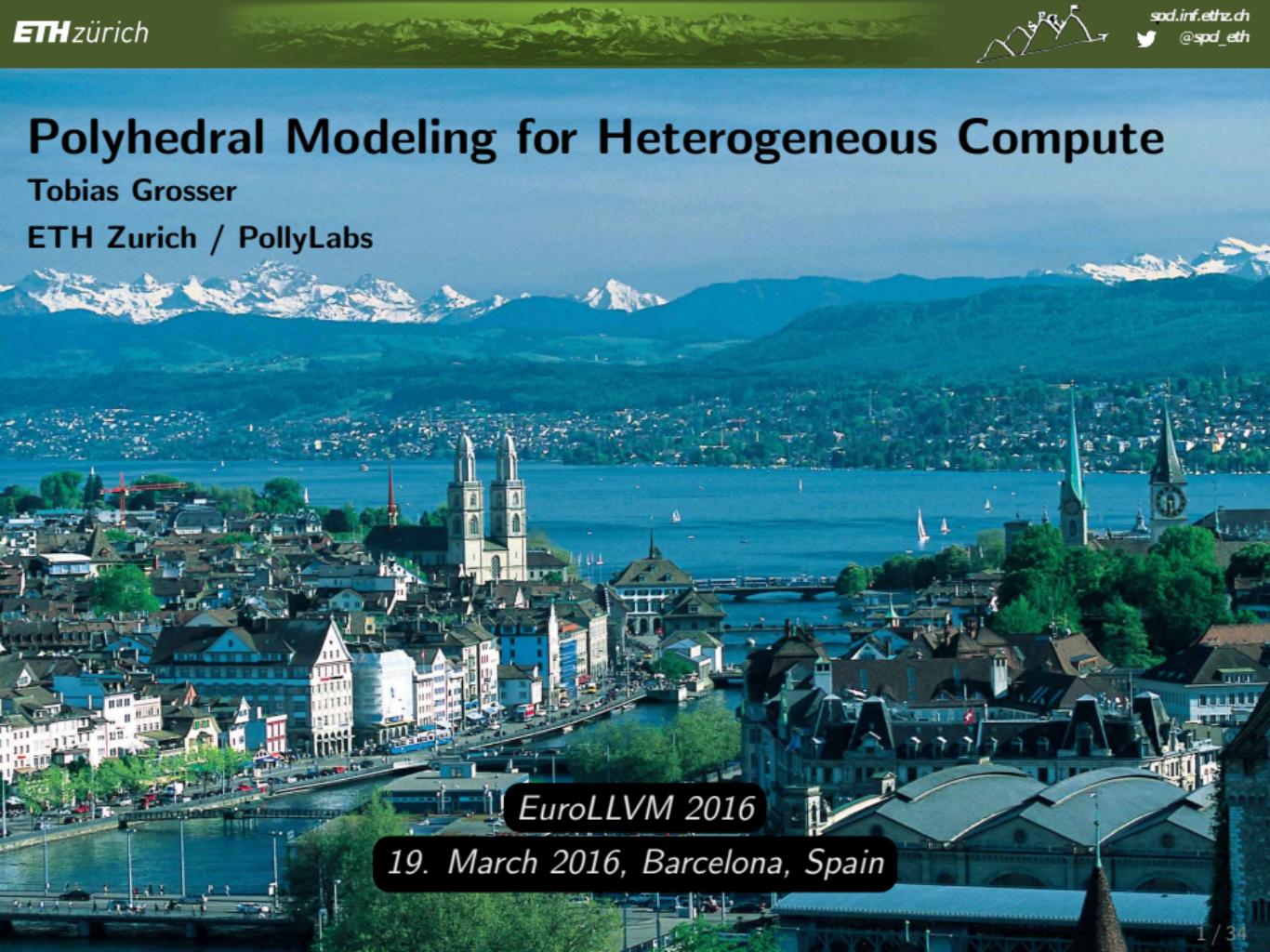


# Polyhedral Modeling for Heterogeneous Compute

Tobias Grosser

ETH Zurich / PollyLabs

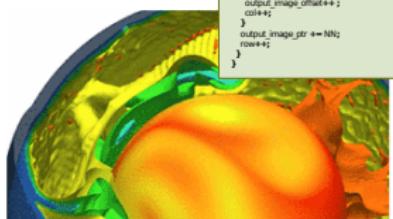


EuroLLVM 2016

19. March 2016, Barcelona, Spain

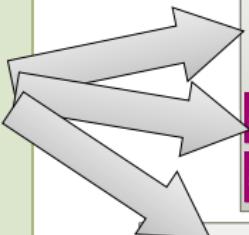
# Objective

Sequential Software  
Fortran  
C/C++/11  
Julia

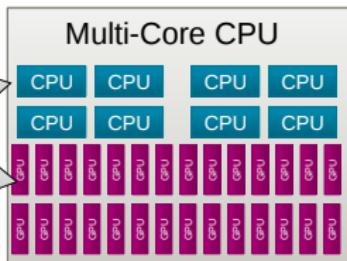


```
row = 0;
output_image_ptr = output_image;
output_image_offset += NIN * row;
for (r = 0; r < NIN * KX * KZ + 4; r++) {
    output_image_offset += output_image_ptr;
    output_image_offset += dead_col;
    output_image_offset += dead_col;
}

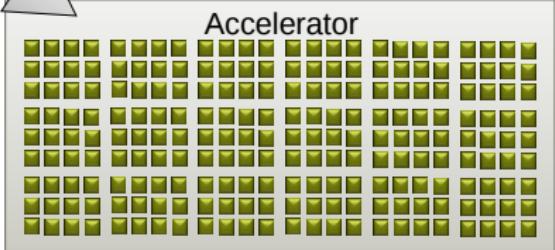
for (c = 0; c < NN - KX + 1; c++) {
    input_image_ptr = input_image;
    input_image_offset += (NN * r) * col;
    kernel_ptr = kernel;
    S1: output_image_offset = 0;
    for (w = 0; w < KX + 4; w++) {
        input_image_offset += input_image_ptr;
        input_image_offset += col;
        kernel_offset = kernel_ptr;
        kernel_offset += w;
        for (j = 0; j < KZ + 4; j++) {
            S2: temp1 = kernel_offset * KZ;
            temp2 = *kernel_offset + 4;
            S3: *output_image_offset += temp1 * temp2;
        }
        kernel_ptr += KZ;
        input_image_ptr += NN;
    }
    S4: output_image_offset = (*output_image_offset) /
        normal_factor;
    output_image_offset += col;
    col += 4;
}
output_image_ptr += NN;
row += 2;
}
```



