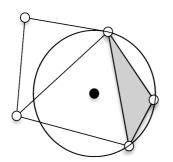
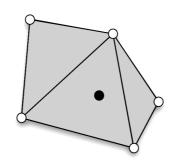
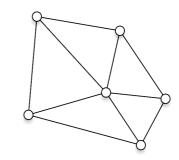
Parallel Graph Algorithms







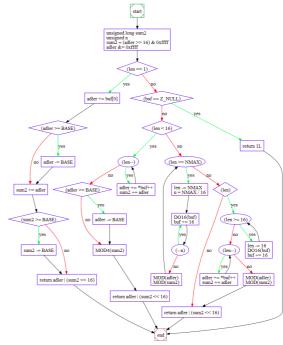
Rupesh Nasre.

IIT Madras



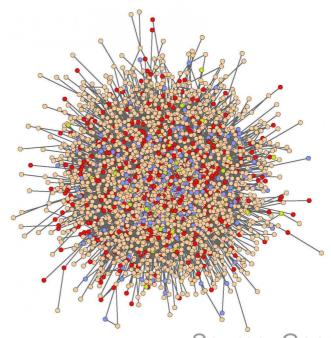






Graphs are Everywhere!





Graphs

- Where do we encounter graphs?
 - Social networks, road connections, molecular interactions, planetary forces, ...
 - snap, florida, dimacs, konect, ...
- Why treat them separately?
 - They provide structural information.
 - They can be processed more efficiently.
- What challenges do they pose?
 - Load imbalance, poor locality, ...
 - Irregularity

What is IrReg_uLari^Ty?

 Data-access or control patterns are unpredictable at compile time.

Irregular data-access

```
int a[N], b[N], c[N];
readinput(a);
c[5] = b[a[4]];
```

Irregular control-flow

```
int a[N];
readinput(a);
if (a[4] > 30) {
    ...
}
```

Needs dynamic techniques

Pointer-based data structures often contribute to irregularity.

Source: google image

Scalability

Meta / Facebook

- 2.2 billion active users
- 1.3 billion is India's population
- e.g. top people in the world

Milky Way

- over 100 billion stars
- e.g. finding possibility of life

Human Brain

- 100 billion neurons
- Artificial intelligence







Finding betweenness centrality on a million node graph (in a sequential manner) takes several weeks!

Handling Large Graphs

Storage

- Distributed setup
 - Graph is partitioned across a cluster.
- External memory algorithms
 - Graph partitions are processed sequentially.
- Algorithms on compressed data
 - Compression needs to maintain retrieval ability.
- Maintaining graph core
 - Removal of unnecessary subgraphs.

Time

- Parallelism
 - Multi-core, distributed,
 GPUs
- Approximations
 - Approximate computing

Parallelism Approaches

- Manual
 - OpenMP, MPI, CUDA
- Libraries
 - Galois, Ligra, LonestarGPU, Gunrock, ...
- Domain-Specific Languages
 - Green-Marl, Elixir, Falcon, ...



Specifying Parallelism

- Do not specify.
 - Sequential input, completely automated, currently very challenging in general
- Implicit parallelism
 - aggregates, aggregate functions, primitive-based processing, ...
- Explicit parallelism
 - pthreads, MPI, OpenCL, ...

Identifying Dependence

```
for (ii = 0; ii < 10; ++ii) {
    a[2 * ii] = ... a[2 * ii + 1] ...
}
```

Dependence equations

$$0 \le ii_w \le ii_r \le 10$$

 $2 * ii_w = 2 * ii_r + 1$

which can be written as

Is there a flow dependence between different iterations?

Flow dependence is read-after-write (to the same memory location). $w \rightarrow \rightarrow \rightarrow r$

Parallel Architectures

Multicore CPUs

- Intel, ARM, ...
- pthreads, OpenMP, ...

