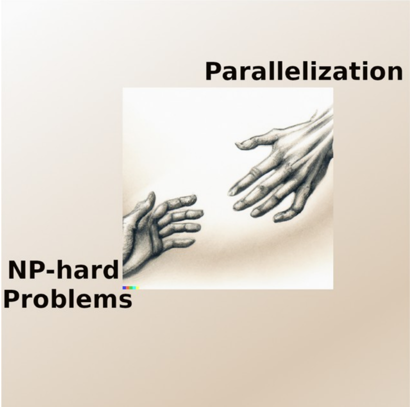
NP-Hard Problems Meet Parallelization



23-Apr-2024

Rajesh Pandian M
www.cse.iitm.ac.in/~mrprajesh
IIT MADRAS
Indian Institute of Technology Madras

intel

Our Philosophy

... take a **fresh look** at some of the classic graph algorithms and devise <u>**faster**</u> and more parallel GPU and CPU implementations.

- Fallin et. al.

+
NP-hard

=
Our Philosophy

A High-Performance MST Implementation for GPUs

Alex Fallin
Dept. of Computer Science
Texas State University
San Marcos, Texas, USA
waf13@txstate.edu

Andres Gonzalez
Dept. of Computer Science
Texas State University
San Marcos, Texas, USA
ag1548@txstate.edu

Jarim Seo
Dept. of Computer Science
Texas State University
San Marcos, Texas, USA
j_s1195@txstate.edu

Martin Burtscher
Dept. of Computer Science
Texas State University
San Marcos, Texas, USA
burtscher@txstate.edu

ABSTRACT

Finding a minimum spanning tree (MST) is a fundamental graph algorithm with applications in many fields. This paper presents ECL-MST, a fast MST implementation designed specifically for GPUs. ECL-MST is based on a parallelization approach that unifies Kruskal's and Borůvka's algorithm and incorporates new and existing optimizations from the literature, including implicit path compression and edge-centric operation. On two test systems, it outperforms leading GPU and CPU codes from the literature on all of our 17 input graphs from various domains. On a Titan V GPU, ECL-MST is, on average, 4.6 times faster than the next fastest code, and on an RTX 3080 Ti GPU, it is 4.5 times faster. On both systems, ECL-MST running on the GPU is roughly 30 times faster than the fastest parallel CPU code.

CCS CONCEPTS

• **Computing methodologies → Massively parallel algorithms.**

KEYWORDS

Minimum spanning tree, minimum spanning forest, parallelism, performance optimization, GPU implementation

lines. In this example, the cheapest distribution grid that allows everyone to deliver or receive electricity is the MST shown.

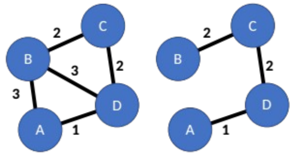


Figure 1: Example of a weighted graph on the left and the resulting MST on the right

Computing an MST (or MSF[1]) is a fundamental graph algorithm with applications in many fields. For instance, it is a key building block in network analysis [12], chip design [1], eye tracking [17], route planning [13], and medical diagnostics like tumor recognition [4]. Since some of these applications repeatedly generate an MST, increasing the performance of this step is important and has the potential to speed up lifesaving computations.

There are three classic MST algorithms. Borůvka's algorithm [11]

SC'23

Outline

PhD Journey

- Motivation
  - Philosophy
  - Landscape
- Steiner Tree
  - Example
  - Algorithm
  - Halt-Optimization
  - GPU Optimization
  - Two-level parallelism
- Vehicle routing
  - Example
  - Local search algorithm
  - Experiments
- Future directions
- Summary

Current status

Irregular Mem. access

Poly-time Problems

- Parallelization is easier
- Algorithms are simpler
- Run few seconds on million/billion-scale
- Solution search space is small
- Exact solution

- **Examples**
  - Minimum Spanning Tree
  - Single Source Shortest Path

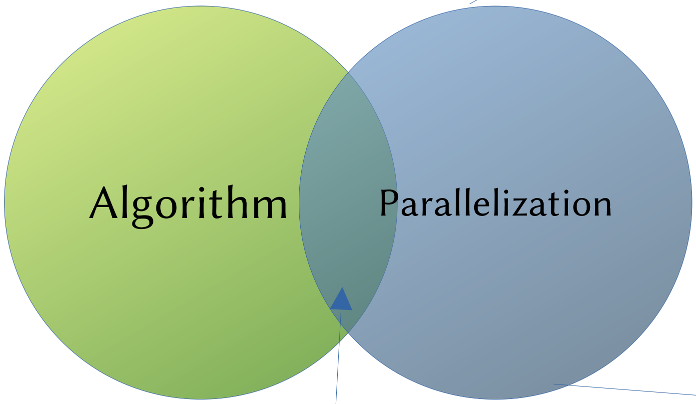
NP-Hard Problems

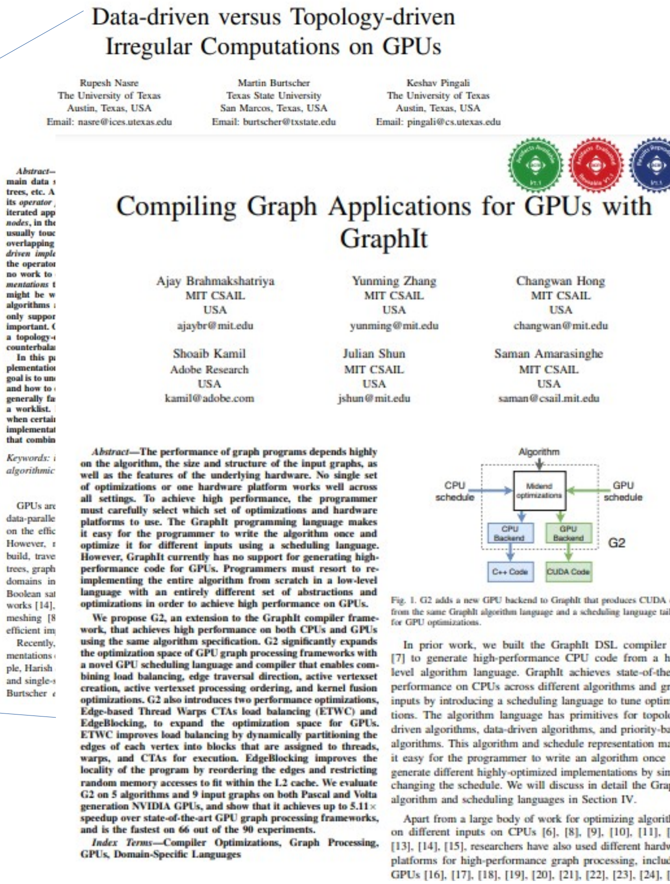
- Comparitively difficult.
- Complicated algorithms
- Few hours for thousand-sized instances
- Solution search space is large
- Approximate solution mostly - tradeoff
  - Steiner Tree Problem
  - Travelling Salesman Problem
  - Vehicle routing problem
- More practical applications

Solve largest Benchmark instances from DIMACS/PACE Challenges

Algorithms and Optimizations

- Parallel Implementations chosen from
  - Efficient serial algorithm
  - Algorithm amenable for parallelization
  - Design parallelism-friendly algorithms
- Optimizations





Data-driven versus Topology-driven Irregular Computations on GPUs

Rupesh Nasre, The University of Texas, Austin, Texas, USA, Email: nasre@ices.utexas.edu
Martin Burtscher, Texas State University, San Marcos, Texas, USA, Email: burtscher@txstate.edu
Keshav Pingali, The University of Texas, Austin, Texas, USA, Email: pingali@cs.utexas.edu