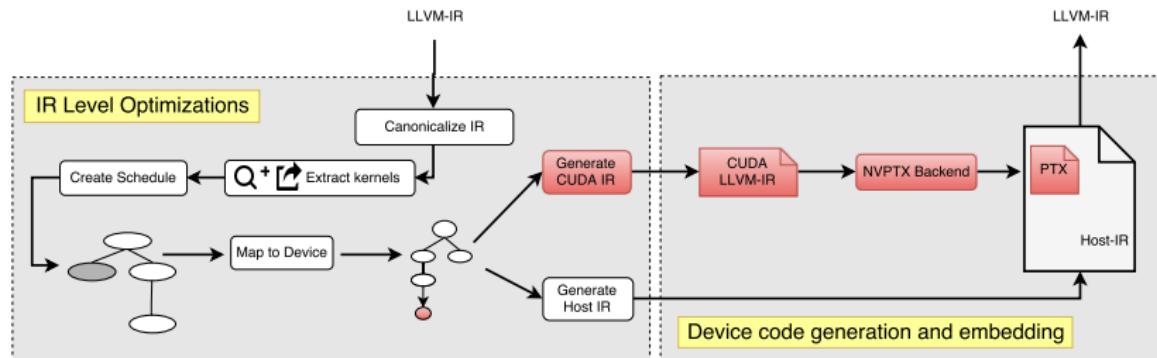
HPC



Embedded



# Architecture



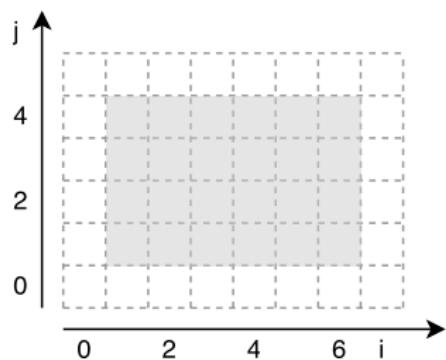
# Mapping computations to thread-blocks and threads

```
for (i = 1; i <= 6; i++)  
    for (j = 1, j <= 4; i++)  
S:  B[i][j] = A[i][j] + A[i+1][j] + A[i-1][j]  
     + A[i][j+1] + A[i][j-1];
```



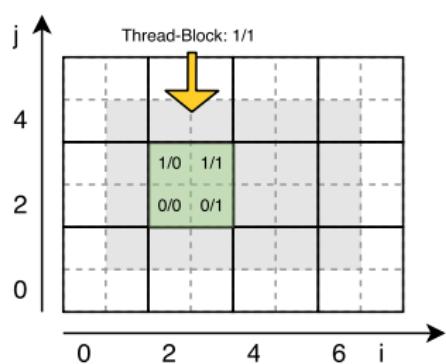
# Mapping computations to thread-blocks and threads

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for (i = 1; i <= 6; i++)
    for (j = 1, j <= 4; i++)
S:   B[i][j] = A[i][j] + A[i+1][j] + A[i-1][j]
            + A[i][j+1] + A[i][j-1];
```



# Mapping computations to thread-blocks and threads

```
for (i = 1; i <= 6; i++)  
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S:   B[i][j] = A[i][j] + A[i+1][j] + A[i-1][j]  
           + A[i][j+1] + A[i][j-1];
```



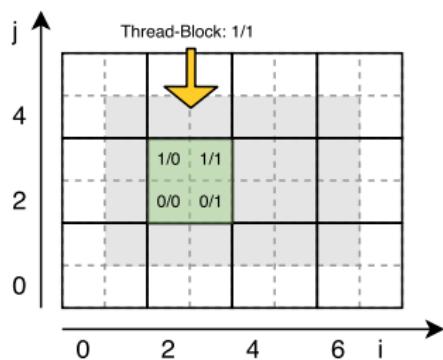
## Mappings:

- $\{S[i,j] \rightarrow \text{blocks}[\text{floor}(i/2), \text{floor}(j, 2)]\}$
- $\{S[i,j] \rightarrow \text{threads}[i \bmod 2, j \bmod 2]\}$



# Mapping computations to thread-blocks and threads

