# Concord: Homogeneous Programming for Heterogeneous Architectures

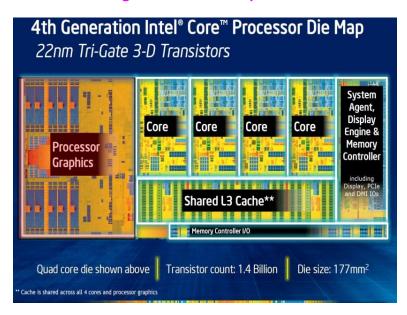
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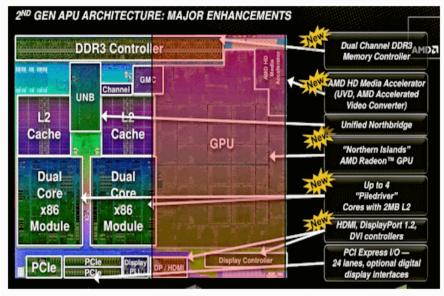
## Heterogeneous Platforms

- Heterogeneity is ubiquitous: mobile devices, laptops, servers, & supercomputers
- Emerging hardware trend: CPU & GPU cores integrated on same die, share physical memory & even last-level cache

Intel 4th generation core processors

**AMD Trinity** 





Source: http://www.hardwarezone.com.mv/feature-amd-trinity-apu-look-inside-2nd-generation-apu/conclusion-118

How do we program these integrated GPU systems?

# Motivation: GPU Programming

- Existing work: regular data-parallel applications using arraybased data structures map well to the GPUs
  - OpenCL 1.x, CUDA, OpenACC, C++ AMP, ...
- Enable other existing multi-core applications to quickly take advantage of the integrated GPUs
  - Often use object-oriented design, pointers
    - Enable pointer-based data structures on the GPU
  - Irregular applications on GPU: benefits are not well-understood
    - Data-dependent control flow
      - Graph-based algorithms such as BFS, SSSP, etc.

#### Widen the set of applications that target GPUs

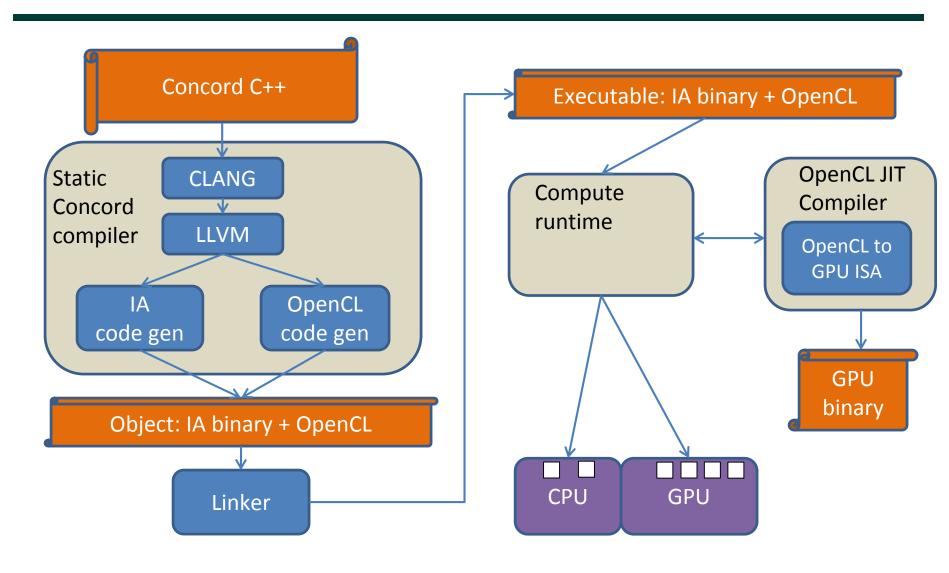
#### Contributions

- <u>Concord</u>: a seamless C++ heterogeneous programming framework for integrated CPU and GPU processors
  - Shared Virtual Memory (SVM) in software
    - · share pointer-containing data structures like trees
  - Adapts existing data-parallel C++ constructs to heterogeneous computing: TBB, OpenMP
  - Supports most C++ features including virtual functions
  - Demonstrates programmability, performance, and energy benefits of SVM



 Available open source at <u>https://github.com/IntelLabs/iHRC/</u>

### Concord Framework



# Concord C++ programming constructs

#### Concord extends TBB APIs:

bool device):

#### Existing TBB APIs:

template <typename Index, typename Body> parallel\_for (Index first, Index last, const Body& B)

template <typename Index, typename Body> parallel\_reduce (Index first, Index last, const Body& B)

#### Supported C++ features:

- Classes
- Namespaces
- Multiple inheritance
- Templates
- Operator and function overloading
- Virtual functions