Compiling Graph Applications for GPUs with GraphIt

Ajay Brahmakshatriya, MIT CSAIL, USA, ajaybr@mit.edu
Yunming Zhang, MIT CSAIL, USA, yunming@mit.edu
Changwan Hong, MIT CSAIL, USA, changwan@mit.edu
Shoaib Kamil, Adobe Research, USA, kamil@adobe.com
Julian Shun, MIT CSAIL, USA, jshun@mit.edu
Saman Amarasinghe, MIT CSAIL, USA, saman@csail.mit.edu

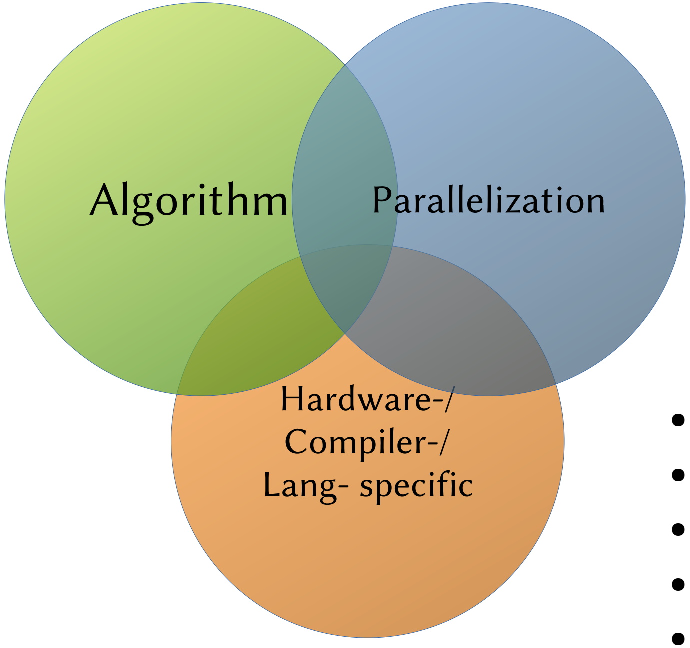
Abstract—The performance of graph programs depends highly on the algorithm, the size and structure of the input graphs, as well as the features of the underlying hardware. No single set of optimizations or one hardware platform works well across all settings. To achieve high performance, the programmer must carefully select which set of optimizations and hardware platforms to use. The GraphIt programming language makes it easy for the programmer to write the algorithm once and optimize it for different inputs using a scheduling language. However, GraphIt currently has no support for generating high-performance code for GPUs. Programmers must resort to re-implementing the entire algorithm from scratch in a low-level language with an entirely different set of abstractions and optimizations in order to achieve high performance on GPUs.

We propose G2, an extension to the GraphIt compiler framework, that achieves high performance on both CPUs and GPUs using the same algorithm specification. G2 significantly expands the optimization space of GPU graph processing frameworks with a novel GPU scheduling language and compiler that enables combining load balancing, edge traversal direction, active vertexset creation, active vertexset processing ordering, and kernel fusion optimizations. G2 also introduces two performance optimizations, Edge-based Thread Warps CTAs load balancing (ETWC) and EdgeBlocking, to expand the optimization space for GPUs. ETWC improves load balancing by dynamically partitioning the edges of each vertex into blocks that are assigned to threads, warps, and CTAs for execution. EdgeBlocking improves the locality of the program by reordering the edges and restricting random memory accesses to fit within the L2 cache. We evaluate G2 on 5 algorithms and 9 input graphs on both Pascal and Volta generation NVIDIA GPUs, and show that it achieves up to 5.11× speedup over state-of-the-art GPU graph processing frameworks, and is the fastest on 66 out of the 90 experiments.

Index Terms—Compiler Optimizations, Graph Processing, GPUs, Domain-Specific Languages

For peek performance

- Input Charateristics
  - Diameter
  - Max degree
  - Road/social network
- Properties of substeps



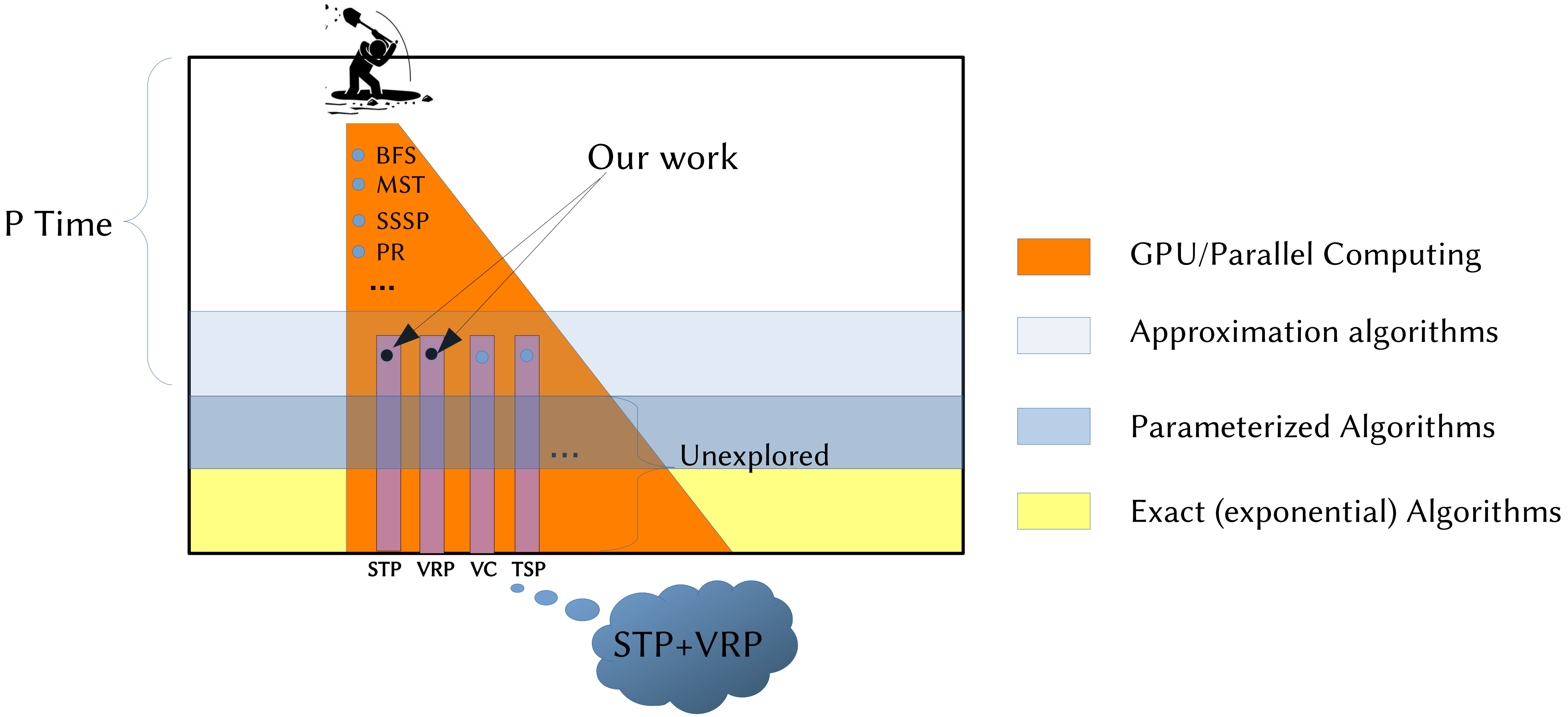
- Vertex-/Edge -centric
- Data-/Topology- driven
- Push/Pull-based
- Load-balancing

  …

Is that all?

