Non-affine Extensions to Polyhedral Code Generation

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Polyhedral Transformations & Code Generation

Stage 1 :

Loop Bounds Extraction & Iteration Space Construction

Input Code:
```
for(i=0; i < n; i++)
    s0: a[i]=b[i];
```

Iteration Space (IS):
s0 ={[i] : 0 <=i <= n}

Stage 2 :

Transformation (T) Application (Eg. Loop shifting)

Input IS:
{[i] : 0 <=i <= n}

T = {[i]->[i+4]}

Output IS:
{[i] : 4 <= i < n + 4}

Stage 3 :

Original Loop Iterators obtained as functions of new iterators

Update statement macro with T_inv. Apply Polyhedra Scanning

T_inv = {[i]->[i-4]}

Output Code:
```
for(i=4; i < n+ 4; i++)
    s0: a[i-4]=b[i-4];
```

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Motivation

- Limitation of the Polyhedral Model
  - Loop bounds, array access expressions and transformations must be affine, i.e. of the form: $a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n$
- Important non-affine construct:

  Indirection through index arrays such as B[i] in A[B[i]]
  - Common in sparse matrix and molecular dynamics computations
  - Compiler cannot determine memory access patterns statically
- Key observations:

  Non-affine iteration spaces/accesses can sometimes be tolerated

  Run-time inspection reveals mapping of iterations to array indices
  - Enables locality and parallelizing run-time transformations

Sparse Matrix-Vector Multiply (SpMV)

```
for (i=0; i < n; i++)
    for (j=index[i]; j<index[i+1]; j++)
        y[i]+=a[j]*x[col[j]];
```

Non-affine loop bounds

Non-affine subscript

Compressed Sparse Row (CSR) format

- Sparse matrix computations
  - Avoid redundant computation and space for zero-valued elements
  - Results in non-affine index arrays to derive column and row
  - SpMV libraries support multiple matrix formats and parallelization strategies to exploit matrix structure (e.g., CUSP for GPUs)

Related Work

Run-time Approaches for Sparse Matrix Vector Multiply(SpMV)

- Basumallik and Eigenmann (PPoPP'06)
  - Use a loop restructuring run-time transformation on irregular loops
- Ravishankar et al. (SC'12)
  - Generate run-time I/E code for partitioning irregular loops on a distributed memory system

Non-affine Polyhedral Abstractions

- Pugh and Wonnacott ('94)
  - Represent non-affine accesses for array dependence analysis
- Strout et al.(LCPC'12)
  - Represent run-time Inspector/Executor (I/E) transformations as non-affine transformations

Contributions

1. Represent iteration spaces for non-affine loop bounds
   - Enables further iteration space transformations
2. Support non-affine transformations using run-time inspection
3. Simplify array access expressions resulting from non-affine mappings
4. Demonstrate high-performance compiler-generated code on GPU
   - Performance of Sparse Matrix Vector Multiply (SpMV) kernel comparable to manually-tuned CUSP library

Non-affine Loop Bounds

Loop Bounds
Extraction & Iteration
Space Construction

a) Without Extension

```
SpMV Code:
for(i=0; i < n; i++)
  s0: for(j=index[i];j<index[i+1];j++)
        y[i]+=a[j]*x[col[j]]
```

???

b) With Extension

```
SpMV Code:
for(i=0; i < n; i++)
   for(j=index[i];j<index[i+1];j++)
      s0:  y[i]+=a[j]*x[col[j]]
```

Inner j-loop bounds abstracted as index(i) & index(i+1)

Iteration Space (IS):
{[i,j] : 0 <= i < n && index(i) <= j && j < index(i+1)}

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Non-affine Loop Bounds

- Un-interpreted Function Symbols
  - "Un-interpreted" as exact function mapping is not known
- Use to represent non-affine loop bounds in the iteration space
  - Enables other iteration space transformations (e.g., tiling)

```
for(i=0; i < n;i++)
  for(j=index[i];j<index[i+1];j++)
        y[i]+=a[j]*x[col[j]]
```

```
for (i = 0; i <= n; i ++)
   for (jj = index[i];jj<index[i+1];jj+=4)
      for (j = jj; j <min(index[i+1],jj + 4); j += 1)
            y[i] += (a[j] * x[col[j]]);
```

Non-affine Transformations

- Generalized loop coalescing transformation
  - Flatten a multi-dimensional loop nest into a single loop

```
Input Loop:
for(i)
  for(j)
    .....
      s0;
```

$T_{coalesce} = \{[i,j] \rightarrow [k] \mid k = c(i,j) \wedge 0 \leq k < NNZ\}$

Coalesce

- Benefit
  - Enables other transformations (e.g., longer vectors, more tiling)

```
Output Loop:
for(k)
   s0;
```

Non-affine Transformations

- Mapping from input loop iterators to output loop iterator determined at run-time
- An ***Inspector*** records this mapping
  - Code with updated references is termed the ***Executor***
- Code Generation utilizes the run-time map constructed for the un-interpreted function to "fill-in" the inverse mapping
  - Eg. i = c_inv[k][0] & j = c_inv[k][1]

Inspector Data Structure:

```
struct access_relation {
     // array to track old iterators
     int c_inv[][2];
     // variable to keep track of k
     int k;
     void create_mapping(int i,int j){
           c_inv[k][0] = i;
           c_inv[k][1] = j;
           k++;
     }
}
```