```
for (i = 1; i <= 6; i++)  
    for (j = 1, j <= 4; i++)  
S:  B[i][j] = A[i][j] + A[i+1][j] + A[i-1][j]  
        + A[i][j+1] + A[i][j-1];
```



## Mappings:

- { $S[i,j] \rightarrow \text{blocks}[\text{floor}(i/2), \text{floor}(j, 2)]\}$ }
- { $S[i,j] \rightarrow \text{threads}[i \bmod 2, j \bmod 2]\}$ }

In case we create more thread-blocks than supported in hardware, thread-blocks are assigned round-robin!



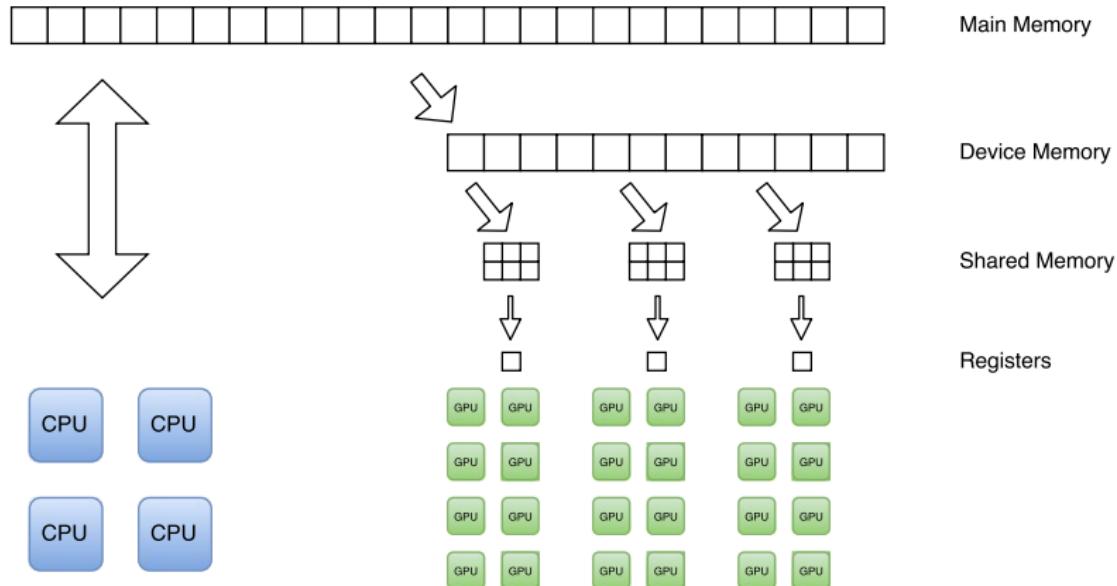
## Generated accelerator code

```
void kernel(float A[][][6], float B[][][6]) {
    int b0 = blockIdx.y; int b1 = blockIdx.x;
    int t0 = threadIdx.y; int t1 = threadIdx.x;