- Shared memory
- Warp-Intrincics
- Data accesses within reg/caches
- Vectorization loads/adds
- Language-specific 128b CAS CC9+
- Architecture-specific #L1-3 Caches
- Use profilers and https://godbolt.org

Landscape of Parallelization



Steiner Tree Problem (STP) – Example

Input : Graph G(V, E, W) $W: E \rightarrow Z^+$ and $L \subseteq V$ terminals.
Output: A tree $T'(V' \supseteq L, E' \subseteq E)$ of G such that minimize $W(E')$.
// Minimum weighted tree with all terminals.

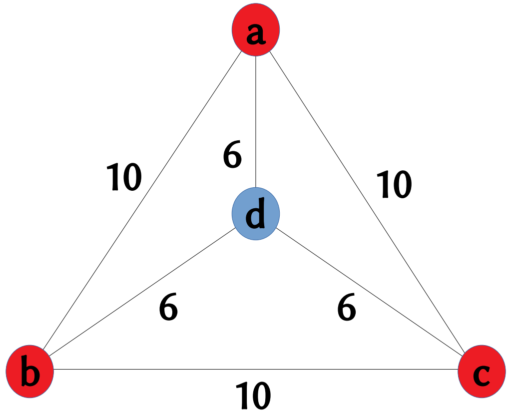


Fig 1 (a)

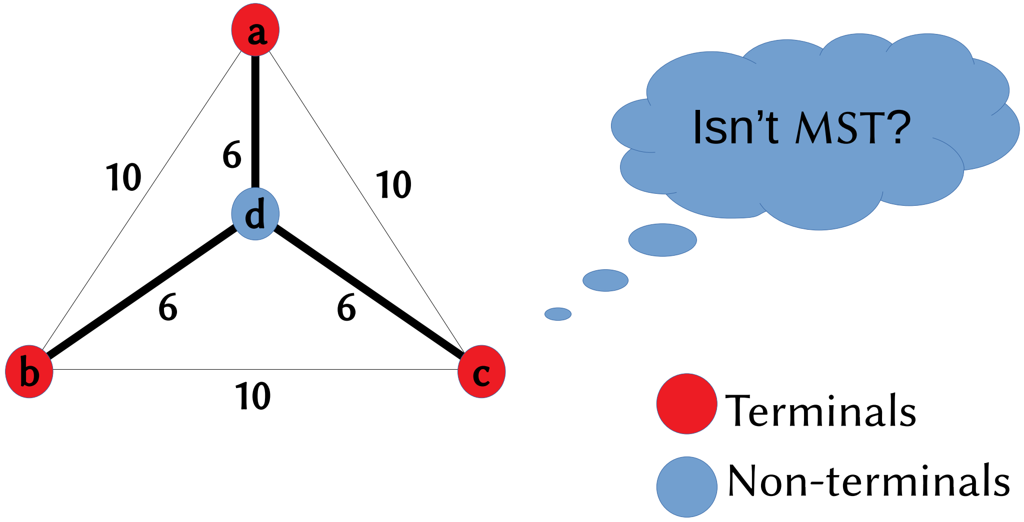


Fig 1 (b)

Steiner Tree Problem (STP) – Example

Input : Graph G(V, E, W) W:E→ Z^+ and L⊆V terminals

Output : Minimum weighted tree with all terminals

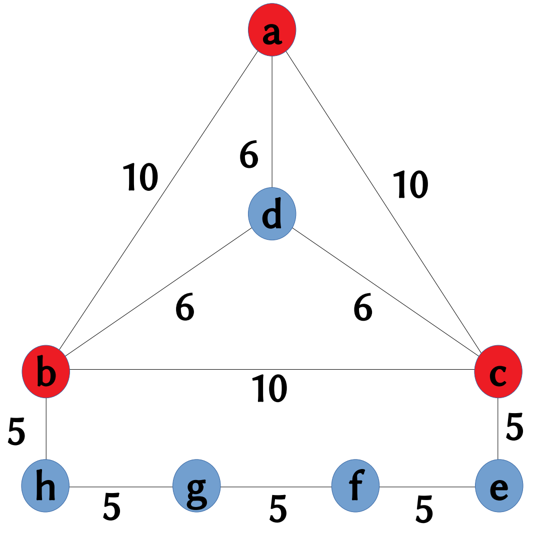


Fig 2 (a)

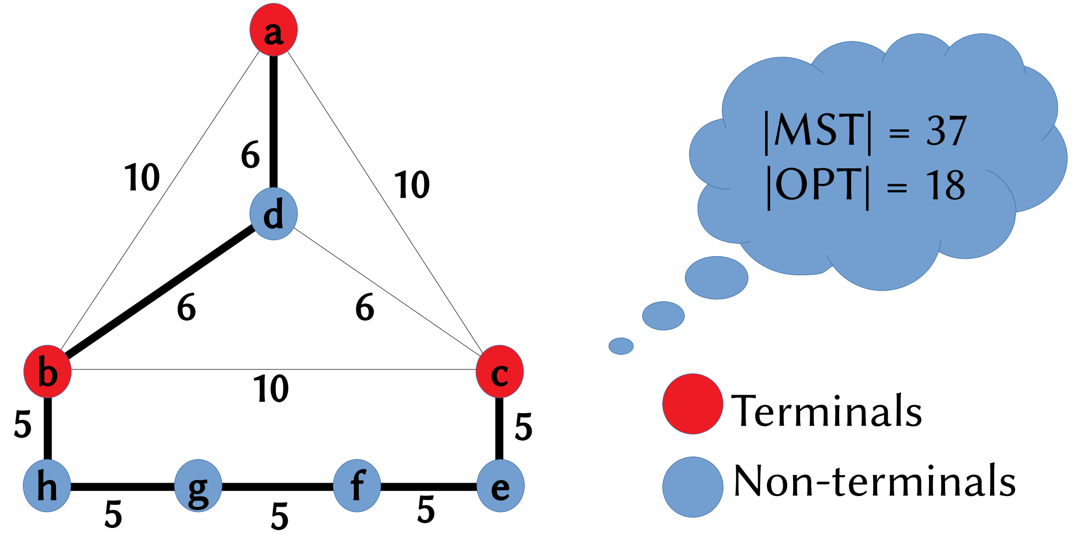


Fig 2 (b)

Steiner Tree Problem (STP) - Hardness

<u>Input</u> : Graph G(V, E, W) $W:E \rightarrow Z^+$ and $L \subseteq V$ terminals
<u>Output</u> : Minimum weighted tree with all terminals

2		n

Take away

- MST solution is a valid feasible Steiner Tree solution
- However, solution can be arbitrarily bad w.r.t OPT.

Special cases

- L = {u,v} or k = 2 STP=ShortestPath_In_G(u,v)
- L = V or k = n STP=MST(G)

In P Time

- In general STP is NP-Hard

Approximation algorithms

How to deal with NP-Hardness

- What could be naive solutions? Enumerate all Spanning trees.

<u>Approximation algorithm</u>

- Runs in Polynomial time.
- Outputs an approximate solution with some guarantee.
  - e.g 2 or some constant, log n, etc.