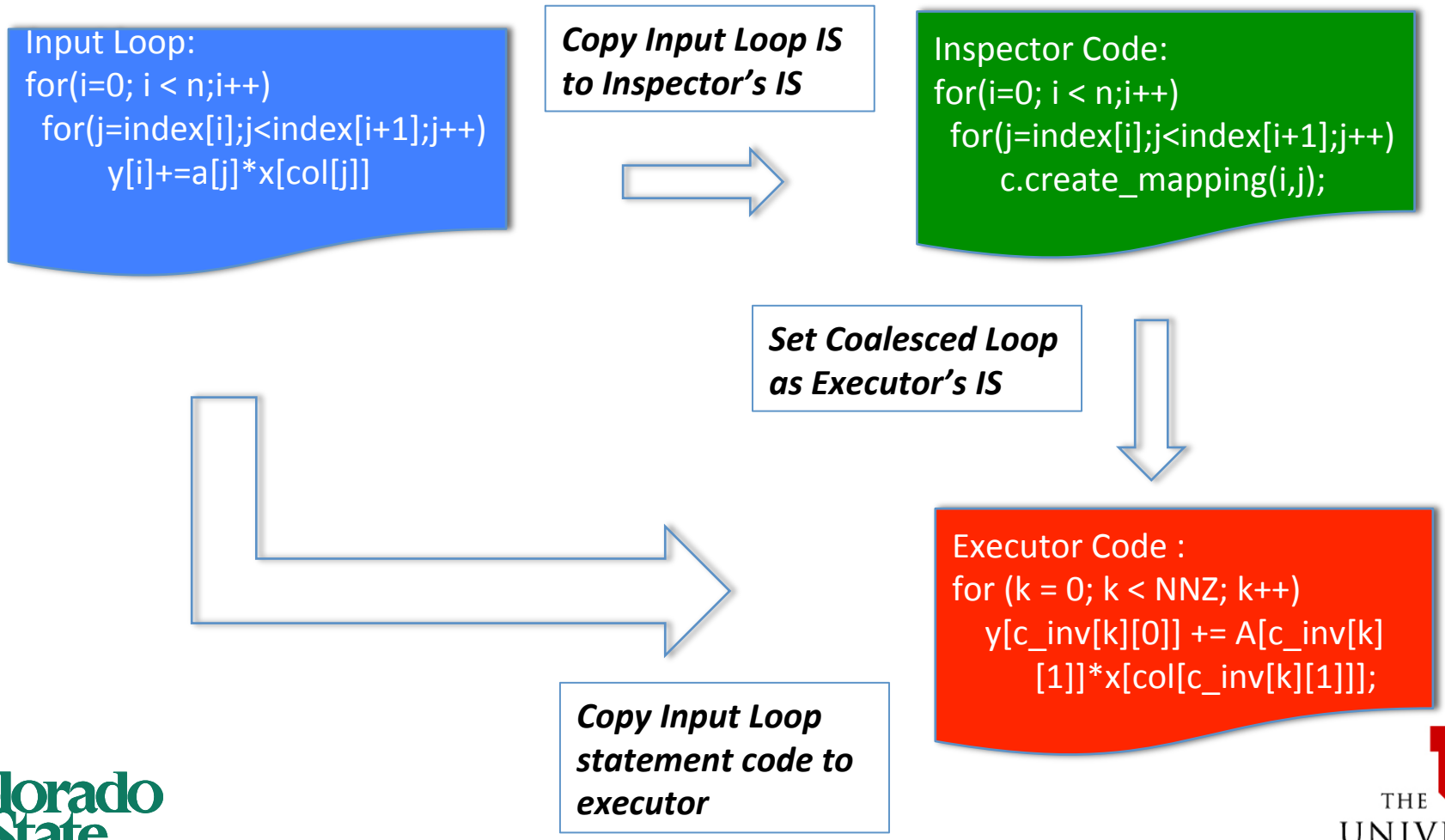
Inspector Code:

```
struct access_relation c;
for (i=0; i<=n-1; i++)
   for (j=index[i]; j<=index[i+1]-1; j++)
         c.create_mapping(i,j);
```

Executor Code:

```
for (k = 0; k < NNZ; k++)
y[c_inv[k][0]]
 += A[c_inv[k][1]]*x[col[c_inv[k][1]]];
```

Non-affine Transformations



Optimizations

- Un-simplified Output Loop:

  for (k = 0; k < NNZ; k++)

  *y[**c_inv[k][0]**] += A[**c_inv[k][1]**]*x[col[**c_inv[k][1]**]];*

  - Array access Indirection incurs extra memory load instruction overheads

- Inspector provides additional information that iterator ***j*** in input loop is equal to iterator ***k*** in output loop