Distributed systems

- CPUs with interconnects
- MPI

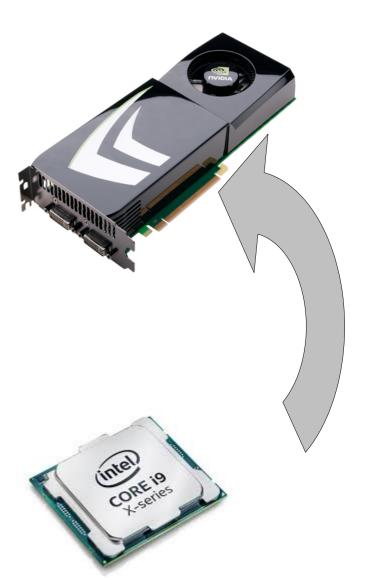
Manycore GPUs

- NVIDIA, AMD, ...
- CUDA, OpenCL, ...

CPU-GPU processing concepts have similarity with those in distributed systems.

What is a GPU?

- Graphics Processing Unit
- Separate piece of hardware connected using a bus
- Separate address space than that of the CPU
- Massive multithreading
- Warp-based execution



What is a Warp?



GPU Computation Hierarchy

Hundreds of **GPU** thousands Tens of Multi-processor thousands **Block** 1024 32 Warp **Thread** 13

Challenges with GPUs

- Warp-based execution (pre-Volta)
- Locking is expensive
- Dynamic memory allocation is costly
- Limited data-cache
- Programmability issues
 - separate address space
 - low recursion support
 - complex computation hierarchy
 - exposed memory hierarchy

_

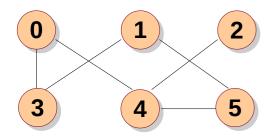
Challenges in Graph Algorithms

Synchronization

- locks are prohibitively expensive on GPUs
- atomic instructions quickly become expensive

Memory latency

- locality is difficult to exploit
- low caching support
- Thread-divergence (pre-Volta)
 - work done per node varies with graph structure
- Uncoalesced memory accesses
 - warp-threads access arbitrary graph elements



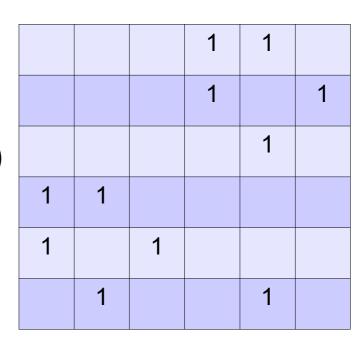
Graph Representation

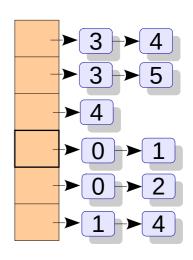
1. Adjacency matrix

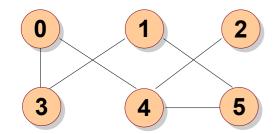
- |V|x|V| matrix
- Each entry [i, j] denotes if edge (i,j) is present in G
- Useful for dense graph
- Finding neighbors is O(|V|)

2. Adjacency list

- |V| + |E| size
- Each vertex i has a list of its neighbors
- Useful for sparse graphs
- Finding neighbors is O(max. degree)







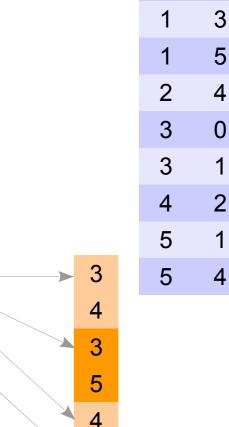
Graph Representation

3. Edge list / Coordinate list (COO)

- |E| pairs
- Useful for edge-based algorithms
- Typically sorted on vertex id

4. Compressed sparse row (CSR)

- Concatenated adjacency lists
- Useful for sparse graphs
- Useful for data transfer