- There are several algorithms
  - Kou, Markowsky and Berman[KMB81]
  - Mehlhorn [M88]
  - Robins and Zelikovsky [RZ2000]

KMB

$|ALG| <= 2\ |OPT|$

L. Kou, G. Markowsky, and L. Berman. A fast algorithm for Steiner trees. *Acta Informatica, 1981.*

KMB Algorithm G(V,E,W,L)

Phase 1

// Input G

Computes the shortest distance between every **pair** of terminals

Phase 2

// Construct G'= K_L

Build a graph G' over terminals, having edge-weights corresponding to the shortest distances computed in Phase 1

// Every edge in G' corresponds to a path in G

MST (G')

Phase 3

// Construct G''

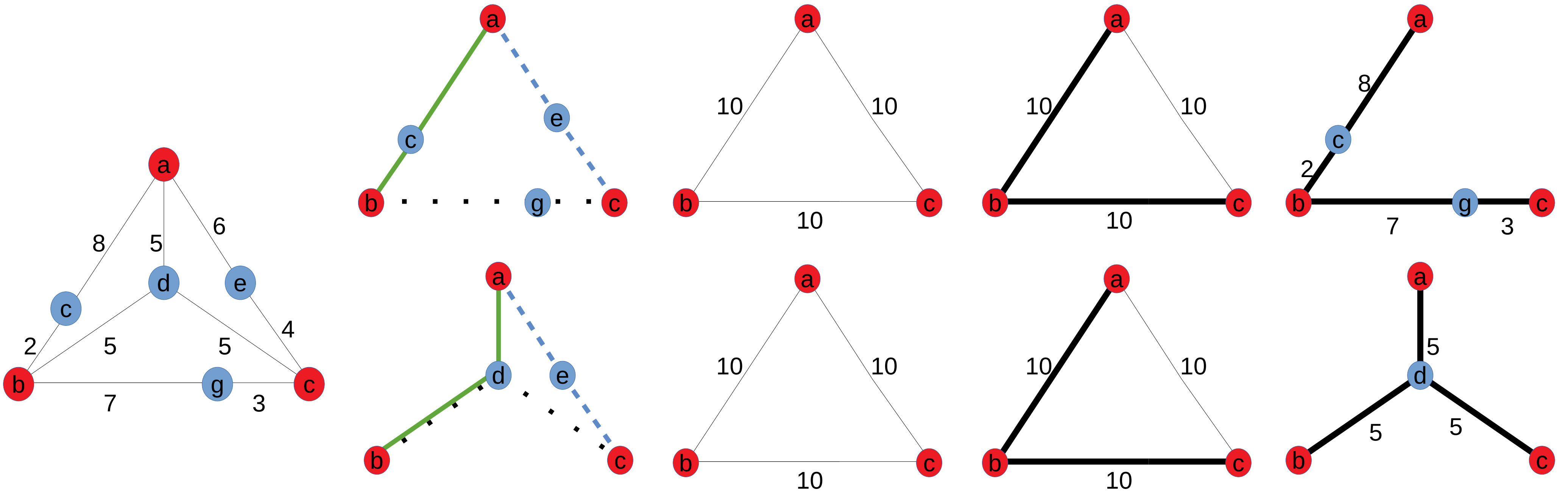
For every edge in MST(G') substitute the edges with the corresponding shortest path in G

// Collect all the edges & vertices of the corresponding path to construct G''

MST(G'')

Takeaway: One more invocation for SSSP/MST algorithm. G→G'→G''

KMB Algorithm – Running example



(i) G (ii) SSSP (iii) G' (iv) G'+MST (v) G''+MST

1) A parallel KMB may output a different answer. (2) Last MST may be avoided

Fig. 3 Execution steps of KMB algorithm, where are terminals and are non-terminals.

KMB Algorithm G (V,E,W), L

Phases 1 & 2

For u in L {
  For v in L {
    P_{uv} = ShortestPath(u,v)
    $W'(u,v) = |P_{uv}|$
  }
}
$T' = MST(G', W')$

Observe:
Two For-loops.
Naive?

Phase 3

For (u,v) in edges of T' {
  $G'' = G'' \cup P_{uv}$
  //Add vertices & edges of P_{uv}
}

$T'' = MST(G'', W)$

KMB Algorithm G (V,E,W,L)

Input: Graph G(V, E, W, L)

Output: 2-approx Steiner Tree T (V_T, E_T) $V_T \supseteq L$

For u ∈ L {
    SSSP (G, W , L, u)   with Halt
    Compute W' incrementally
}
T' = MST(G' ,W')

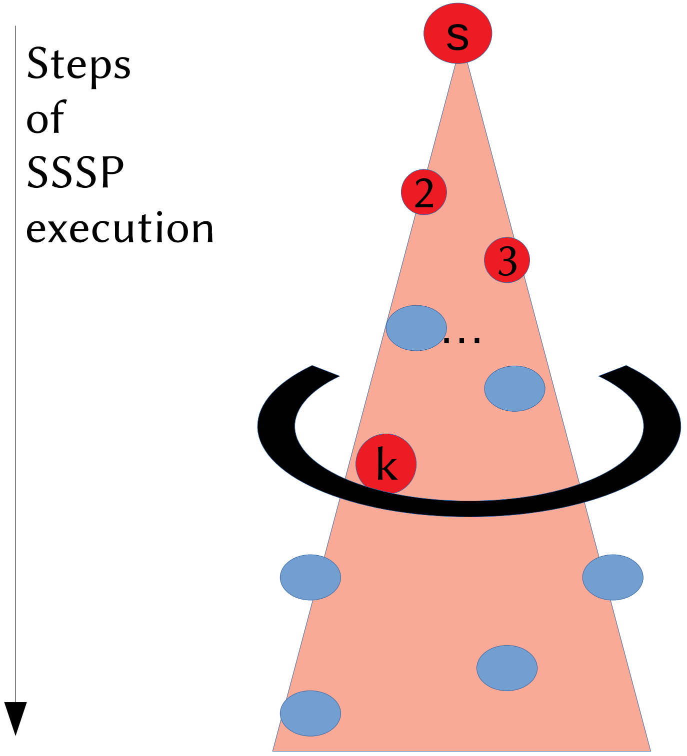
Compute G'' and its vertices, adjList using T'
T'' = MST(G'' ,W)

return T''

Single For-loop but runs SSSP to Completion

CPU Implementation - Optimization

- SSSP-halt optimization



Dijkstra Property: when a node u is picked from Q for processing then the distance[u] is saturated using all the visited nodes.

Halt SSSP when all terminals are visited

Fig. 4 SSSP-halt visualization

KMB Algorithm G (V,E,W,L)

Input: Graph G(V, E, W, L)

Output: 2-approx Steiner Tree T (V_T, E_T) $V_T \supseteq L$

For u ∈ L {
    parallel SSSP(G, W , L, u);
    Compute W′ incrementally;
}

T' = parallel MST(G', W');

Compute G'' and its vertices, adjList ;

T'' = parallel MST(G'', W);

return T''

A novel aspect of our work is to run multiple parallel-SSSPs in parallel.