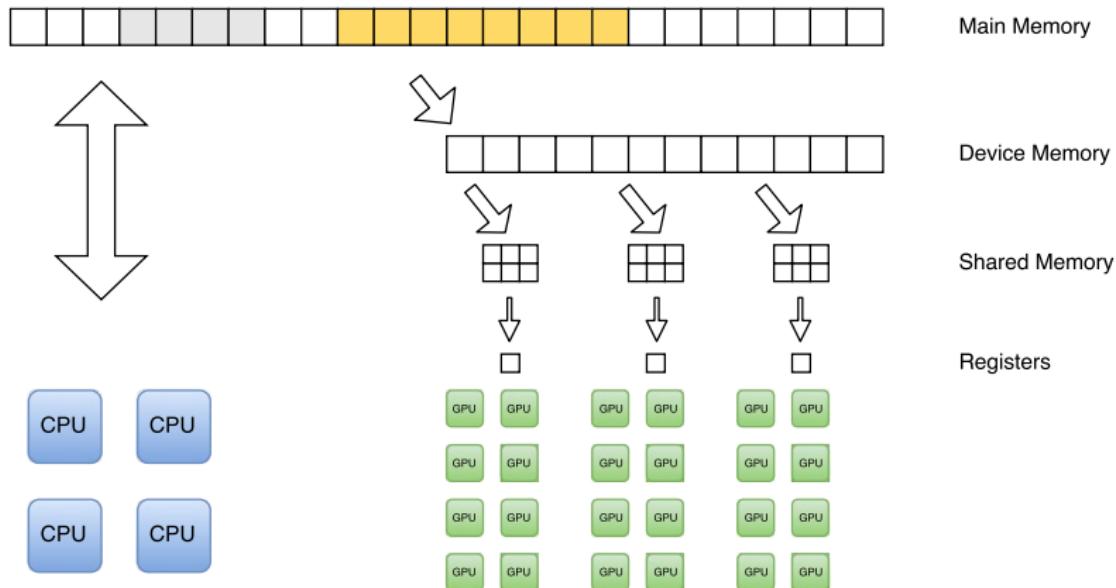
    int i = 2 * b0 + t0;
    int j = 2 * b1 + t1;
    S: B[i][j] += A[i+1][j] + A[i-1][j]
        + A[i][j+1] + A[i][j-1];
}
```

Commonly not a single computation per-kernel, but also loops/synchronizations.

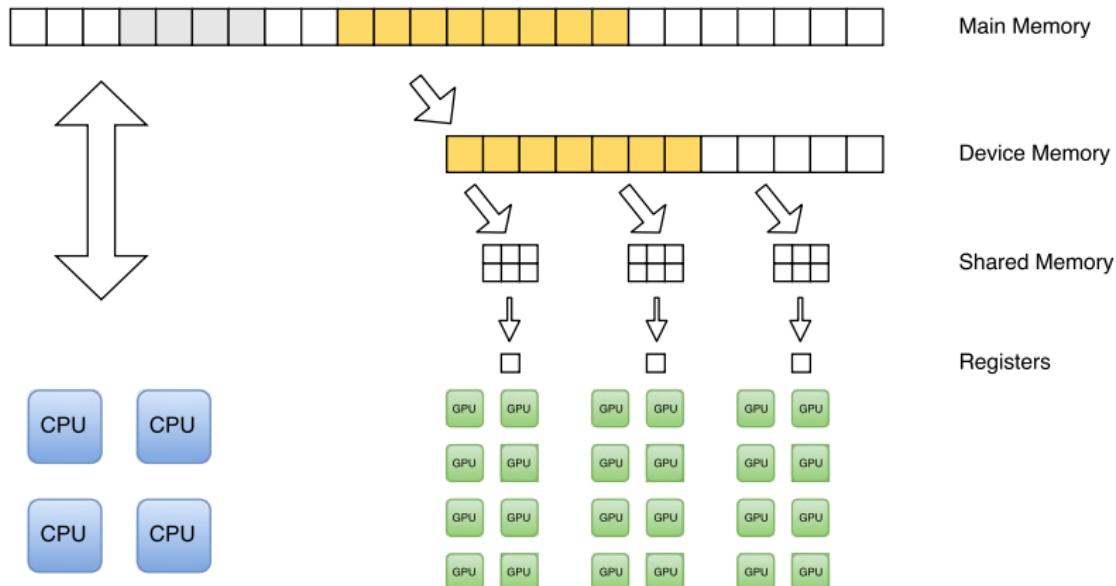
# Memory hierarchy of an accelerator system



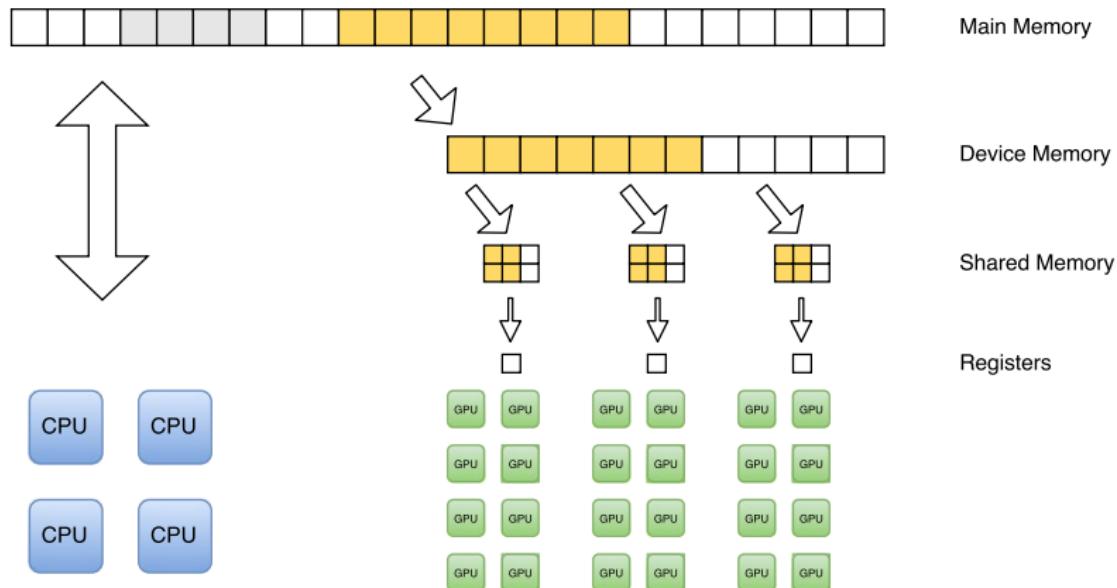
# Memory hierarchy of an accelerator system



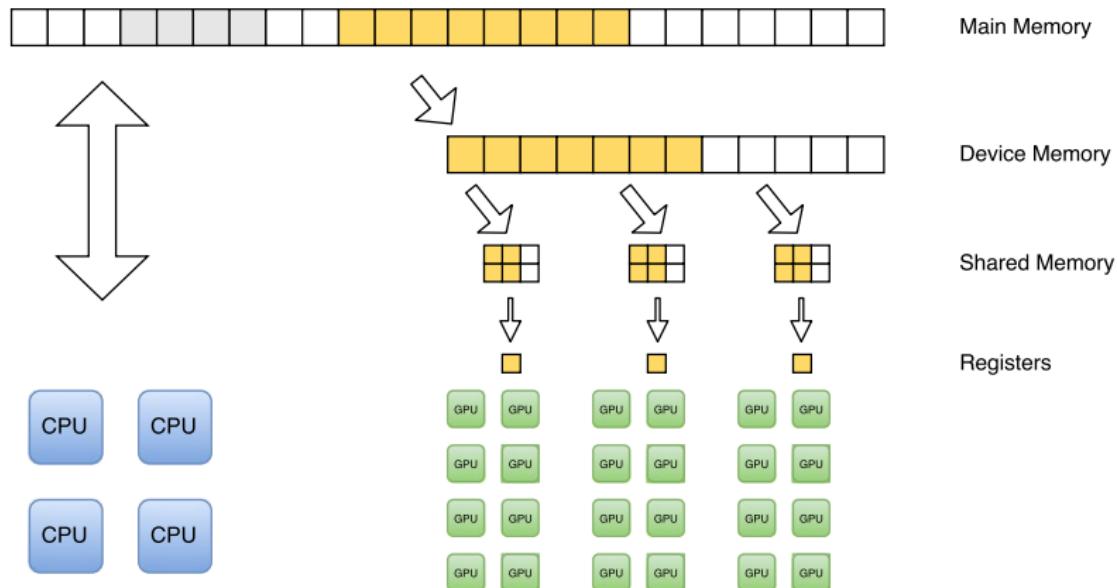
# Memory hierarchy of an accelerator system



# Memory hierarchy of an accelerator system



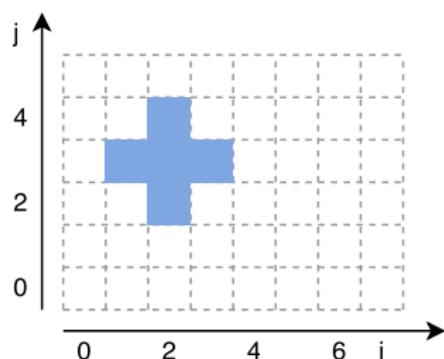
# Memory hierarchy of an accelerator system





# Identify array subregions accessed by threadblock

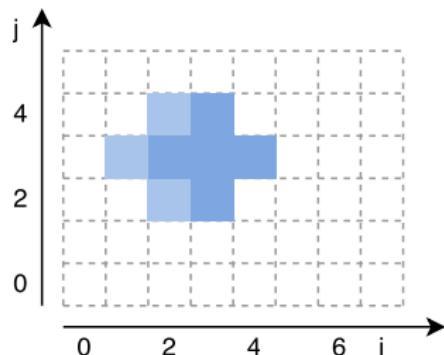
```
for (i = 1; i <= 6; i++)  
    for (j = 1, j <= 4; i++)  
S:   B[i][j] += A[i+1][j ] + A[i-1][j ]  
        + A[i ][j+1] + A[i ][j-1];
```





# Identify array subregions accessed by threadblock

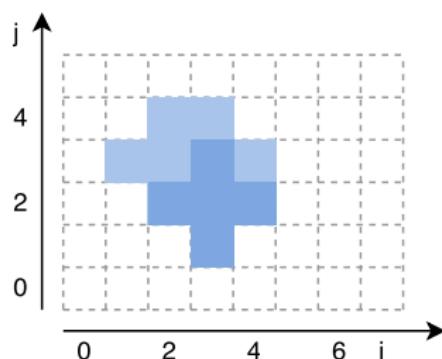
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for (i = 1; i <= 6; i++)  
    for (j = 1, j <= 4; i++)  
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        + A[i ][j+1] + A[i ][j-1];
```