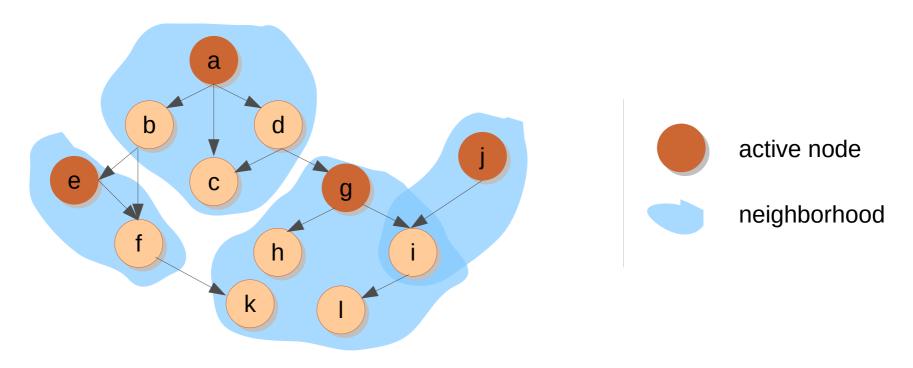


2

4

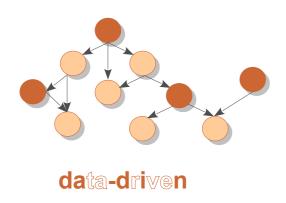
3

TAO Classification

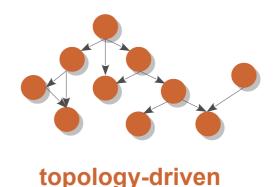


- Operator formulation: Computation as an iterated application of operator
- Topology-driven processing: operator is applied at all the nodes even if there is no work to do at some nodes (e.g., Bellman-Ford SSSP)
- Data-driven processing: operator is applied only at the nodes where there might be work to be done (e.g., SSSP with delta-stepping)

Data-driven vs. Topology-driven



- work-efficient
- centralized worklist
- fine-grained synchronization using atomics
- complicates implementation

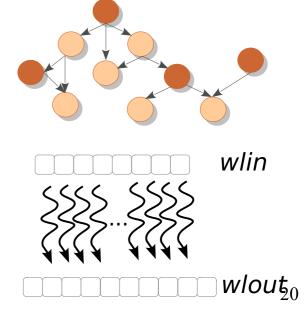


- performs extra work
- no worklists
- coarse-grained synchronization using barriers
- easier to implement

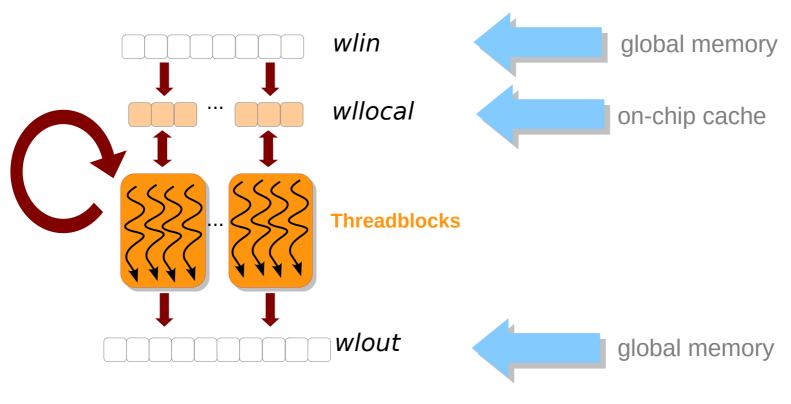
Data-driven: Base Version

```
cpu gpu
main {
    read input
    transfer input
    initialize_kernel
    initialize_worklist(wlin)
    clear wlout
    while wlin not empty {
        operator(wlin, wlout, ...)
        transfer wlout size
        clear wlin
        swap(wlin, wlout)
    transfer results
```

```
sssp_operator(wlin, wlout, ...) {
    src = wlin[...]
    dsrc = distance[src]
    forall edges (src, dst, wt) {
        ddst = distance[dst]
        altdist = dsrc + wt
        if altdist < ddst {
            distance[dst] = altdist
            wlout.push(dst)
} }
</pre>
```