Subroutines?
Gunrock

Design choice for parallelization

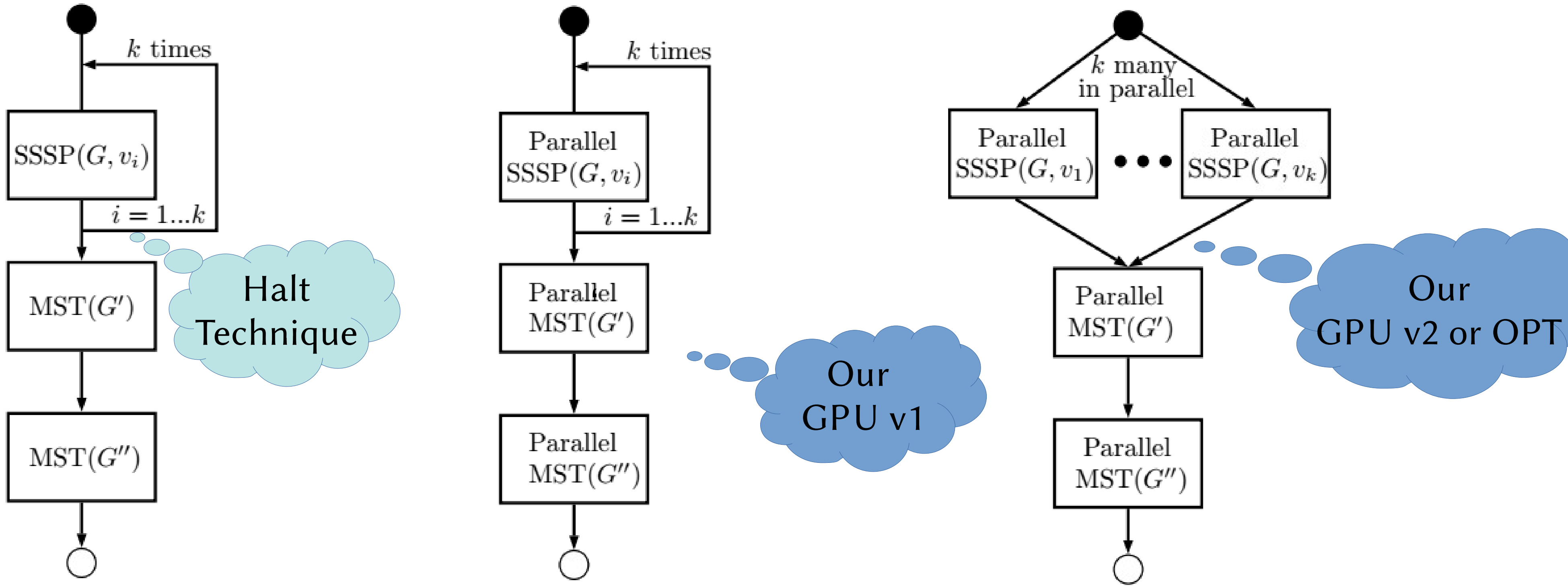


Fig. 5 Sequential vs GPU v1 vs GPU v2

KMBCPU
KMBGPU

GPU Implementation - SSSP

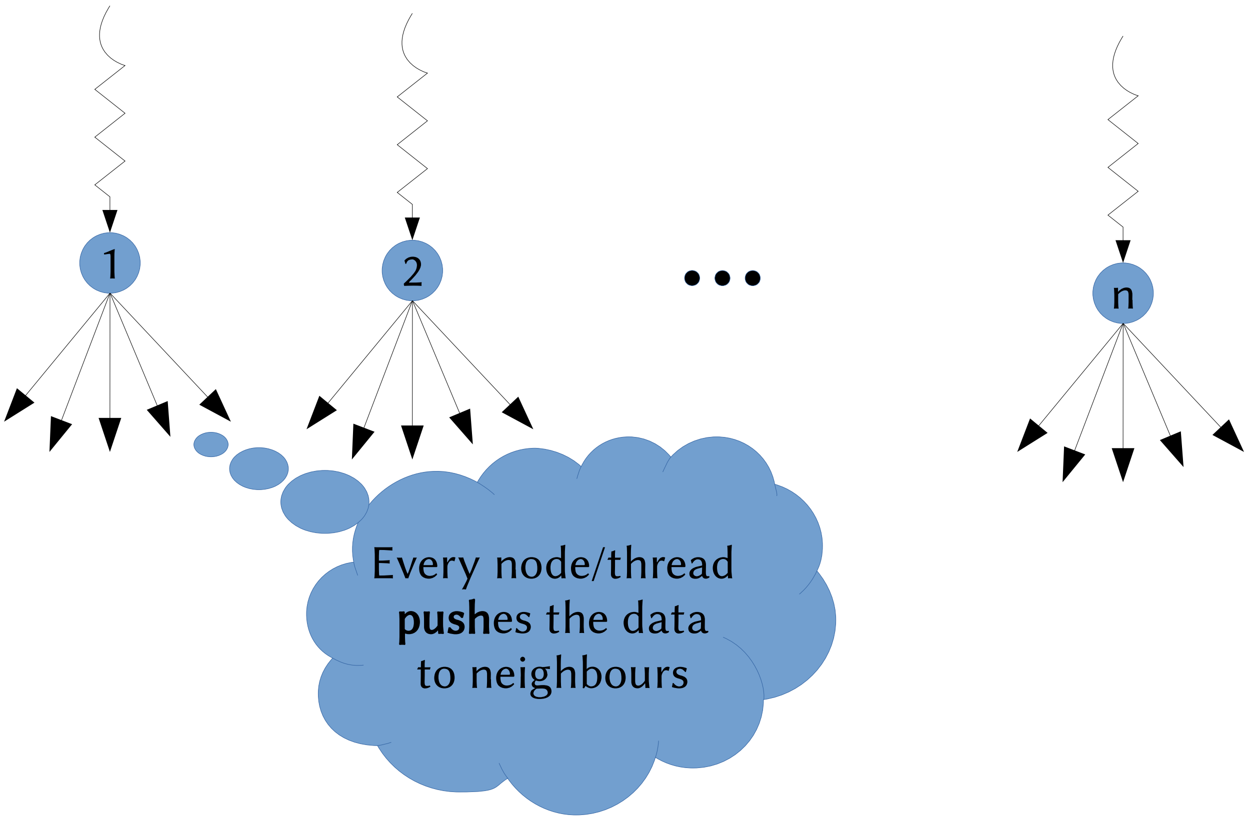


Fig. 6 push SSSP

- n-threads
- One thread for each node
- Performs RELAX in parallel
- RELAXes its neighbours
- Till there is no change

KMB Algorithm G(V,E,W,L)

```
MAIN
For s in L {
  ThdsPerBlk = 512; // or 1024
  Blks = ⌈n/ThdsPer Blk⌉;
  do {
     INIT-KERNEL<Blks,ThdsPerBlk>(s, d_s , p_s , n);
     SSSP-KERNEL<Blks,ThdsPerBlk>(.., s, d_s , p_s , changed, n);
     CopyTo(DArray, d_s );             //= = = = =
     CopyTo(PArray, p_s );             // From Device to Host
     CopyTo(hChanged, changed); // = = = = =
  } while (hChanged);
}
```

- Note we reuse d[] p[] across iterations
- We need the p[] for knowing the intermediate vertices in the shortest path

KMB Algorithm G(V,E,W,L)

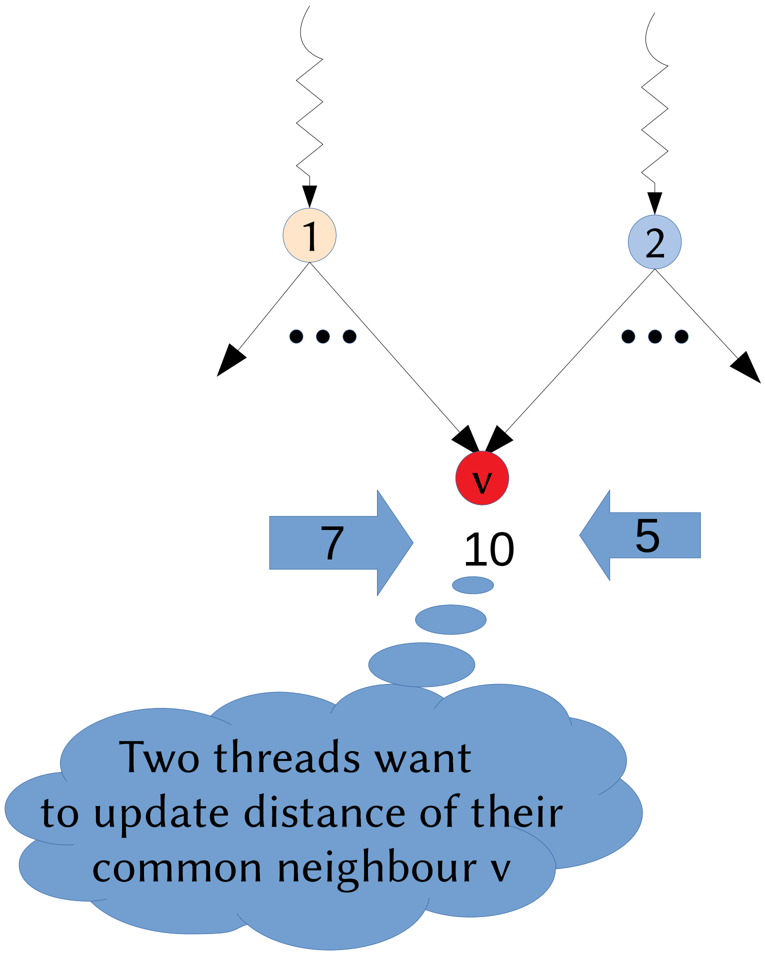
```
SSSP-KERNEL(..,s, d_s , p_s , changed, n) {
u = tid  // compute tid;
If tid < n  {
   For v ∈ adjacent[u] { // Using CSR arrays
      // Relax Operation (u, v, W(u,v))
      newCost = d_s[u] + W(u, v) ;
      old = d_s[v];
      If newCost < old
           Atomic-MIN(d_s[v], newCost);
      // Updates Parent array
      If Atomic-MIN is success {
         p_s[v] = u;
         changed = true;
      }
}}
```

Is it enough?