# Identify array subregions accessed by threadblock

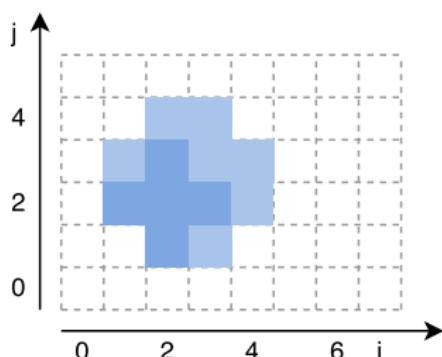
```
for (i = 1; i <= 6; i++)  
    for (j = 1, j <= 4; i++)  
S:   B[i][j] += A[i+1][j ] + A[i-1][j ]  
        + A[i ][j+1] + A[i ][j-1];
```





# Identify array subregions accessed by threadblock

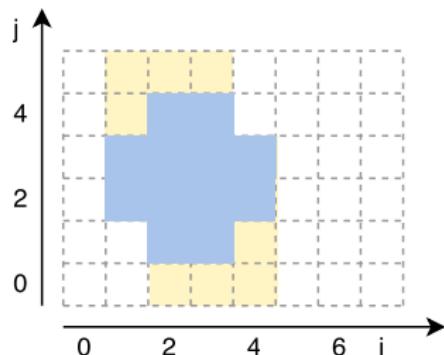
```
for (i = 1; i <= 6; i++)  
    for (j = 1, j <= 4; i++)  
S:   B[i][j] += A[i+1][j ] + A[i-1][j ]  
        + A[i ][j+1] + A[i ][j-1];
```



Maximal storage efficiency possible with counting (barvinok).  
BUT, accesses become inefficient.

# Identify array subregions accessed by threadblock

```
for (i = 1; i <= 6; i++)
    for (j = 1, j <= 4; i++)
S:   B[i][j] += A[i+1][j ] + A[i-1][j ]
        + A[i ][j+1] + A[i ][j-1];
```

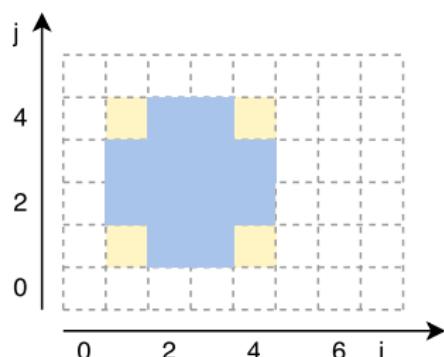


Copying a one-dimensional set of memory addresses (including untouched addresses in between).



# Identify array subregions accessed by threadblock

```
for (i = 1; i <= 6; i++)  
    for (j = 1, j <= 4; i++)  
S:   B[i][j] += A[i+1][j ] + A[i-1][j ]  
        + A[i ][j+1] + A[i ][j-1];
```



Copying a multi-dimensional set of array locations (including untouched addresses in between).  
⇒ More efficient!



# Map array subregions to shared memory

- ▶ For each array subregion identified, check if:
    - ▶ data-elements are used multiple times  
or
    - ▶ accesses to global memory are not coalesced
    - ▶ and the dataset size fits into shared memory
- ⇒ allocate shared memory for subregion

## Generated code when using shared memory

**Each thread-block executes:**

- ▶ Copy global  $\Rightarrow$  shared (new)
- ▶ synchronize()
- ▶ Compute in shared memory (changed)
- ▶ synchronize()
- ▶ Copy shared  $\Rightarrow$  global (new)

# Optimizing the copy code

## Global $\Rightarrow$ Shared

- ▶ Data element is read in thread-block
- ▶ ... but has not been computed earlier in the same thread block
- ▶ Over approximate data to load with the rectangle to simplify code

## Shared $\Rightarrow$ Global

- ▶ Data element is written in thread-block
- ▶ ... and is used later outside of the thread block but not overwritten in between.
- ▶ Do not over-approximate storage set.