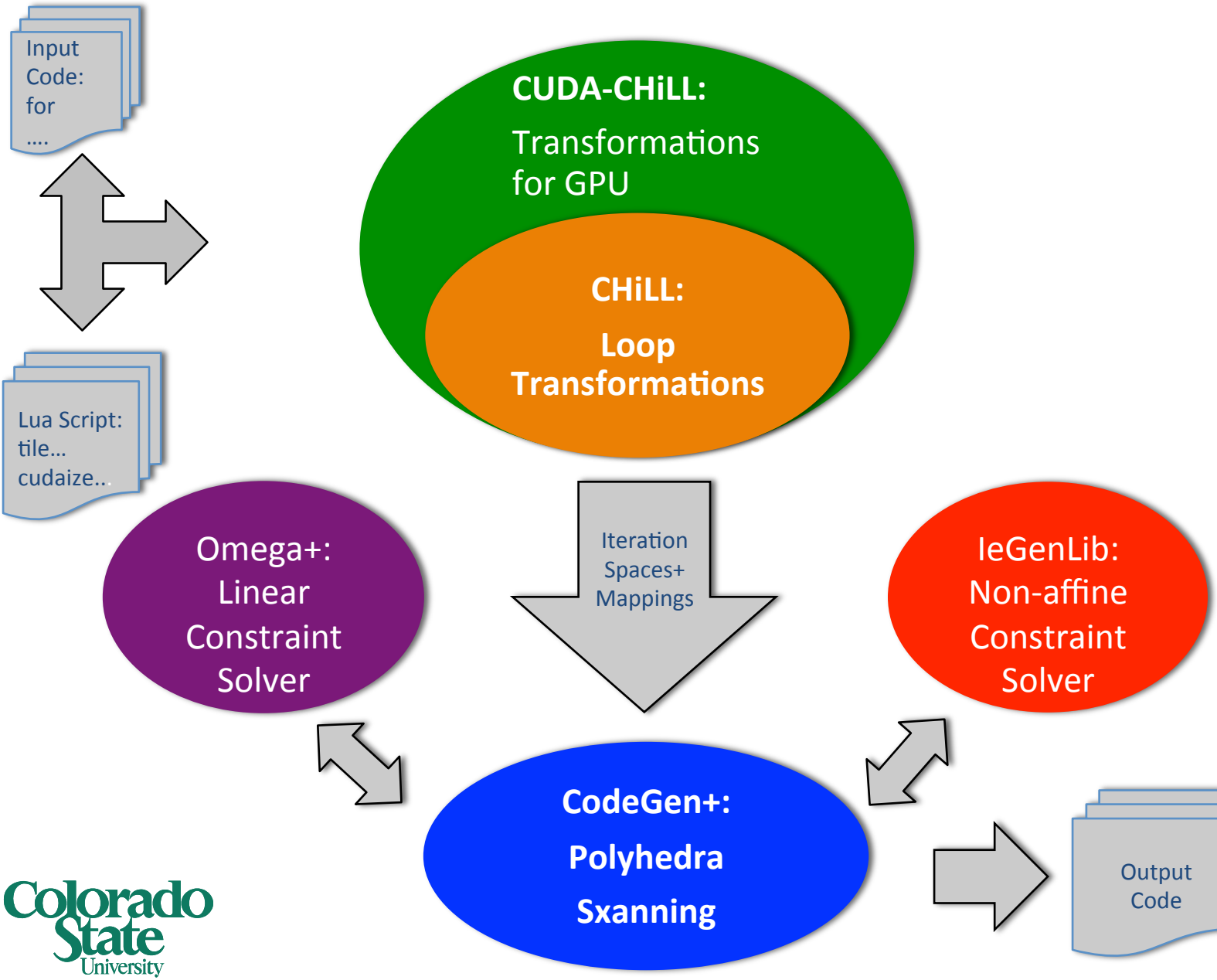
$$T_{coalesce} = \{[i,j] \rightarrow [k] \mid k = c(i,j) \wedge 0 \leq k < NNZ\} \wedge \boldsymbol{j=k}\}$$

- Inverse mapping simplification results in optimized Output Loop:

  for (k = 0; k < NNZ; k++)