Note :

- Parent of v should be updated if the Atomic-MIN is success

Parent update - Challenge



<snip>

..

newCost = $d_s[u]$ + W(u, v) ;

old = $d_s[v]$;

If newCost < old

    Atomic-MIN($d_s[v]$, newCost);

// Updates Parent array

If Atomic-MIN is success {

    $p_s[v]$ = u;

    changed = true;

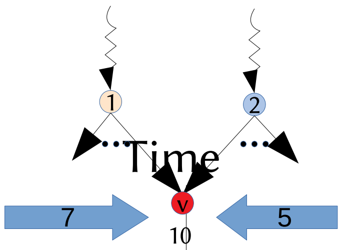
}

</snip>

Fig. 7 Challenges in parent update

Parent update - Challenge

Shared
d[], p[]



Thread 1	Thread 2
newCost=7 old=10	newCost=5 old=10
d[v]=7 //oldA=10	
	d[v]=5 //oldA=7
	p[v]=2
p[v] =1	

Wrong!

```
<snip>
newCost = d[u] + W (u, v) ;
old = d[v];
If newCost < old
   oldA=Atomic-MIN(d[v], newCost);

// Atomic-MIN is Success
If oldA != old {
   // Update's Parent array
    p[v] = u;
    changed = true;
}
```

It is a challenge to find which "thread" updated d[v] to the minimum

How to update both distance and parent at the same time? Locks?

Synchronization optimization • Pull

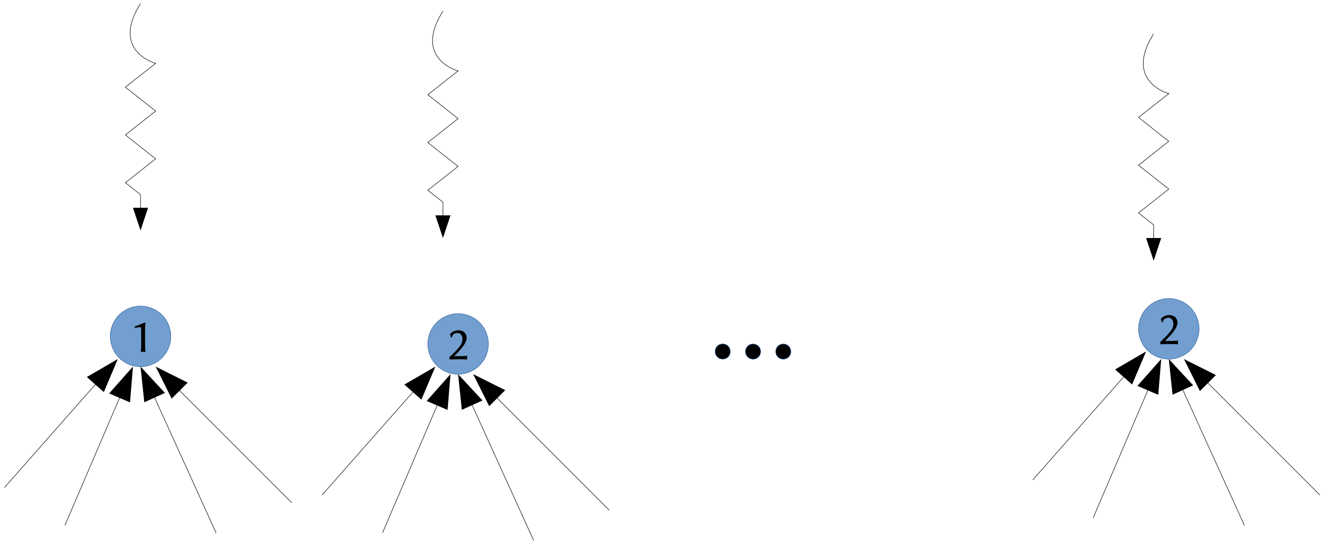


Fig. 8 Pull-SSSP

```
<snip>
newCost = d[v] + W (tid, v) ;
old = d[u];
If newCost < old {
   d[u] = newCost
   p[u] = tid;
   changed = true;
}

</snip>
```

No Atomics
Parent update is easy

Because, one thread is writing to an index

GPU Optimizations

- Synchronization
  - Push
  - Pull
- Computation
  - Data-driven
  - Edge-based
  - Controlled Computation unrolling
    - Δ^2
    - 2Δ
    - $t\Delta$
- Memory
  - Shared memory

Δ – max degree of the graph

GPU Optimizations

- Synchronization
  - Push
  - **Pull**
- Computation
  - Data-driven
  - Edge-based
  - **Controlled Computation unrolling**
    - Δ^2
    - 2Δ
    - **$t\Delta$**
- Memory
  - **Shared memory**

These worked best for us!

Δ – max degree of the graph

Compute optimization

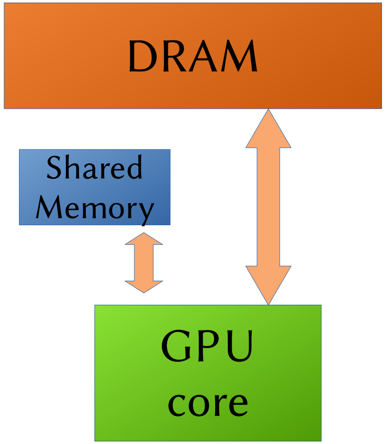
- Computation Unrolling
  - Instead of one thread doing Δ work, perform more work per thread
  - Update also neighbours of neighbours (Δ^2)
  - **Repeat the work**; Say 2 times or t times (2Δ or tΔ); e.g. we do pull 3 times in the kernel – 3-pull

- Data-driven
  - Needs Worklist (WL)
  - Active/Change nodes are inserted into WL

- Edge-based optimization
  - m-threads are launched
  - RELAXes one edge or a group of edges

Give more work
or repeat the work?

Memory optimization



- Programmable shared memory can be useful
- When there are multiple reads to DRAM
- We can move data to shared memory

- For e.g. In 3-pull, we moved CSR AdjList to shared
- As the neighbours AdjList is accessed 3 times
- Of the total 48K per block
- when using 512 threadPerBlock we have 24 words to store per thread

- Hence, if degree(node) < 25 we use shared, we move CSR AdjList[node] to Shared
- With shared memory we achieve 25% of improvement in 3-pull

Double-barrel approach

- SSSP happens in parallel
- To run two SSSP, we have to run one after the other
- Instead we use Double-barrel approach
- This can be generalized (p-SSSP)

In our Double-barrel approach, we run two individually parallel SSSPs also in parallel.