# Local memory / registers

- ▶ Algorithm mirrors shared memory mapping
- ▶ Use local memory in case data remains thread-local
- ▶ Unroll computation to ensure constant access expressions:

```
for (i = t0; i < 128; i+=32)
    A[floor(i / 32)] = i;
```

↓

```
A[0] = t0;
A[1] = t0 + 32;
A[2] = t0 + 64;
A[3] = t0 + 96;
```

# Lowering of arrays of parametric size in LLVM

```
void gemm(int n, int m, int p,
          float A[n][p], float B[p][m], float C[n][m]) {
L1:   for (int i = 0; i < n; i++)
L2:     for (int j = 0; j < m; j++)
L3:       for (int k = 0; k < p; ++k)
            C[i][j] += A[i][k] * B[k][j];
}
```



# C99 arrays lowered to LLVM-IR

```
define void @gemm(i32 %n, i32 %m, i32 %p, float* %A, float* %B, float* %C) {
; for i:
;   for j:
;     for k:
        %A.idx = mul i32 %i, %p
        %A.idx2 = add i32 %A.idx, %k
        %A.idx3 = getelementptr float* %A, i32 %A.idx2
        %A.data = load float* %A.idx3
        %B.idx = mul i32 %k, %m
        %B.idx2 = add i32 %B.idx, %j
        %B.idx3 = getelementptr float* %B, i32 %B.idx2
        %B.data = load float* %B.idx3
        %C.idx = mul i32 %i, %m
        %C.idx2 = add i32 %C.idx, %j.0
        %C.idx3 = getelementptr float* %C, i32 %C.idx2
        %C.data = load float* %C.idx3
        %mul = fmul float %A.data, %B.data
        %add = fadd float %C.data, %mul
        store float %add, float* %C.idx3
}
```



# Recovery of Index Expressions using SCEV

Recovered accesses are:

- ▶ Single dimensional
- ▶ *Polynomial*

```
void gemm(int n, int m, int p,
          float A[], float B[], float C[]) {
L1:   for (int i = 0; i < n; i++)
L2:     for (int j = 0; j < m; j++)
L3:       for (int k = 0; k < p; ++k)
            C[i * m + j] += A[i * p + k] * B[k * M + j];
}
```



# The Problem

**Given a set of single dimensional memory accesses with index expressions that are multivariate polynomials and a set of iteration domains, derive a multi-dimensional view:**

- ▶ A multi-dimensional array definition
- ▶ For each original array access:  
a new multi-dimensional access function

Grosser Tobias, Pop Sebastian, Pouchet Louis-Noel, Sadayappan P,  
Ramanujam J. **Optimistic Delinearization of Parametrically Sized Arrays**,  
International Conference on Supercomputing (ICS), 2015

# Conditions

- ▶ **R1 - Affine**

New access functions are affine

- ▶ **R2 - Equivalence**

Addresses in original and multi-dimensional view are identical

- ▶ **R3 - In-Bounds**

Array subscripts are within bounds (except outer dimension)

If **R3** not statically provable → derive run-time conditions.

## Example: Initialize subarray (I)

- ▶ Array size:  $n_0 \times n_1 \times n_2$
- ▶ Subarray position:  $o_0 \times o_1 \times o_2$
- ▶ Subarray size:  $s_0 \times s_1 \times s_2$

```
void set_subarray(float A[],  
                  size_t o0, size_t o1, size_t o2,  
                  size_t s0, size_t s1, size_t s2,  
                  size_t n0, size_t n1, size_t n2) {  
    for (size_t i = 0; i < s0; i++)  
        for (size_t j = 0; j < s1; j++)  
            for (size_t k = 0; k < s2; k++)  
S:          A[(n2 * (n1 * o0 + o1) + o2)  
           + n1 * n2 * i + n2 * j + k] = 1;  
           // A[o0 + i, o1 + j, o1 + k] = 1  
}
```



## Example: Initialize subarray (II)

### 1. Start

$$(n_2(n_1o_0 + o_1) + o_2) + n_1n_2i + n_2j + k$$

### 2. Expand expression

$$n_2n_1o_0 + n_2o_1 + o_2 + n_1n_2i + n_2j + k$$

### 3. Extract Terms containing induction variables

$$\{n_1n_2i, n_2j, k\}$$

### 4. Drop non-parameters and sort terms by #elements

$$\{n_1n_2, n_2\}$$

### 5. Assumed size

A [] [n1] [n2]