  *y[**c_inv[k][0]**] += A[**k**]*x[col[**k**]];*

Implementation

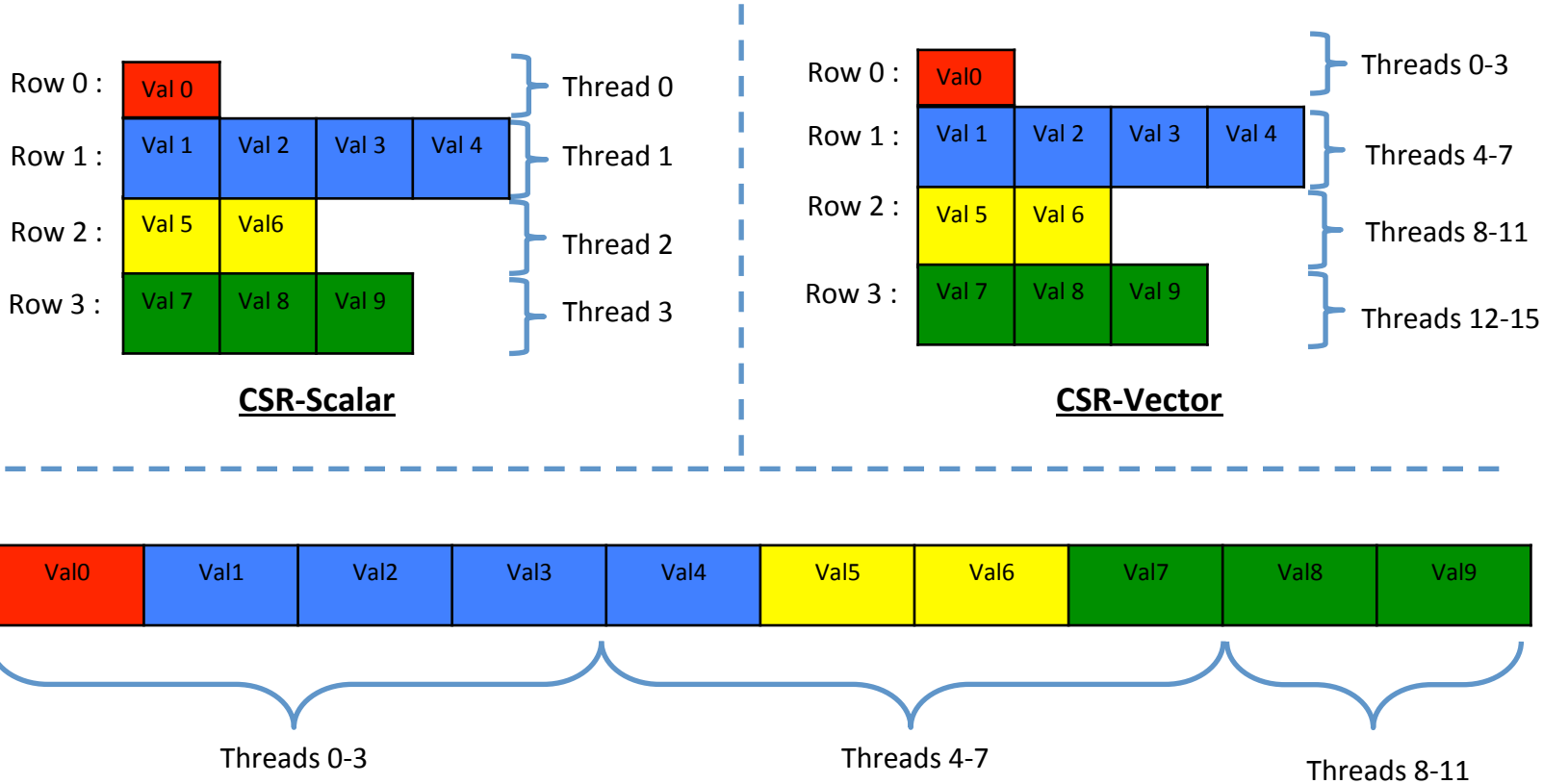


GPU Optimization Strategies

- GPUs are massively multithreaded
  - Compiler should expose as many parallel computations as possible
- Optimize for memory coalescing => Adjacent threads accessing contiguous memory locations increase effective memory bandwidth
- Compiler interfaces transformed code with architecture-specific reduction library routines
  - Tiling transformations allow controlling the granularity of the reduction
- Parallel reductions desired as they
  - Increase degree of parallelism
  - Improve memory coalescing

Case Study : SpMV

- Highly optimized parallel derivations for the SpMV kernel targeting GPUs
- Parallelization Strategies as in Bell and Garland (SC'09)



SpMV CSR Scalar

Tile i-loop

SpMV Code:

```
for(i=0; i < n; i++)
  for(j=index[i];j<index[i+1];j++)
    s0:  y[i]+=a[j]*x[col[j]]
```

CUDA block and thread dimensions

SpMV Code:

```
for(ii=0; ii < n; i+=Ti)
  for(i=ii; i< ii+Ti;i++)
    for(j=index[i];j<index[i+1];j++)
      s0:  y[i]+=a[j]*x[col[j]]
```

a. CSR Scalar Script

tile_by_index(0, {“i”},{Ti}, {l1_control=“ii”}, {“ii”, “i”,”j”}

cudaize(0,”spmv_GPU, {a=NNZ, x=N, y=N, col=NNZ, index=NNZ}, {block={“ii”}, thread={“i”}},{})

b. CSR Scalar Code

```
__global__ void spmv_GPU (float *y, float *a, float
*x, int *col, int *index){

      if(tx <= NROWS –Ti*bx – 1)
            for(j=index(Ti*bx + tx);
                  j  <= index__(Ti*bx + tx) – 1; j+=1)
                        y[Ti*bx + tx]+=(a[j]*x[col[j]]);
}
```

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SpMV CSR Vector

- Tiling for parallel row computations
- Second tiling for intra warp parallelization within row

c. CSR Vector Script

```
tile_by_index(0,{"i"},{Ti}, {l1_control="ii"},{"ii","i","j"})CU=1
tile_by_index(0,{"j"},{Tj},{l1_control="jj",l1_tile="j"}, {"ii","i","j",
"jj"},strided)CU=1
scalar_expand_by_index(0,{"i","j"},"RHS", CP_TO_SHARED,
NO_PAD,ACCUMULATE_THEN_ASSIGN)
cudaize(0,"spmv_GPU",{ a=NNZ,x=N,y=N, col=NNZ,index=NNZ},
{block={"ii"}, thread={"j", "i"}},{})
reduce_by_index(0,{"jj"}, "reduce_warp",{}, {"tx"})
```

d. CSR Vector Code

```
#define index_(i) index[i]
#define index__(i) index[i + 1]
__global__ void spmv_GPU(float *y,float *a,float *x,int *col,int *index) {
...
__device__ __shared__ float _P1[TILESZ*WARPSZ];
if (ty <= NROWS - TILESZ* bx - 1) {
   if (tx <= index__(ty + TILESZ* bx) - index_(ty + TILESZ* bx) - 1)
      _P1[tx + ty * WARPSZ] = 0;
   if (tx <= index__(ty + TILESZ* bx) - index_(ty + TILESZ* bx) – 1){
      for (jj = index_(ty + TILESZ* bx); jj <= -tx + index__(ty +
TILESZ* bx) - 1; jj += WARPSZ)
           _P1[tx + ty * WARPSZ] += (a[tx + jj] * x[col[tx + jj]]);
      reduce_warp(&y[ty + TILESZ* bx],&_P1[tx + ty * WARPSZ],
          _lt(31,index__(ty + TILESZ* bx) - index_(ty + TILESZ* bx) - 1));
   }
}}
```