Image source: https://stock.adobe.com/

Double-barrel approach

```
Result Array: d[n]
Initialize(d=INTMAX )
d[src] = 0
FixedPoint{
        doRELAX(G, d, changed ...);
}
```

```
Result Array: d[2n]
Initialize(d=INTMAX)
d[src1] = 0; d[n+src2] = 0
FixedPoint{
        doRELAX(G, dist, changed, ...);
}
```

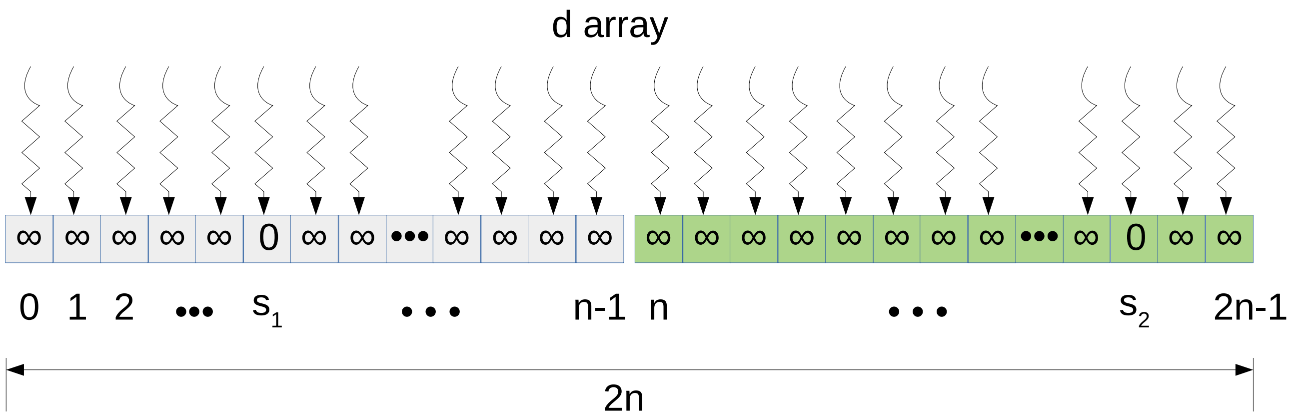


Fig. 9 Double-barrel approach.

Tunable
arbitary value

Key takeaways so far

- Solving Steiner Tree Problem is NP-hard
- KMB Algorithm, a 2-approximation algorithm
- CPU implementation has SSSP-halt optimization
- SSSP with parent array update <u>was</u> challenging
- Pull-based SSSP is great for KMBGPU even without SSSP-halt
- Parallel-SSSPs in parallel (p-SSSP)

Experimental setup & Graphsuite

CPU

- Intel(R) Xeon(R) E5-2640 v4 @ 2.40GHz
- 64GB RAM

GPU

- Tesla P100 @ 1.33 GHz
- 12GB global memory

- CentOS Linux release 7.5
- GCC 7.3.1 with O3
- CUDA 10.2

Graphsuite

- Total 14 Graphs
  - 11 from PACE Challenge [PACE2018]
  - 2 from SteinLib
  - 1 from SNAP
- n : 17K – 235K
- m : 27K – 498K
- k : 0.1K – 6K

Baselines

- PACE'18 Winner – CIMAT [PACE2018]
- ODGF's KMB/JEA [BC19]

- PACE 2018 - https://pacechallenge.org/2018/steiner-tree/
- CIMAT Team - https://github.com/HeathcliffAC/SteinerTreeProblem
- S. Beyer and M. Chimani, Strong Steiner Tree Approximations in Practice, JEA 2019.

Challenges in parallelizing KMB

- Graph algorithms in general has an irregular access pattern.
  - Defies the scope of parallelizing
- Involvement of multiple primitive algorithms (such as SSSP and MST)
  - Dependence on an algorithm input from the output of previous algorithm
- Maintaining consistent parent information in SSSP along with distances.
  - Individual atomic instructions may not lead to atomic transactions.
- Parallel KMB may output different solutions during different invocations,
  - Makes it difficult to validate the solution,

Experiments - Speed-up

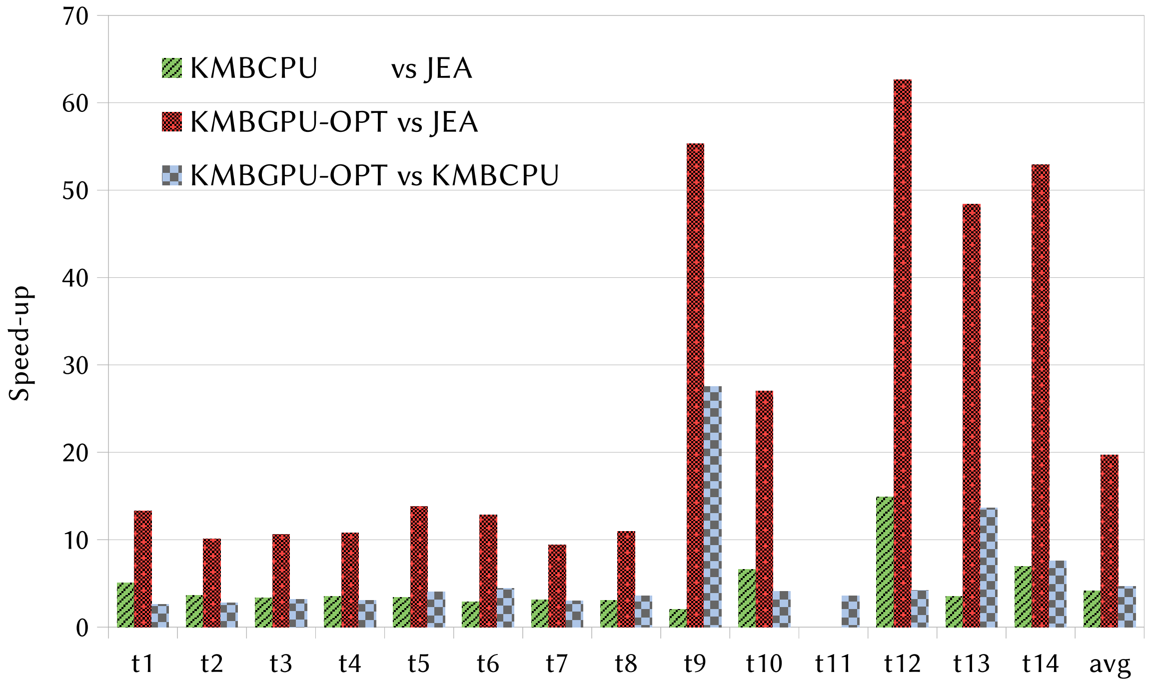


Fig. 10 Speed-up comparisons of the implementations (higher is better). JEA timed-out on t11

Takeaway: KMBCPU and KMBGPUOPT is better than JEA

Comparison of GPU time with Shared mem.