## Example: Initialize subarray (III)

6. **Inner dimension:** divide by  $n_2$

Quotient:  $n_1o_0 + o_1 + n_1i + n_2j$

Remainder:  $o_2 + k \rightarrow A[?][?][k + o_2]$

7. **Second inner dimension:** divide by  $n_1$

Quotient:  $o_0 + i \rightarrow A[i + o_0][?][?]$

Remainder:  $o_1 + j \rightarrow A[?][j + o_1][?]$

8. **Full array access:**  $A[i + o_0][j + o_1][k + o_2]$

9. **Validity conditions:**

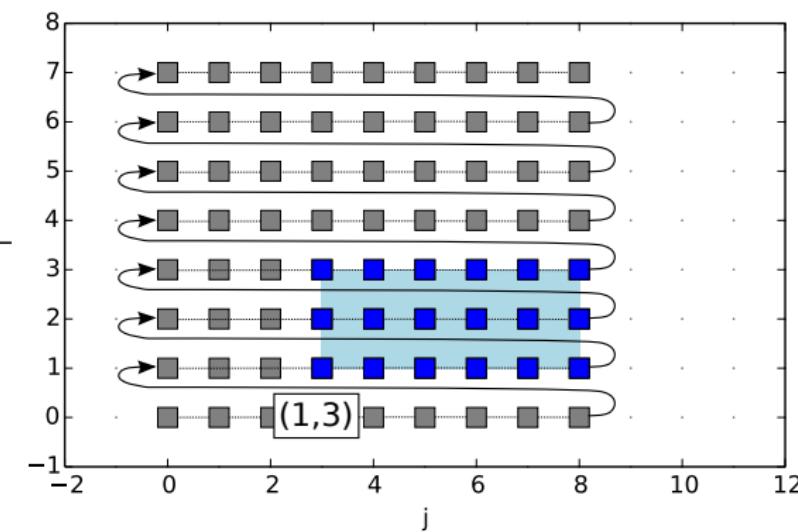
$$\forall i, j, k : 0 \leq i < s_0 \wedge 0 \leq j < s_1 \wedge 0 \leq k < s_2 :$$

$$0 \leq k + o_2 < n_2 \wedge 0 \leq j + o_1 < n_1 \wedge 0 \leq i + o_0$$

$$\Rightarrow o_1 \leq n_1 - s_1 \wedge o_2 \leq n_2 - s_2$$

# Why validity conditions?

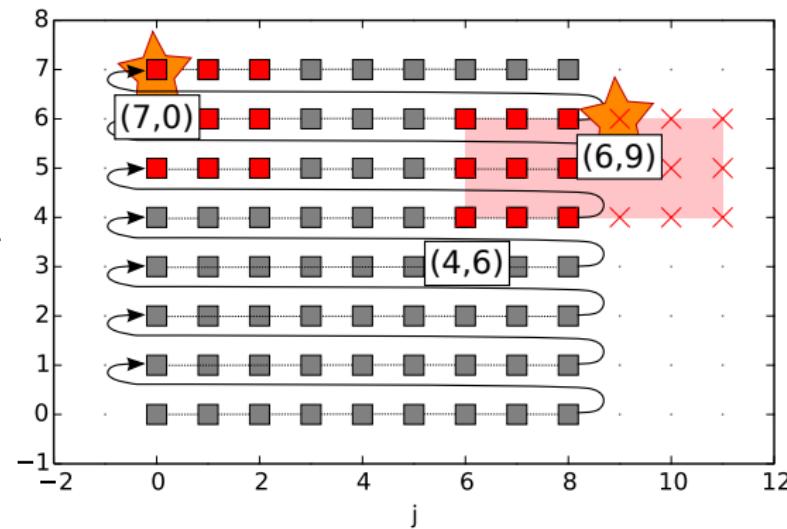
- ▶ Array size ( $n_0 = 8, n_1 = 9$ )
- ▶ Subarray offset ( $o_0 = 1, o_1 = 3$ ), size ( $s_0 = 3, s_1 = 6$ ).



- ▶ Run-time condition:  $o_1 \leq n_1 - s_1 \Rightarrow 3 \leq 9 - 6 \rightarrow \top$

# Why validity conditions?

- ▶ Array size ( $n_0 = 8, n_1 = 9$ )
- ▶ Subarray offset ( $o_0 = 4, o_1 = 6$ ), size ( $s_0 = 3, s_1 = 6$ ).



- ▶ Run-time condition:  $o_1 \leq n_1 - s_1 \Rightarrow 6 \leq 9 - 6 \Rightarrow \perp$
- ▶ A[6][9] and A[7][0] alias ↳



# Delinearization in LLVM's ScalarEvolution

```
// Delinearization of a single access
void delinearize(const SCEV *Expr,
    SmallVectorImpl<const SCEV *> &Subscripts,
    SmallVectorImpl<const SCEV *> &Sizes,
    const SCEV *ElementSize);

// Functions to derive a delinearization for a set of accesses:
void collectParametricTerms(const SCEV *Expr,
    SmallVectorImpl<const SCEV *> &Terms);
void findArrayDimensions(SmallVectorImpl<const SCEV *> &Terms,
    SmallVectorImpl<const SCEV *> &Sizes,
    const SCEV *ElementSize);
void computeAccessFunctions(
    const SCEV *Expr, SmallVectorImpl<const SCEV *> &Subscripts,
    SmallVectorImpl<const SCEV *> &Sizes);
```

! Validity conditions still need to be generated (available in Polly) !

# Using shared memory: Apply a simple mapping function

```
void kernel(float A[] [6], float B[] [6]) {  
    int b0 = blockIdx.y; int b1 = blockIdx.x;  
    int t0 = threadIdx.y; int t1 = threadIdx.x;  
    int i = 2 * b0 + t0; int j = 2 * b1 + t1;  
    S: B[i] [j] = A[i] [j] + A[i+1] [j ] + A[i-1] [j ]  
        + A[i ] [j+1] + A[i ] [j-1];  
}
```

Original access relation:  $\{S[i,j] \rightarrow A[i,j]\}$



# Using shared memory: Apply a simple mapping function

```
void kernel(float A[] [6], float B[] [6]) {  
    int b0 = blockIdx.y; int b1 = blockIdx.x;  
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    S: B[i] [j] = A[i] [j] + A[i+1] [j] + A[i-1] [j]  
        + A[i] [j+1] + A[i] [j-1];  
}
```

Original access relation:  $\{S[i, j] \rightarrow A[i, j]\}$

Block mapping:  $\{S[i, j] \rightarrow \text{blocks}[\text{floor}(i/2), \text{floor}(j, 2)]\}$