## Concord C++ Example: Parallel LinkedList Search

TBB Version

Concord Version

Minimal differences between two versions

Run on CPU or GPU

# Example: parallel\_for\_hetero

## Example: parallel\_reduce\_hetero

```
class Bar {
   float *A, sum;
   public:
      Bar(float *a_): A(a_), sum(0.0f) { }
      void operator()(int i) { // execute in parallel
          sum = f(A[i]); // compute local sum
      void join(Bar &rhs) {
          sum += rhs.sum; // perform reduction
}:
Bar *b = new Bar(A);
parallel_reduce_hetero (1024, *b, GPU); // Data parallel reduction on GPU
```

#### Restrictions

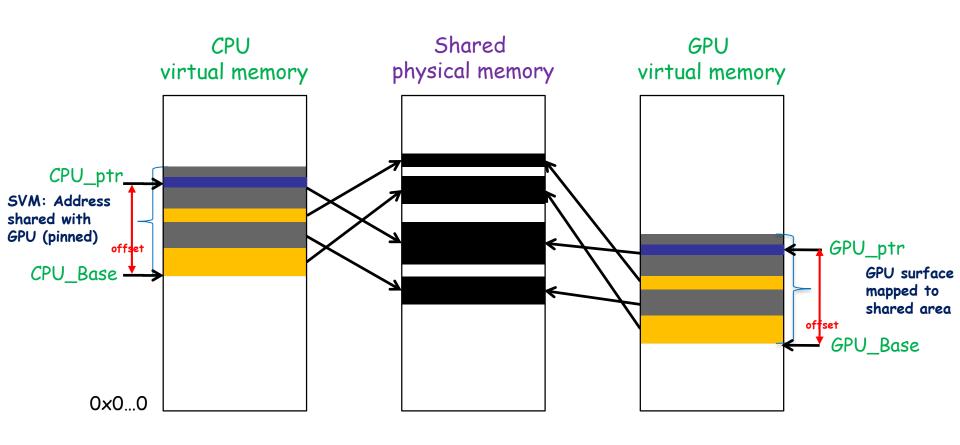
- No guarantee that the parallel loop iterations will be executed in parallel
- No ordering among different parallel iterations
  - Floating-point determinism is not guaranteed
- Features not yet supported on the GPU
  - Recursion (except tail recursion which can be converted to loop)
  - Exception
  - Taking address of local variable
  - Memory allocation and de-allocation
  - Function calls via function pointers (virtual functions are handled)

Silently execute on CPU if these features are present in GPU code

# Key Implementation Challenges

- Shared Virtual Memory (SVM) support to enable pointersharing between CPU and GPU
  - Compiler optimization to reduce SVM translation overheads
- Virtual functions on GPU
- Parallel reduction on GPU
- Compiler optimizations to reduce cache line contention

# SVM Implementation on x86



# SVM Translation in OpenCL code

```
//_global char * svm_const = (GPU_Base - CPU_Base);
#define AS_GPU_PTR(T,p) (__global T *) (svm_const + p)
__kernel void opencl_operator (
    __global char *svm_const,
    unsigned long B_ptr) {

    AS_GPU_PTR(LinkedList, list)->key...
}
```

Concord C++

Generated OpenCL

- svm\_const is a runtime constant and is computed once
- Every CPU pointer before dereference on the GPU is converted into GPU addressspace using AS\_GPU\_PTR

## Compiler Optimization of SVM Translations

```
int **a = data->a:
                                                for ( int i=0; i<N; i++)
                                                 \dots = \alpha[i];
                                                // a[i] is not used after this
                          Eager
                                                                                        Best
int **a = AS_GPU_PTR(int *, data->a);
                                             int **a = data->a;
                                                                                       int **a = AS GPU_PTR(int *, data->a);
for ( int i=0; i<N; i++)
                                             for ( int i=0; i<N; i++)
                                                                                      for ( int i=0; i<N; i++)
  ... = AS_CPU_PTR(int,
                                                ... = AS_GPU_PTR(int *, a)[i];
                                                                                        \dots = a[i];
      AS_GPU_PTR(int, a[i]));
                                                                                                Overhead: 1
      Overhead: 2N + 1
                                                    Overhead: N
```

#### Best strategy:

- Eagerly convert to GPU addressspace & keep both CPU & GPU representations
- If a store is encountered, use CPU representation
- Additional optimizations
  - · Dead-code elimination
  - · Optimal code motion to perform redundancy elimination and place the translations