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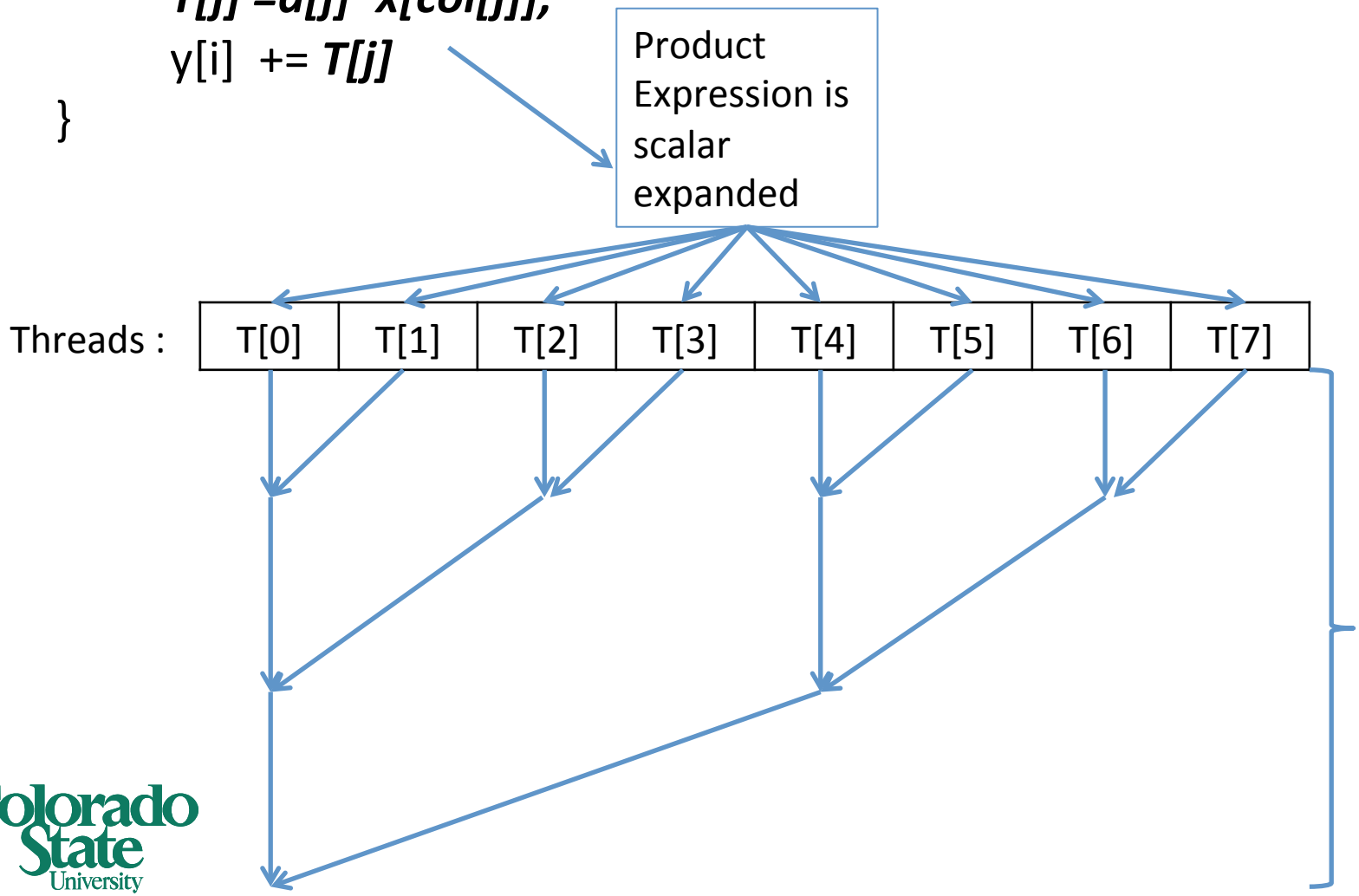
SpMV CSR Vector

```
for (i=0; i < n; i++)
    for (j=index[i]; j<index[i+1]; j++){
        T[j] =a[j]*x[col[j]];
        y[i]  += T[j]
}
```