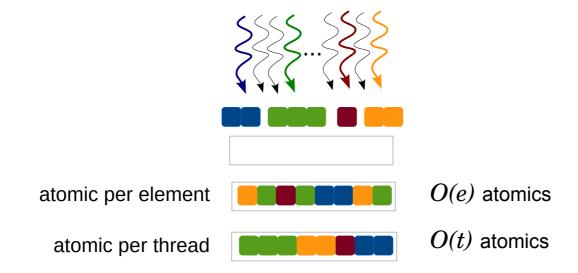


Data-driven: Hierarchical Worklist



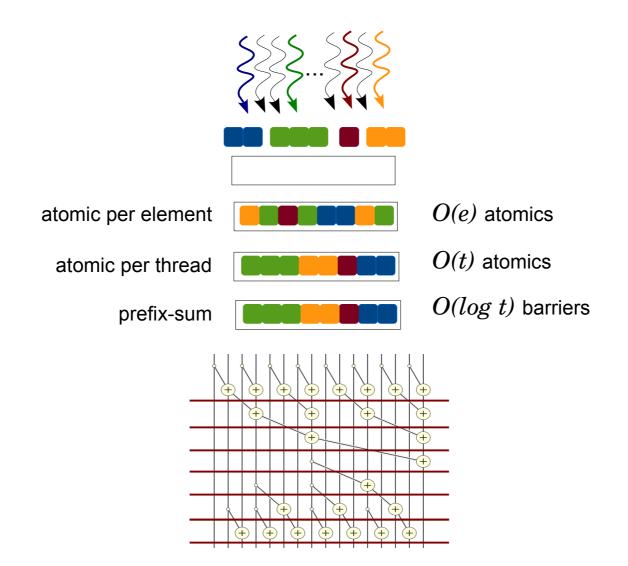
- Worklist exploits memory hierarchy
- Makes judicious use of limited on-chip cache

Data-driven: Work Chunking



- Reserves space for multiple work-items in a single atomic
- May reduce overall synchronization

Data-driven: Atomic-free Worklist Update



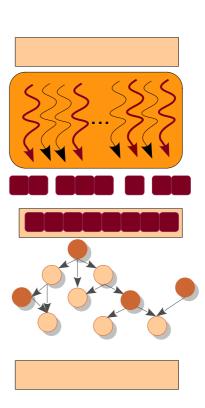
Data-driven: Work Donation

```
donate_kernel {
    shared donationbox[...];
    // determine if I should donate
    --barrier--

    // donate
    --barrier--

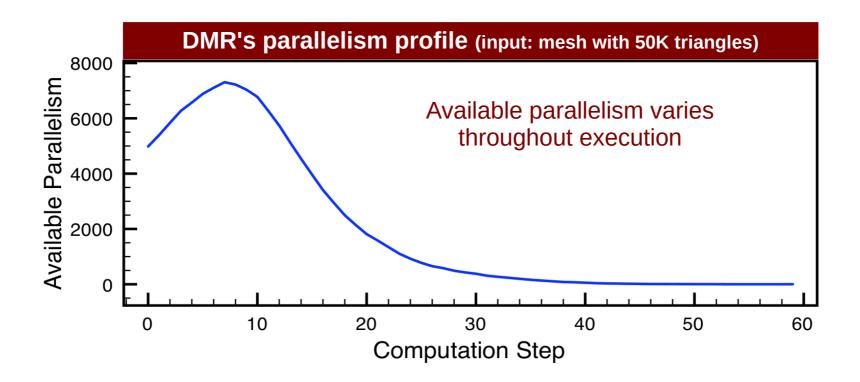
    // operator execution

    // empty donation box
}
```



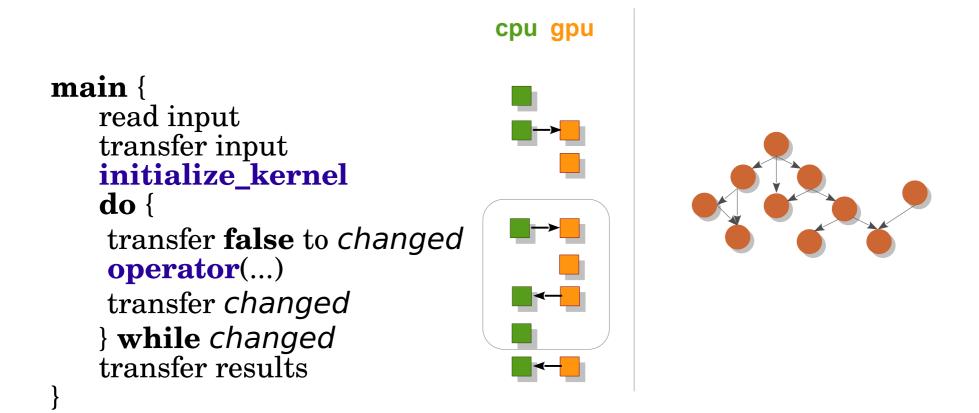
Work-donation improves load balance

Data-driven: Variable Kernel Configuration



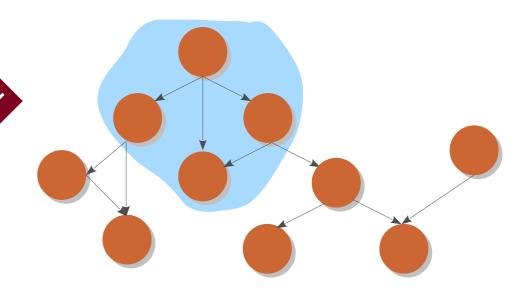
- Varying configuration improves work-efficiency
- It also reduces conflicts and may improve performance