#### Virtual Functions on GPU

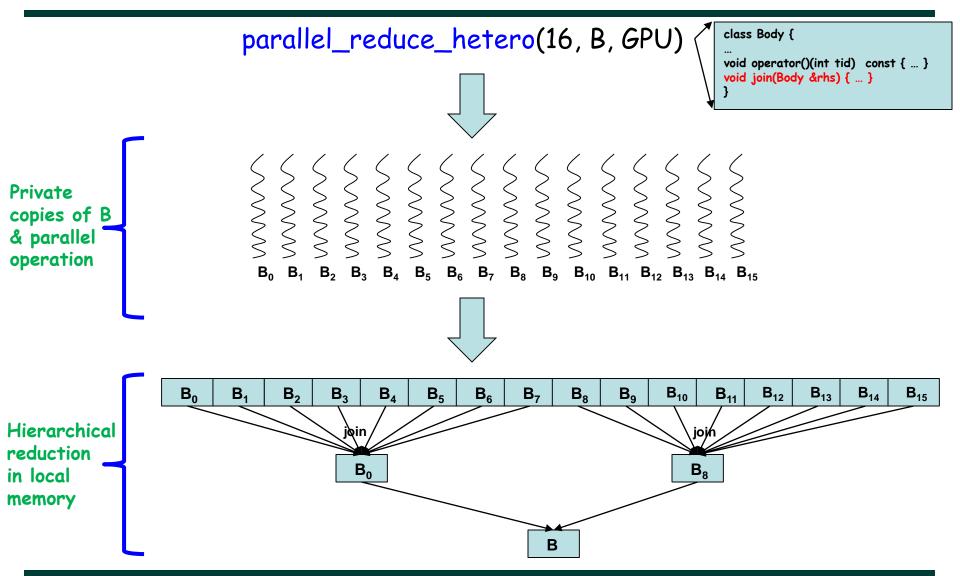
# Original hierarchy: class Shape { virtual void intersect() {...} virtual void compute() {...} }; class Triangle : Shape { virtual void intersect() {...} }; Virtual Function call: void foo(Shape \*s) { s->compute(); }

```
Object layout with vtable:
                           Shape::vtable
   Shape
     vtableptr
                             intersect
                             compute
                                                       Copy to
                                                       shared
   Triangle
                           Triangle::vtable
                                                       memory
     vtableptr
                             intersect
                             Shape:compute
  CPU Virtual Function call:
                                  GPU Virtual Function call:
  void foo(Shape *s) {
                                  void foo(Shape *s, void *gCtx) {
   (s->vtableptr[1])();
                                   if (s->vtableptr[1] == gCtx->
                                              Shape::compute)
                                     Shape::compute();
                      Generated code
```

#### Original code

- Copy necessary metadata into shared memory for GPU access
- Translate virtual function calls into if-then-else statements

#### Parallel Reduction on GPU



## Compiler Optimization for Cache Contention

- Integrated GPUs often use a unified cache among all GPU cores
  - Contention among GPU cores to access same cache line
    - number of simultaneous read and write ports to a cache line may not be same as the number of GPU cores

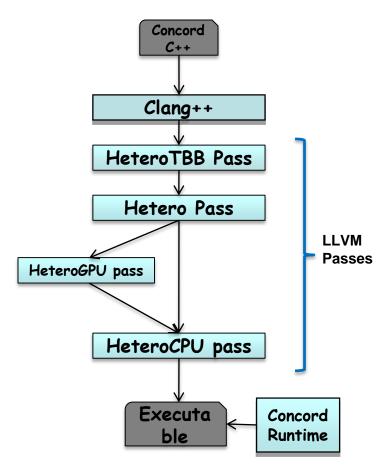
Each GPU core accesses different data

 Key idea: Ensure that the j loop is accessed in a different order for each GPU core

# Using GPU Memory hierarchy

- Stack allocated objects in C++ are promoted to OpenCL private memory
- Reductions are performed in OpenCL local shared memory
- Automatic generation of local memory code for regular applications (work-in-progress)

# Compiler Details



#### HeteroTBB pass:

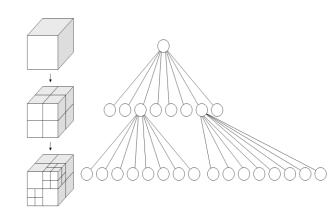
- identify and lower Concord constructs
- Handles virtual functions
- Hetero pass:
  - Check restrictions
  - Generates a list of kernels
- HeteroGPU pass:
  - Perform compiler optimizations
  - Generate OpenCL code
- HeteroCPU pass:
  - Generates x86 executable with embedded OpenCL code

#### Runtime Details

- OpenCL host program
  - Setup shared region and map to an OpenCL buffer
- Extract OpenCL code and JIT to GPU binary
  - Vendor OpenCL compiler
- Compile all the kernels at once
  - Cache the binary per function for future invocations
  - Amortizes the cost
- · Allows heterogeneous CPU+GPU execution

# Case Study: Barnes-Hut

- An efficient algorithm for the N-body problem
  - Approximates far away bodies
- Algorithm:
  - Build an oct-tree representing positions of bodies
  - Update the centers of masses for all subtrees
  - Sort the bodies based on relative positions
  - Calculate gravitational forces between bodies (offload to GPU)
  - Update positions and velocities
- Takes advantage of (shared) pointers