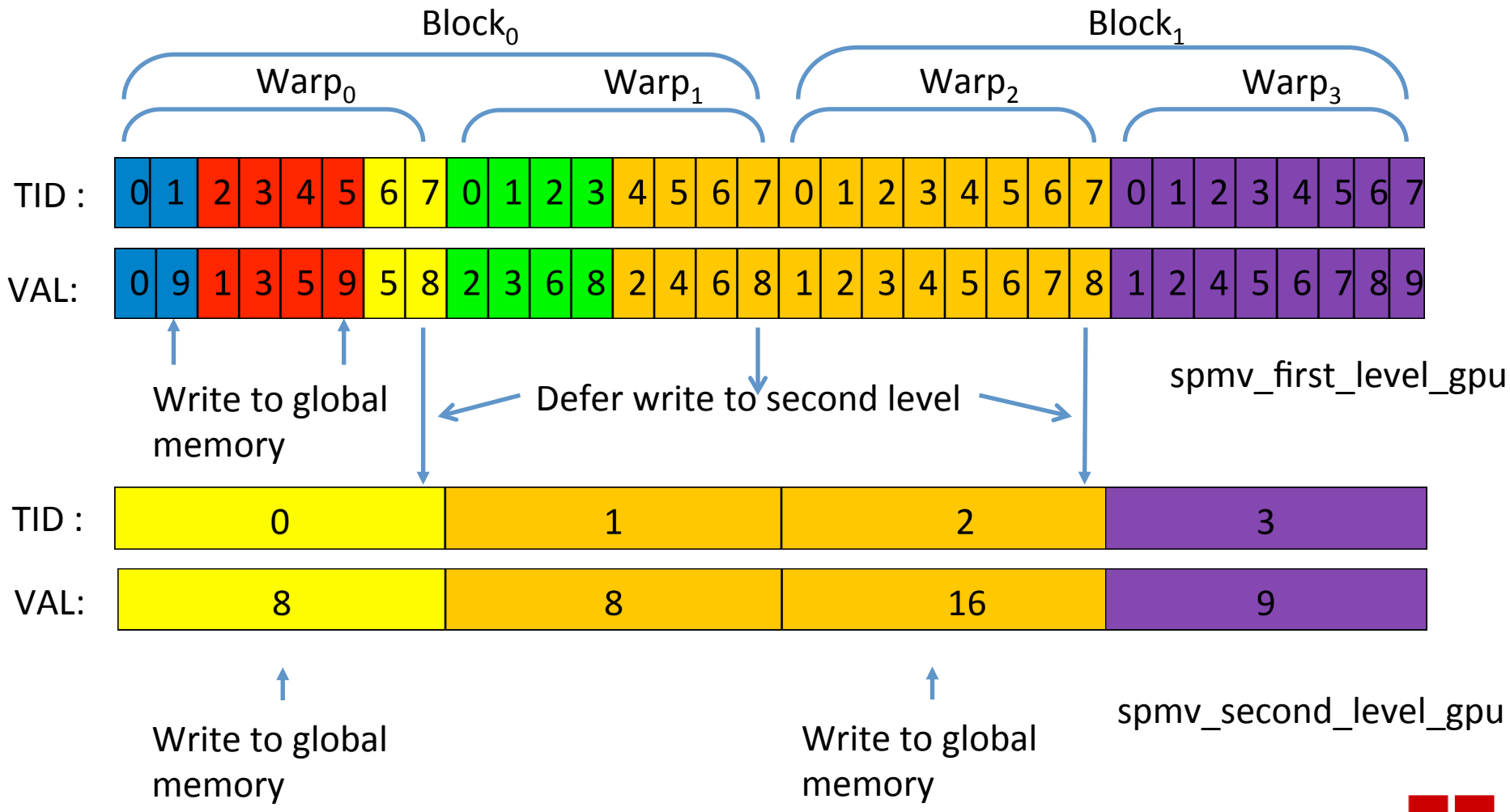


SpMV COO

- Input loop is coalesced and then tiled
  - Each block consists of multiple warps
  - Each warp reduces a partition of non-zeros
  - Rows may span across warp boundaries

- Non-zeros on warp boundaries defer write to global memory to avoid data races
  - Peeling and distribution utilized to separate the update across boundaries from interior points
  - Second level reduction accounts for boundary updates

SpMV COO


Block0
Block1
Warp0
Warp1
Warp2
Warp3
TID :
0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7 0 1 2 3 4 5 6 7
VAL:
0 9 1 3 5 9 5 8 2 3 6 8 2 4 6 8 1 2 3 4 5 6 7 8 1 2 4 5 6 7 8 9
Write to global memory
Defer write to second level
spmv_first_level_gpu
TID :
0 1 2 3
VAL:
8 8 16 9
Write to global memory
Write to global memory
spmv_second_level_gpu