Topology-driven: Base Version



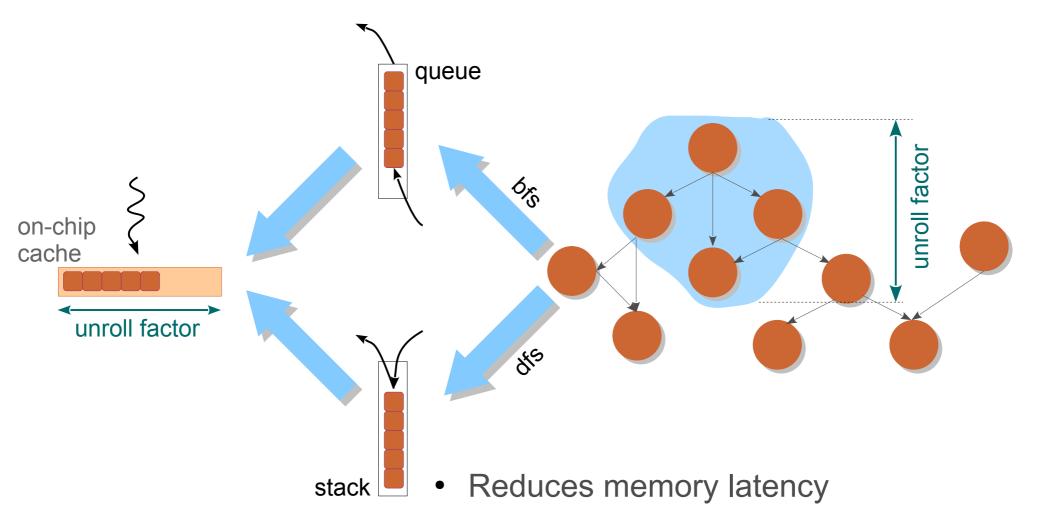
Topology-driven: Kernel Unrolling

```
sssp_operator(src) {
    dsrc = distance[src]
    forall edges (src, dst, wt) {
        ddst = distance[dst]
        altdist = dsrc + wt
        if altdist < ddst
            distance[dst] = altdist
    }
}</pre>
```



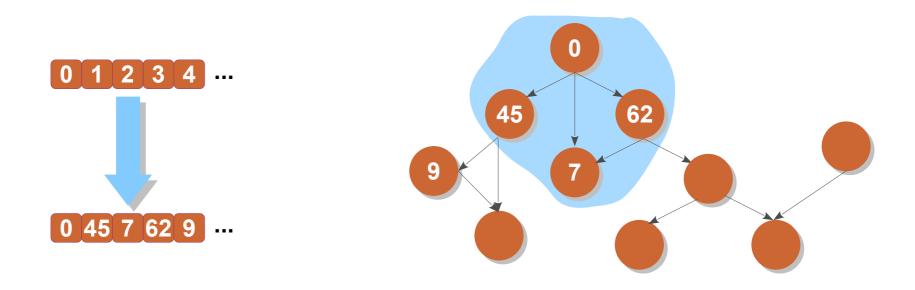
- Improves amount of computation per thread invocation
- Need to ensure absence of races
- Propagates information faster

Topology-driven: Exploiting Memory Hierarchy



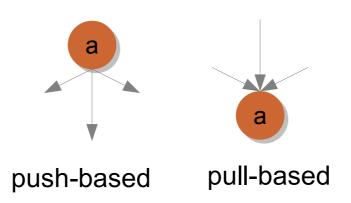
Requires careful selection of unroll factor