## Barnes-Hut CUDA Kernel

```
void ForceCalculationKernel()
                                         // iterate over all bodies assigned to thread
                                         for (k = threadIdx.x + blockIdx.x * blockDim.x;
  if (0 == threadIdx.x) {
                                       k < nbodiesd; k += blockDim.x * gridDim.x) {
  tmp = radiusd;
                                          i = sortd[k]; // get permuted/sorted index
 dg[0] = tmp * tmp * itolsqd;
                                          // cache position info
                                          px = posxd[i];
  for (i = 1; i < maxdepthd; i++)
                                          py = posyd[i];
   dq[i] = dq[i - 1] * 0.25f;
                                          pz = poszd[i];
   dq[i - 1] += epssqd;
                                          ax = 0.0f:
  dq[i - 1] += epssqd;
                                          ay = 0.0f:
                                          az = 0.0f:
  if (maxdepthd > MAXDEPTH) {
    *errd = maxdepthd;
                                          // initialize iteration stack, i.e., push root
                                       node onto stack
                                          depth = i;
                                          if (sbase == threadIdx.x) {
 __syncthreads():
                                           node[j] = nnodesd;
                                           pos[j] = 0;
 if (maxdepthd <= MAXDEPTH) {
 base = threadIdx.x / WARPSIZE:
  sbase = base * WARPSIZE:
                                          while (depth >= j) {
  j = base * MAXDEPTH;
                                           // stack is not empty
  diff = threadIdx.x - sbase:
                                           while ((t = pos[depth]) < 8)
                                            // node on top of stack has more children
 if (diff < MAXDEPTH) {
                                       to process
   da[diff+i] = da[diff];
                                             n = childd[node[depth]*8+t]; // load child
                                       pointer
    syncthreads();
                                             if (sbase == threadIdx.x) {
                                              // I'm the first thread in the warp
                                              pos[depth] = t + 1;
 Source: http://www.gpucomputing.net/?q=node/1314
```

```
if (n >= 0) {
       dx = posxd[n] - px;
       dy = posyd[n] - py;
                                               if (stepd > 0) {
       dz = poszd[n] - pz;
                                                    // update
       tmp = dx*dx + (dy*dy + (dz*dz +
                                               velocity
epssqd)); // compute distance squared
(plus softening)
                                                    velxd[i] += (ax -
       if ((n < nbodiesd) || __all(tmp >=
                                               accxd[i]) * dthfd;
dg[depth])) { // check if all threads
                                                    velyd[i] += (ay -
agree that cell is far enough away (or is
                                               accyd[i]) * dthfd;
a body)
                                                    velzd[i] += (az -
         tmp = rsqrtf(tmp); // compute
                                               acczd[i]) * dthfd;
distance
        tmp = massd[n] * tmp * tmp *
tmp;
                                                   // save computed
         ax += dx * tmp;
         ay += dy * tmp;
                                               acceleration
         az += dz * tmp;
                                                   accxd[i] = ax;
       } else {
                                                   accyd[i] = ay;
         // push cell onto stack
                                                   acczd[i] = az;
         depth++;
         if (sbase == threadIdx,x) {
          node[depth] = n;
          pos[depth] = 0;
      } else {
       depth = max(j, depth - 1); //
early out because all remaining children
are also zero
     depth--; // done with this level
```

~100 Lines of CUDA Code with optimization, hard to read and maintain

#### Barnes-Hut Concord C++ Kernel

```
void update (BH_Tree **stack, Body *body) {
2.
       while(!stack.empty()) {
3.
           Octree *tree = stack.top();
4.
           stack.pop();
5.
           Octree **children = ((OctreeInternal*)tree)->child;
6.
           for(int i=0;i<8;i++) {
7.
              Octree *child = children[i];
8.
              if (!child) continue;
9.
              if (child->nodeType == LEAF || body->pos.distance(child->pos)
10.
                       * THETA > child->box.size()) {
11.
                  computeForce(body, child);
12.
              } else {
13.
                  stack.push(child);
14.
15.
16.}
```

- distance is 5 lines. computeForce is 9 lines. push is 2 lines and pop is 1 line
- Total 33 lines of code
- No extra host code for device malloc and data copy