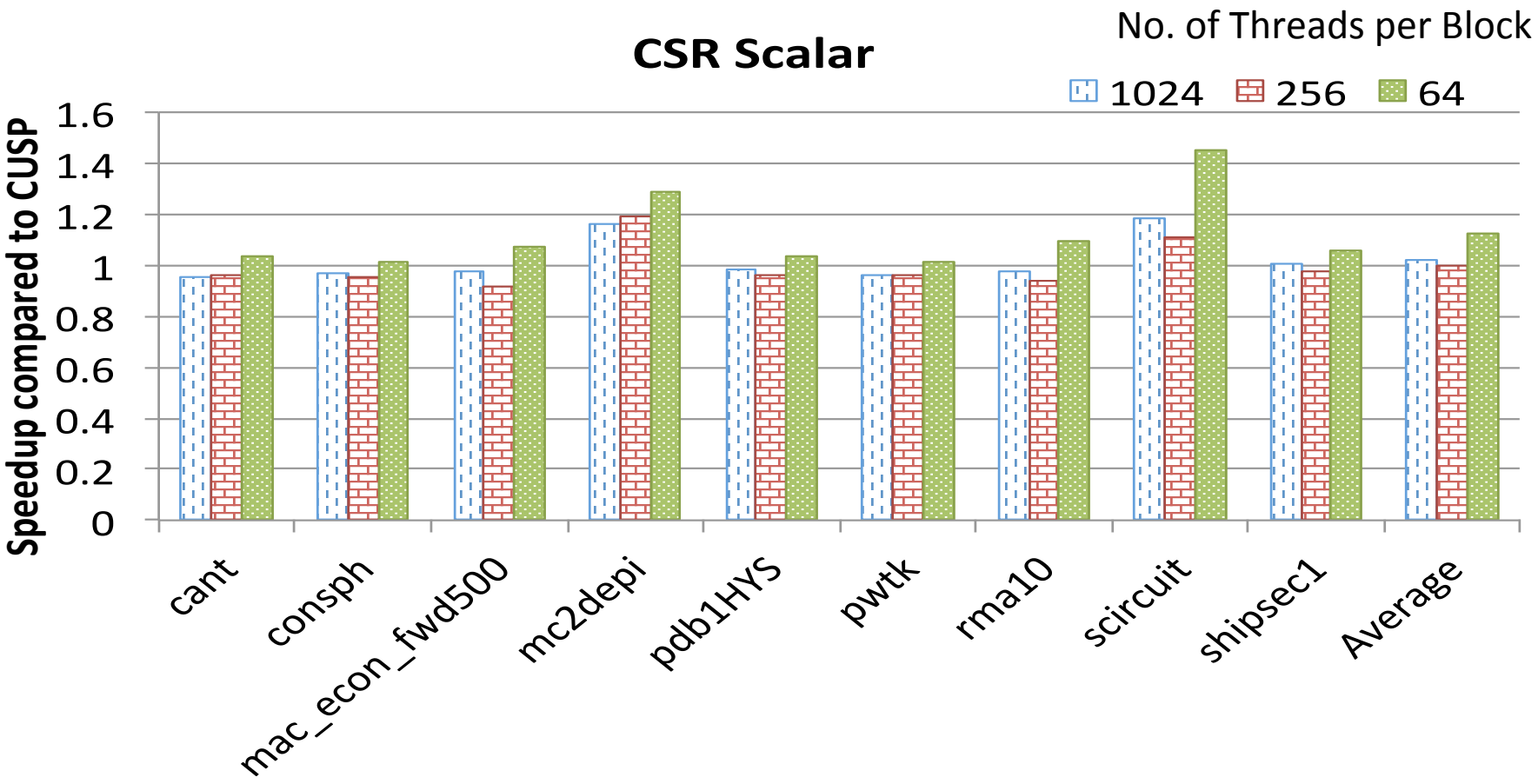
Experiments

- Experiments conducted on Nvidia Tesla C2050 Fermi
  - 14 Streaming Multiprocessors, 32 cores per SM.
  - 1 GB of global memory, 64KB register file per SM.
  - We compare performance of generated code to the corresponding CUSP implementation
- Matrices chosen were from the UFL Sparse Matrix Collection

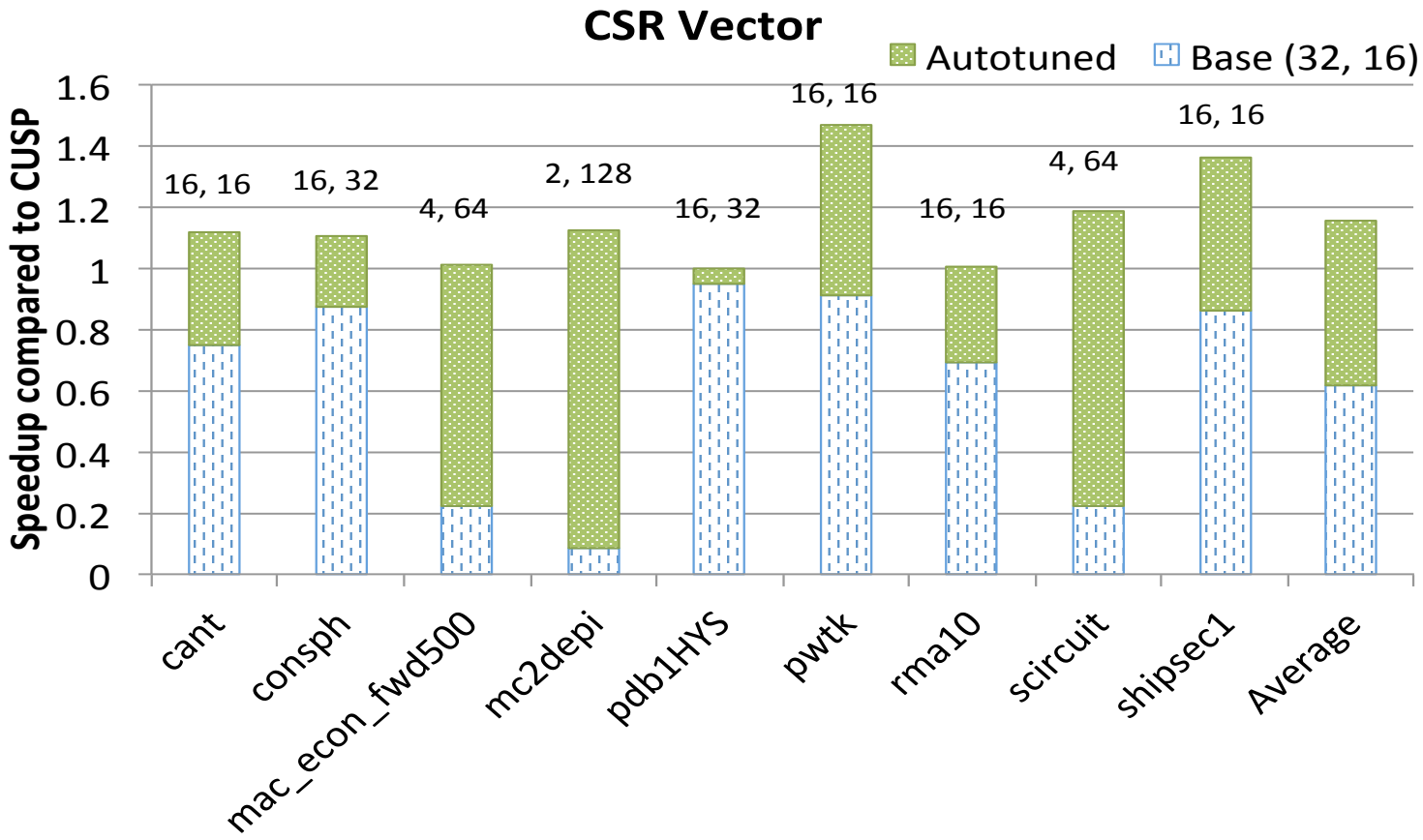
Methodology

- CSR Scalar
  - Each CUDA thread processes 1 row
  - Auto-tuned for different configurations of threads per block
- CSR Vector
  - 2-dimensional blocks
    - 1st dimension for threads per block
    - 2nd dimension for No. of non-zeros within a row being reduced
  - 2nd dimension tuned based on input matrix row length
- COO
  - Optimizations
    - Indirection elimination
    - Padding to eliminate control flow