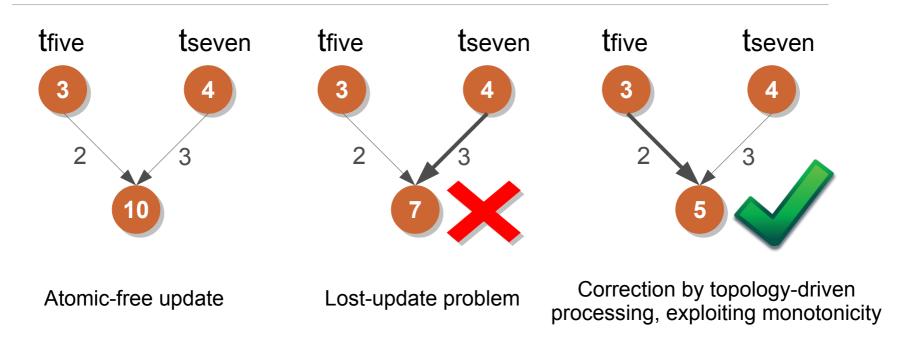
Topology-driven: Improved Memory Layout



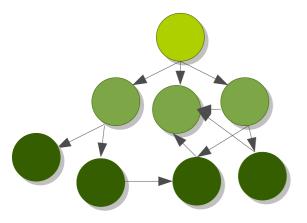
- Bring logically close graph nodes also physically close in memory
- Improves spatial locality

Improving Synchronization

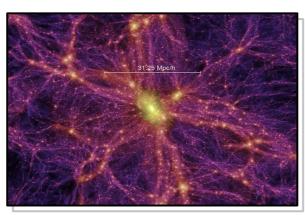




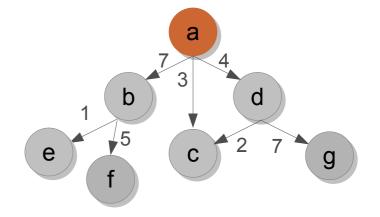
Irregular Algorithms on GPUs







Barnes-Hut n-body simulation



Single-source shortest paths

- Better memory layout
- Kernel unrolling
- Local worklists
- Improved synchronization

Application	Speedup
BFS	48
ВН	90
SSSP	45

Identify the Celebrity



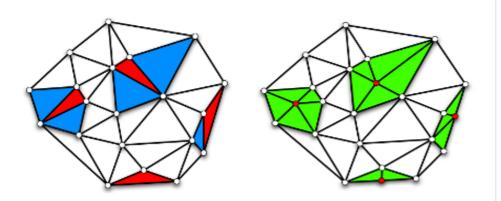
Source: wikipedia

What is a morph?

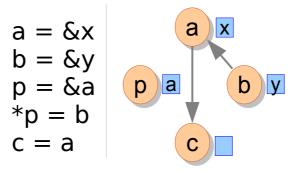


Source: wikipedia

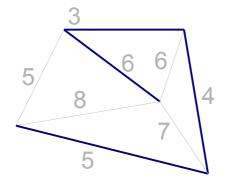
Examples of Morph Algorithms



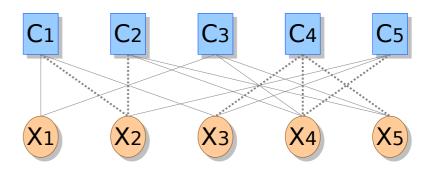
Delaunay Mesh Refinement



Points-to Analysis



Minimum Spanning Tree Computation



Survey Propagation

Challenges in Morph Algorithms

Synchronization

- locks are prohibitively expensive on GPUs
- atomic instructions quickly become expensive

Memory allocation

- changing graph structure requires new strategies
- memory requirement cannot be predicted

Load imbalance

- different modifications to different parts of the graph
- work done per node changes dynamically
- leads to thread-divergence and uncoalesced memory accesses

GPU Optimization Principles

Algorithm selection
Work sorting
Work chunking
Communication onto computation
Following parallelism profile
Pipelined computation

These optimization principles are **critical** for high-performing irregular GPU computations.