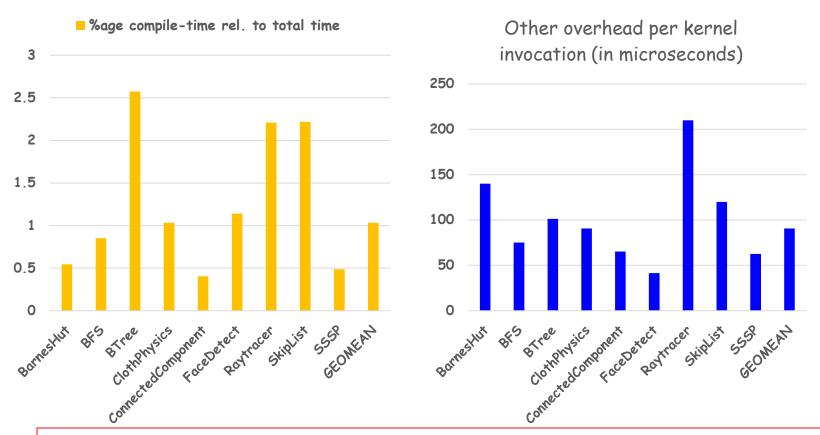
# Experimental setup

- Experimental Platform:
  - Intel Core 4th Generation Ultrabook
    - · CPU: 2 cores, hyper-threaded, 1.7GHz
    - GPU: Intel HD Graphics 5000 with 40 cores, 200MHz-1.1GHz
    - · Power envelope 15W
  - Intel Core 4th Generation Desktop
    - · CPU: 4 cores, hyper-threaded, 3.4GHz
    - · GPU: Intel HD Graphics 4600 with 20 cores, 350MHz-1.25GHz
    - Power envelope 84W
- Energy measurements: MSR\_PKG\_ENERGY\_STATUS
- Comparison with multi-core CPU:
  - 1. GPU-SPEEDUP: speedup using GPU execution
  - 2. GPU-ENERGY-SAVINGS: energy savings using GPU execution

## Workloads

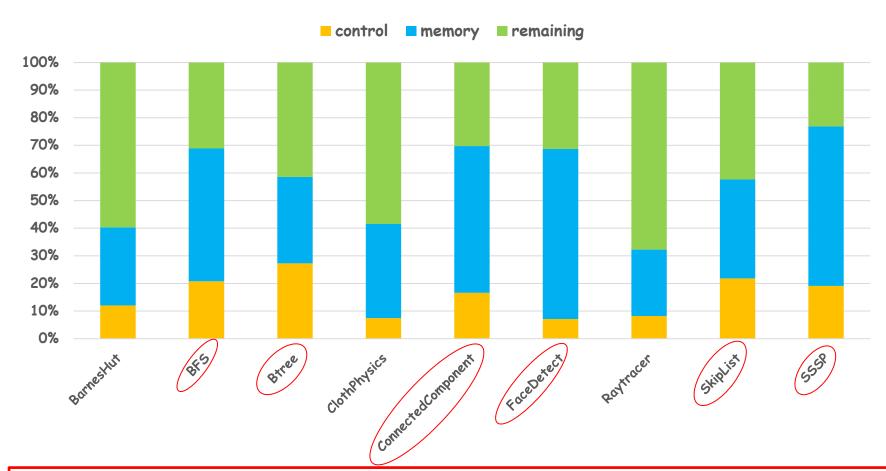
Benchmarks	Origin	Input	LoC	Device LoC	Data Structure	Parallel Construct
BarnesHut	In-house	1M bodies	828	105	Tree	Parallel_for
BFS	Galois	V =6.2M  E =15M	866	19	Graph	Parallel_for
Btree	Rodinia	Command.txt	3111	84	Tree	Parallel_for
ClothPhysics	Intel	V =50K  E =200K	9234	411	Graph	Parallel_reduce
ConnComp	Galois	V =6.2M  E =15M	473	36	Graph	Parallel_for
FaceDetect	OpenCV	3000×2171	3691	378	Cascade	Parallel_for
Raytracer* *uses virtua	In-house    function	sphere=256, material=3, light=5	843	134	Graph	Parallel_for
Skip_List	In-house	50M keys	467	21	Linked-list	Parallel_for
SSSP	Galois	V =6.2M  E =15M	1196	19	graph	Parallel_for

# Overheads (on desktop system)



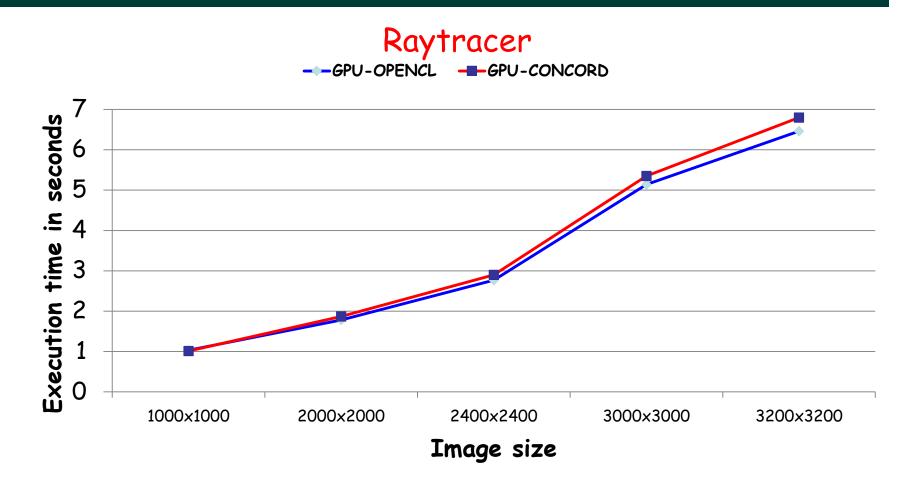
- Compile-time is 1.03% of total execution time
- Other overheads (excluding compile-time) is ~90 microseconds