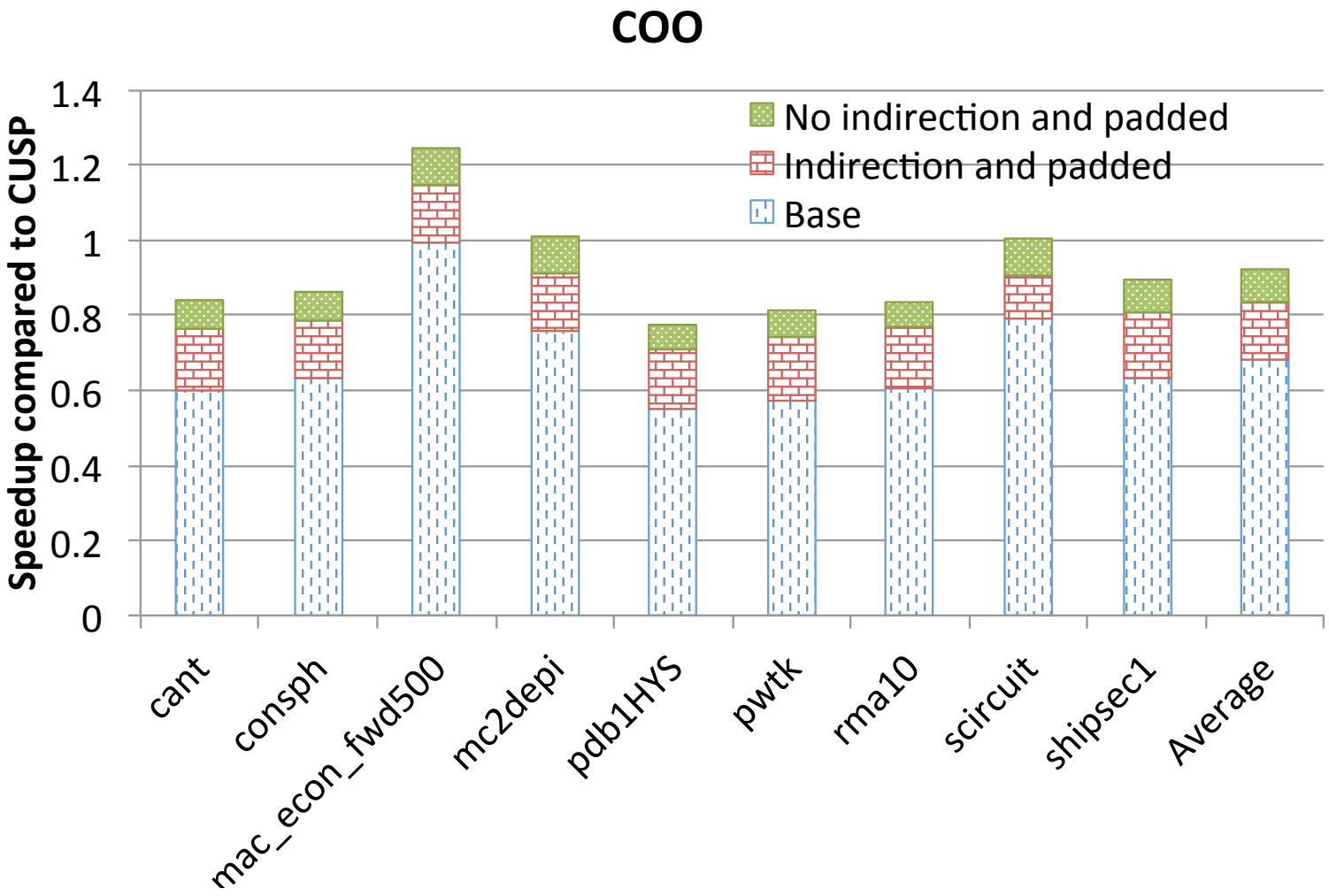
Results


CSR Scalar
No. of Threads per Block
1024
256
64
Speedup compared to CUSP
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
cant
consph
mac_econ_fwd500
mc2depi
pdb1HYS
pwtk
rma10
scircuit
shipsec1
Average

Results


CSR Vector
Autotuned
Base (32, 16)
Speedup compared to CUSP
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
16, 16
16, 32
4, 64
2, 128
16, 32
16, 16
16, 16
4, 64
16, 16
cant
consph
mac_econ_fwd500
mc2depi
pdb1HYS
pwtk
rma10
scircuit
shipsec1
Average

Results


COO
Speedup compared to CUSP
1.4
1.2
1
0.8
0.6
0.4
0.2
0
No indirection and padded
Indirection and padded
Base
cant
consph
mac_econ_fwd500
mc2depi
pdb1HYS
pwtk
rma10
scircuit
shipsec1
Average

Discussion

- Average Performance Improvement of 1.14x over CUSP for CSR Scalar and Vector
  - Auto-tuning to pick optimal block size
  - Significant performance improvement for matrices with exceptionally small row lengths
  - CUSP uses a fixed block size of 256 for CSR Scalar
- COO performs within 8% of CUSP version
  - Performance was traded off for a systematic compiler based reduction implementation derivation

Summary

- Non-affine extensions
  - Support for representing non-affine bounds in iteration space
  - Generalized loop coalescing as non-affine transformation
- Updated code generation
  - Extended statement macro interface for non-affine mappings
  - Simplify multiple indirections in array accesses
- Compiler transformation recipes for high performing SpMV variants on GPU
- Compiler-generated code that performs comparably with manually tuned library, CUSP