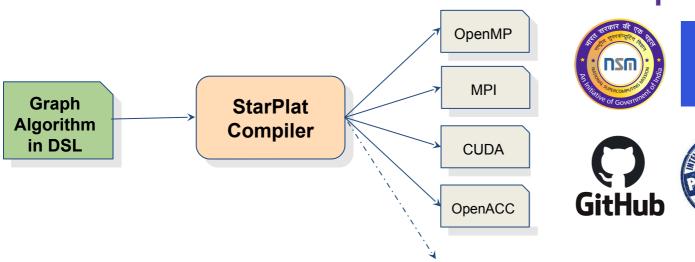
Kernel transformations
Data grouping
Exploiting memory hierarchy

Synchronization

GPU

Avoiding synchronization
Coarsening synchronization
Race and resolve mechanism
Combining synchronization

StarPlat: DSL for Parallel Graph Algorithms

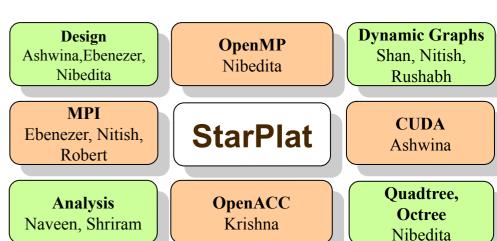




- Generate code for different backends from the same algorithmic specification (OpenMP, MPI, CUDA, OpenACC, Sycl, OpenCL)
- Currently works with static as well as dynamic graphs
- Able to generate code for popular algorithms (SSSP, BC, PR, TC).
- In progress: complex algorithms, program analysis, multi-GPU processing, heterogeneous computing, ...

Achievements

- Qualcomm Innovation Fellowship 2023
- StarPlat's Sycl backend featured at <u>Intel website</u>
- India Patent 432922
- Hardware access from AMD and Intel
- Small survey indicated productivity benefits



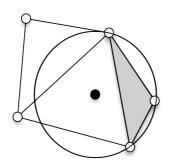
Exercises

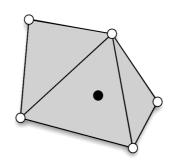
Find if true dependence exists for the loop.

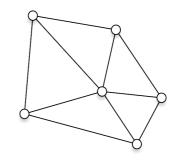
```
for (ii = 0; ii < 10; ++ii) {
    a[2 * ii] = ... a[ii + 1] ...
    a[3 + ii] = ... a[5 * ii] ...
}
```

- Represent a graph as adjacency list on GPU.
- Represent an input graph in CSR format, and then convert it into a COO format.
- Write a kernel to count degrees of various vertices. Check finally that the sum equals the number of edges.
- Implement shortest path algorithm. Check your implementation against that in CUDA SDK.

Parallel Graph Algorithms







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FEEDBACK FOR GPU PROGRAMMING

I shall undergo Thread Divergence As I launch my Feedback Kernel in a poetic way, Thank you Sir, for being a Host par excellence To me, a Thread from another Device, I say.

The Stream of your lectures was appealing, Each day I was hooked, in Pinned Memory, Awaiting your videos on the PCI Express bus each morning, All your programs I did diligently cudaMemcpy.

Owing to Coalescing, I couldn't just watch one lecture, But had to make Strided Access to subsequent ones too; Till I watched them all -- one big Vector!

And so in Global DRAM, I want to thank you!

You patiently resolved all Race Condition Of doubts and questions without making Lost Update, You encouraged interaction and Synchronization, In everyone's Shared Memory, you earned a place great!

As a Warp Representative from this class, I perform an Inclusive Scan of all you taught, You did Reduction of concepts like no one has; atomicAdd(&likes, 1) to all your analogies' lot.

The Prefix Sum of my feedback is this: You taught in a SIMD fashion, With a Global Barrier to ensure no one did miss, Thus, __all(Prof Rupesh is awesome) returns 1.

What did you learn?



Satya Bhagavan • 1st

Mtech CSE IIT Madras | Btech CSE IIT Indore | Ex - Algorithm Developer @ KLA

Ever wondered how to sort numbers by simply sleeping? 😴 Sleep Sort the laziest algorithm out there!

Here is how it works:

- 1. Spawn a thread for each number in your list.
- 2. Each thread takes a nap proportional to its number's value.
- 3. As threads wake up, they print their numbers in order.

It's the only sorting method where procrastination is the key to success!



Disclaimer: Not recommended for actual use unless you have time to kill and a sense of humor.

#multithreading #algorithm #threads #os #SleepSort