# Dynamic estimates of irregularity



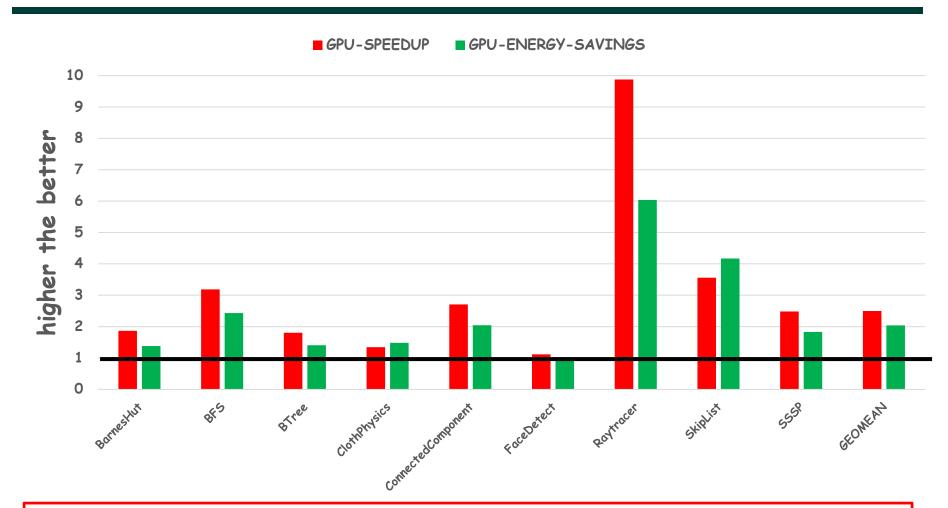
- BFS, Btree, ConnComp, FaceDetect, SkipList & SSSP exhibit a lot of irregularities (>50%)
- FaceDetect exhibits maximum percentage of memory irregularities

## Overhead of SW-based SVM implementation



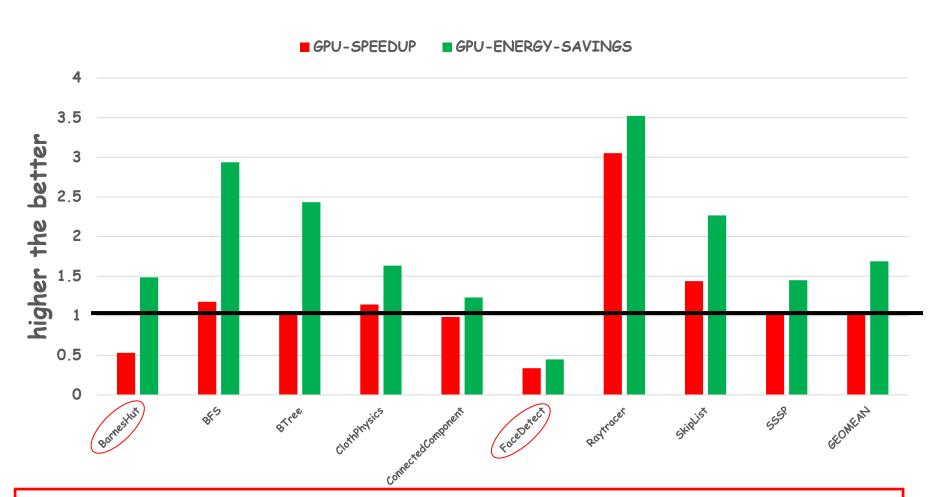
SW-based SVM overhead is negligible for smaller images and is ~6% for the largest image

#### Ultrabook: Speedup & Energy savings compared to multicore CPU



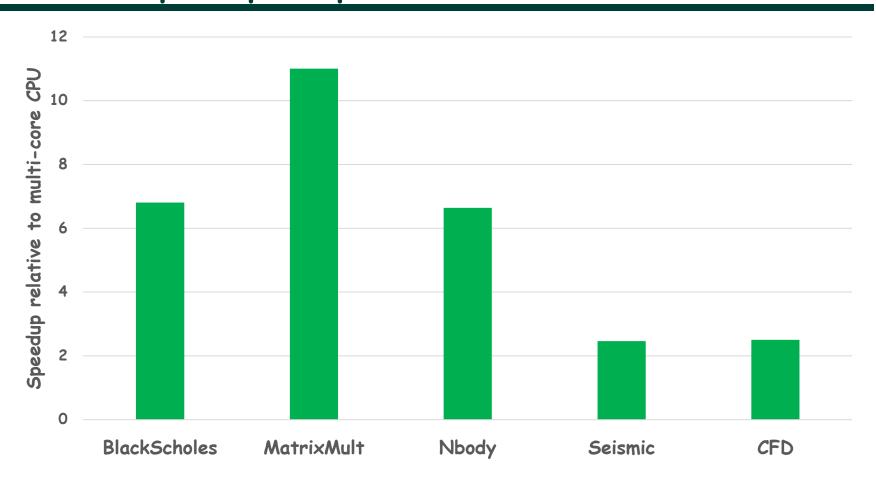
Average speedup of 2.5x and energy savings of 2x vs. multicore CPU