# Using shared memory: Apply a simple mapping function

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void kernel(float A[] [6], float B[] [6]) {  
    int b0 = blockIdx.y; int b1 = blockIdx.x;  
    int t0 = threadIdx.y; int t1 = threadIdx.x;  
    int i = 2 * b0 + t0; int j = 2 * b1 + t1;  
    S: B[i] [j] = A[i] [j] + A[i+1] [j ] + A[i-1] [j ]  
        + A[i ] [j+1] + A[i ] [j-1];  
}
```

Original access relation:  $\{S[i, j] \rightarrow A[i, j]\}$

Block mapping:  $\{S[i, j] \rightarrow \text{blocks}[\text{floor}(i/2), \text{floor}(j, 2)]\}$

Per-block accesses:  $\{\text{blocks}[b0, b1] \rightarrow A[i, j] \mid$

$$2 * b0 - 1 \leq i \leq 2 * b0 + 1 \wedge$$

$$2 * b1 - 1 \leq j \leq 2 * b1 + 1\}$$



# Using shared memory: Apply a simple mapping function

```
void kernel(float A[] [6], float B[] [6]) {  
    int b0 = blockIdx.y; int b1 = blockIdx.x;  
    int t0 = threadIdx.y; int t1 = threadIdx.x;  
    int i = 2 * b0 + t0; int j = 2 * b1 + t1;  
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        + A[i] [j+1] + A[i] [j-1];  
}
```

Original access relation:  $\{S[i, j] \rightarrow A[i, j]\}$

Block mapping:  $\{S[i, j] \rightarrow \text{blocks}[\lfloor i/2 \rfloor, \lfloor j/2 \rfloor]\}$

Per-block accesses:  $\{\text{blocks}[b0, b1] \rightarrow A[i, j] \mid$

$$2 * b0 - 1 \leq i \leq 2 * b0 + 1 \wedge$$

$$2 * b1 - 1 \leq j \leq 2 * b1 + 1\}$$

Minimal element accessed in block:  $(2b0 - 1, 2b1 - 1)$



# Using shared memory: Apply a simple mapping function

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void kernel(float A[] [6], float B[] [6]) {  
    int b0 = blockIdx.y; int b1 = blockIdx.x;  
    int t0 = threadIdx.y; int t1 = threadIdx.x;  
    int i = 2 * b0 + t0; int j = 2 * b1 + t1;  
    S: B[i] [j] = A[i] [j] + A[i+1] [j ] + A[i-1] [j ]  
        + A[i ] [j+1] + A[i ] [j-1];  
}
```

Original access relation:  $\{S[i, j] \rightarrow A[i, j]\}$

Block mapping:  $\{S[i, j] \rightarrow \text{blocks}[\lfloor i/2 \rfloor, \lfloor j/2 \rfloor]\}$

Per-block accesses:  $\{\text{blocks}[b0, b1] \rightarrow A[i, j] |$

$$\begin{aligned}2 * b0 - 1 &\leq i \leq 2 * b0 + 1 \wedge \\2 * b1 - 1 &\leq j \leq 2 * b1 + 1\end{aligned}$$

Minimal element accessed in block:  $(2b0 - 1, 2b1 - 1)$

Extend of accessed region:  $(3, 3)$



# Using shared memory: Apply a simple mapping function

```
void kernel(float A[] [6], float B[] [6]) {  
    int b0 = blockIdx.y; int b1 = blockIdx.x;  
    int t0 = threadIdx.y; int t1 = threadIdx.x;  
    int i = 2 * b0 + t0; int j = 2 * b1 + t1;  
    S: B[i] [j] = A[i] [j] + A[i+1] [j] + A[i-1] [j]  
        + A[i] [j+1] + A[i] [j-1];  
}
```

Original access relation:  $\{S[i, j] \rightarrow A[i, j]\}$

Block mapping:  $\{S[i, j] \rightarrow \text{blocks}[\lfloor i/2 \rfloor, \lfloor j/2 \rfloor]\}$

Per-block accesses:  $\{\text{blocks}[b0, b1] \rightarrow A[i, j] \mid$

$$\begin{aligned}2 * b0 - 1 &\leq i \leq 2 * b0 + 1 \wedge \\2 * b1 - 1 &\leq j \leq 2 * b1 + 1\end{aligned}$$

Minimal element accessed in block:  $(2b0 - 1, 2b1 - 1)$

Extend of accessed region:  $(3, 3)$

Map to shared memory:  $\{A[i, j] \rightarrow A_{\text{shared}}[i - 2b0 + 1, j - 2b1 + 1]\}$



# Kernel code using shared memory

```
void kernel(float A[][][6], float B[][][6]) {
    int b0 = blockIdx.y; int b1 = blockIdx.x;
    int t0 = threadIdx.y; int t1 = threadIdx.x;
    __shared A_shared[3][3];

    A_shared[t0][t1] = A[2 * b0 + t0 - 1][2 * b1 + t1 - 1];
    if (t0 < 1)
        A_shared[t0+2][t1] = A[2 * b0 + t0 + 1][2 * b1 + t1 - 1];
    if (t1 < 1)
        A_shared[t0][t1+2] = A[2 * b0 + t0 - 1][2 * b1 + t1 + 1];
    if (t0 < 1 && t1 < 1)
        A_shared[t0+2][t1+2] = A[2 * b0 + t0 + 1][2 * b1 + t1 + 1];
    __sync_synchronize();
    S: B[i][j] = A_shared[t0+1][t1+1]
        + A_shared[t0+2][t1+1] + A_shared[t0+0][t1+1]
        + A_shared[t0+1][t1+2] + A_shared[i0+1][i1+0];
}
```



# Heterogeneous Compute in Polly

- ▶ Precise memory modeling enables compiler-driven memory management.
- ▶ Polly recovers necessary information to reason about multi-dimensionality.
- ▶ Complex memory accesses transformations made easy.
- ▶ Sophisticated kernel generation with Polly