#### Desktop: Speedup & Energy savings compared to multicore CPU



Average speedup of 1.01x and energy savings of 1.7x vs. multicore CPU

#### Regular Workloads on Quad-core desktop: Speedup compared to multi-core CPU



Automatic local memory code generation can further boost performance

# Comparison with Manual code

BTree from Rodinia: Concord takes 2.68s vs. 3.26s for hand-coded OpenCL on the Desktop Haswell system

## Conclusions & Future work

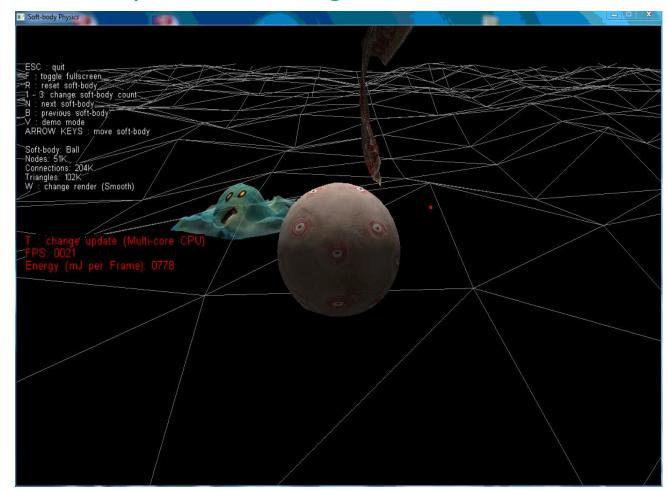
- Runs out-of-the-box C++ applications on GPU
  - No new language invention
- Demonstrates that SVM is a key enabler in programmer productivity of heterogeneous systems
- Implements SVM in software with low-overhead
- Implements virtual functions and parallel reductions on GPU
- Saves energy of 2.04x on Ultrabook and 1.7x on Desktop compared to multi-core CPU for irregular applications
- Future work:
  - Support advanced features on GPU: exceptions, memory allocation, locks, etc.
  - Support combined CPU+GPU heterogeneous execution

#### Cloth Physics demo using Concord:

#### Questions?

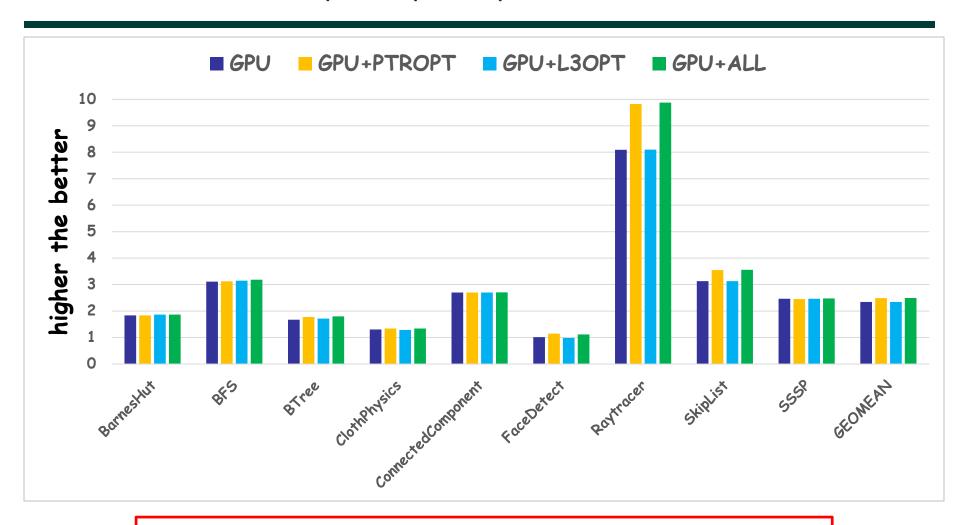
#### Please try it out:

https://github.com/IntelLabs/iHRC/



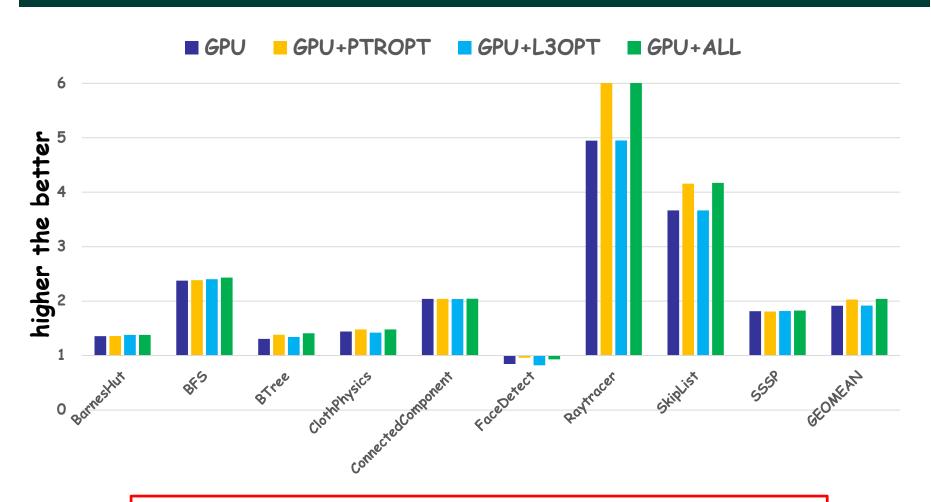
# Backup

#### Ultrabook: Speedup compared to multicore CPU



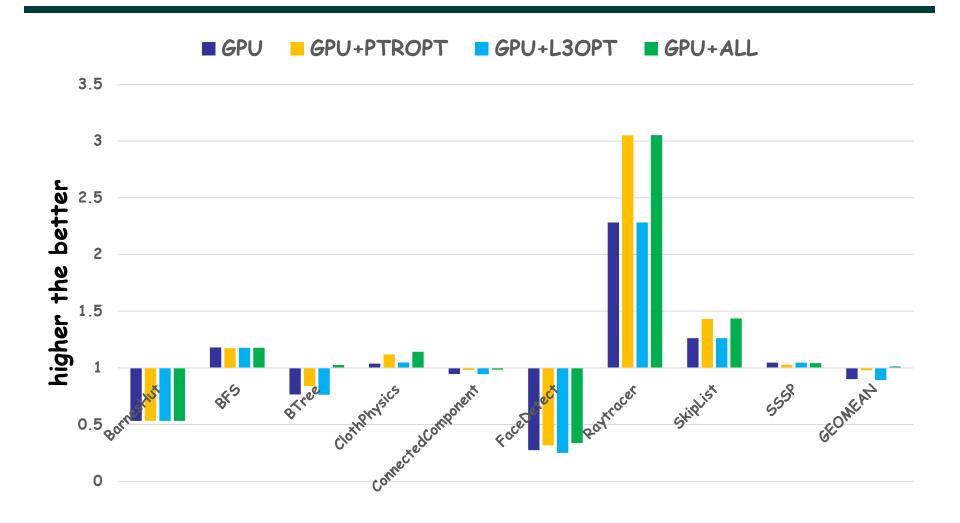
Average speedup of 2.5x vs. multicore CPU

#### Ultrabook: Energy savings compared to multi-core CPU

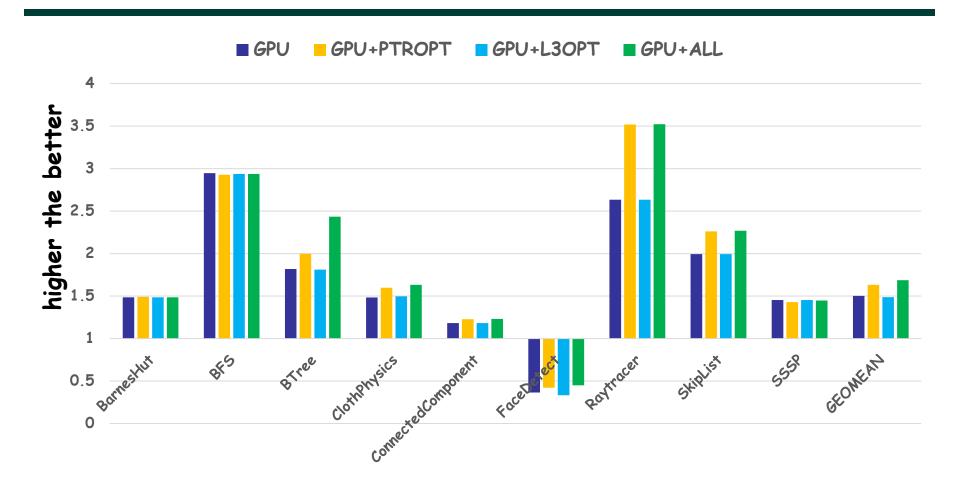


Average energy savings of 2.04x vs. multicore CPU

## Desktop: Speedup compared to multi-core CPU



#### Desktop: Energy savings compared to multi-core CPU



Average energy savings of 1.7x vs. multicore CPU

# GPU Programming is hard