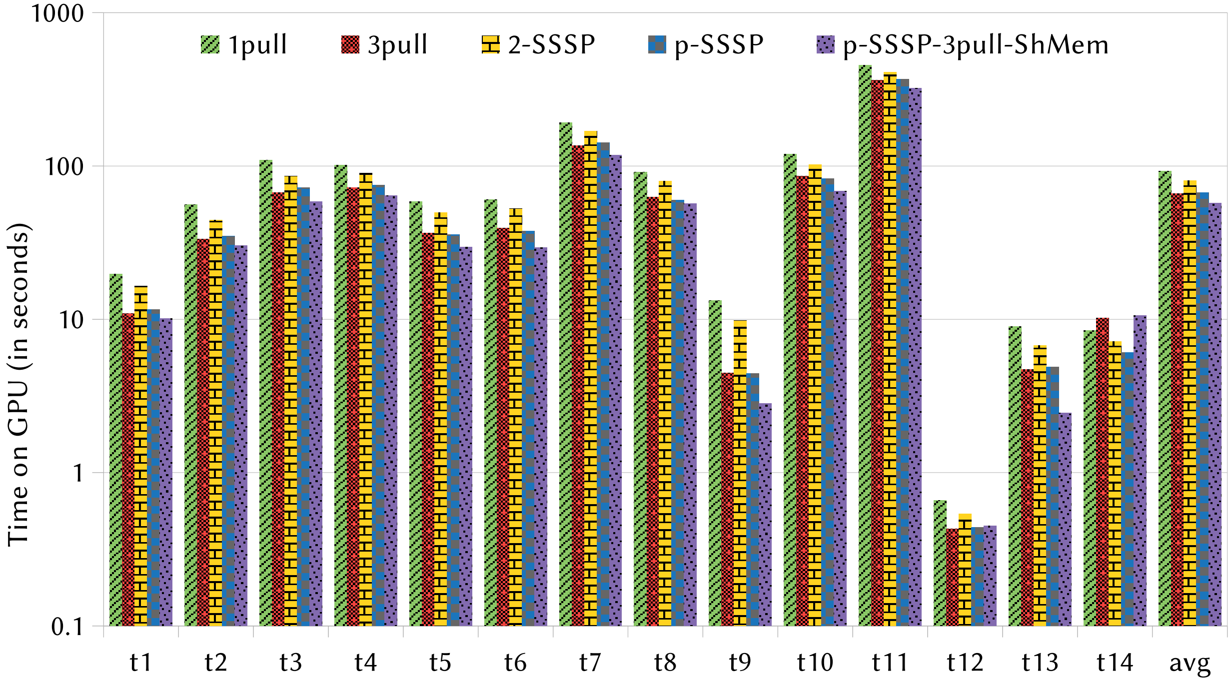


Fig. 11 Comparison of 1-Pull, 3-Pull, Double-barrel & p-SSSP+3-Pull+shared memory (smaller is better). Note: 1-Pull is KMBGPU whereas p-SSSP-3pull-ShMem is KMBGPU-OPT

Takeaway: Combining GPU optimizations p-SSSP, 3-Pull & Shared memory performs best.

Comparison of p-SSSP

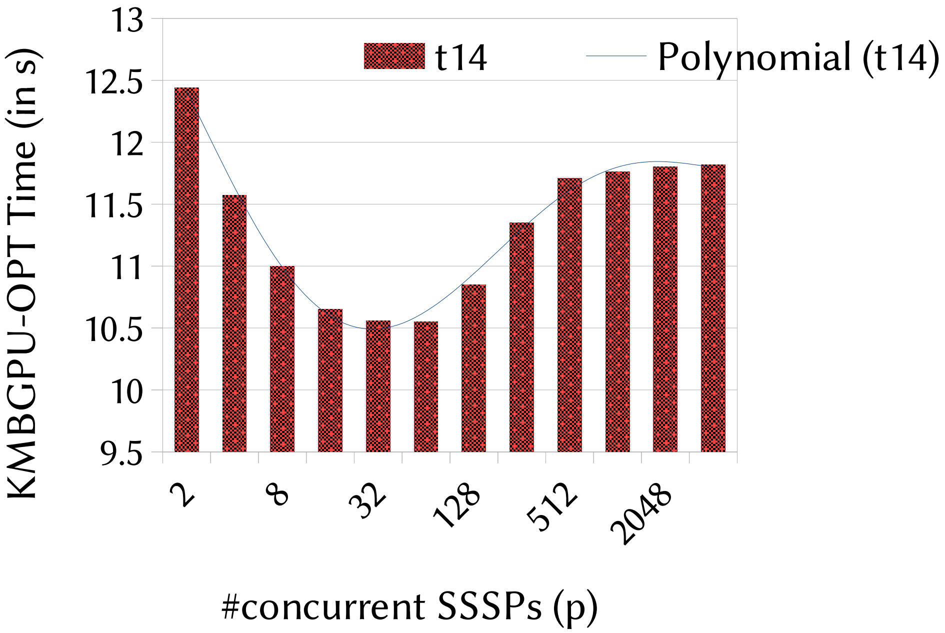


Fig. 12 KMBGPU with varying p-SSSP for the same graphs t14 (Smaller is better).

Takeaway: As we increase the #parallel SSSPs it reaches a point and then increases.

Experiments – Scalability of GPU and CPU

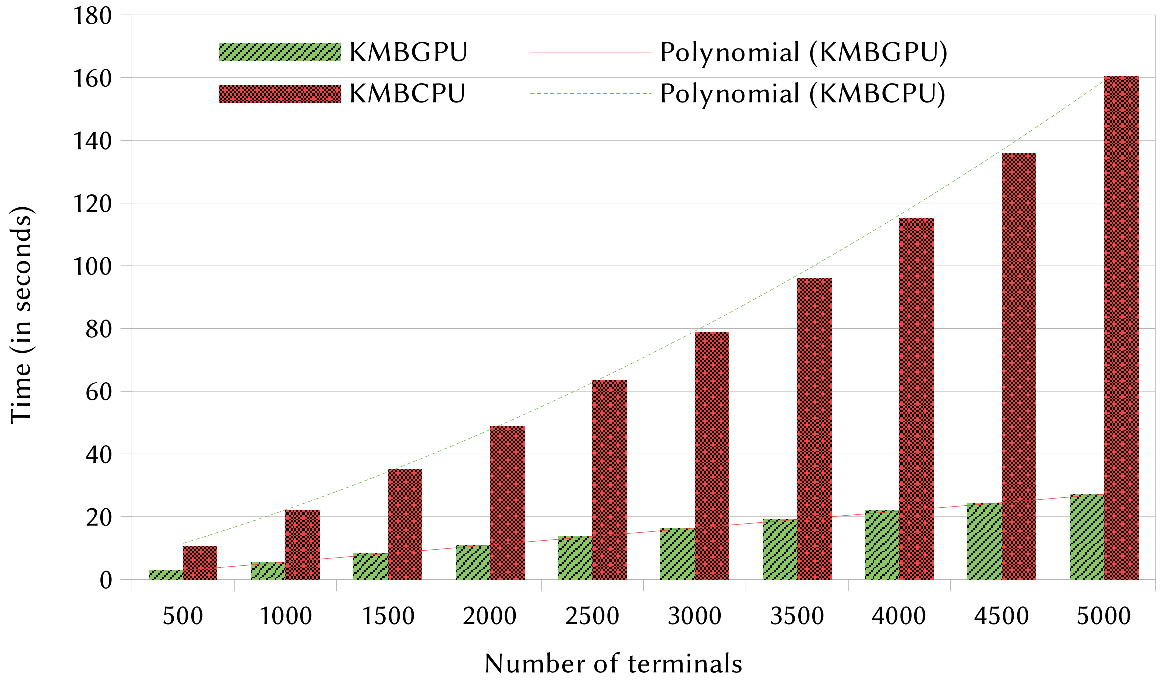


Fig. 13 Scalability plot on **t14** with increasing terminal size (lower is better)

Takeaway: KMBGPU-OPT scales better than KMBCPU

Summary - STP

- Optimized CPU implementation for KMB algorithm
  - Novel SSSP-halt technique
  - Speed-up upto 15x (average 4x) improvement over JEA/OGDF's KMB[BC19]
- Optimized GPU implementation for KMB algorithm
  - Novel p-SSSP technique (multiple parallel-SSSP in parallel)
  - Speed-up upto 27x (average 4x) over sequential CPU [MNN22]
  - Speed-up upto 62x (average 20x) over sequential JEA/OGDF's KMB [BC19]

</work>

S. Beyer and M. Chimani, Strong Steiner Tree Approximations in Practice, JEA 2019.

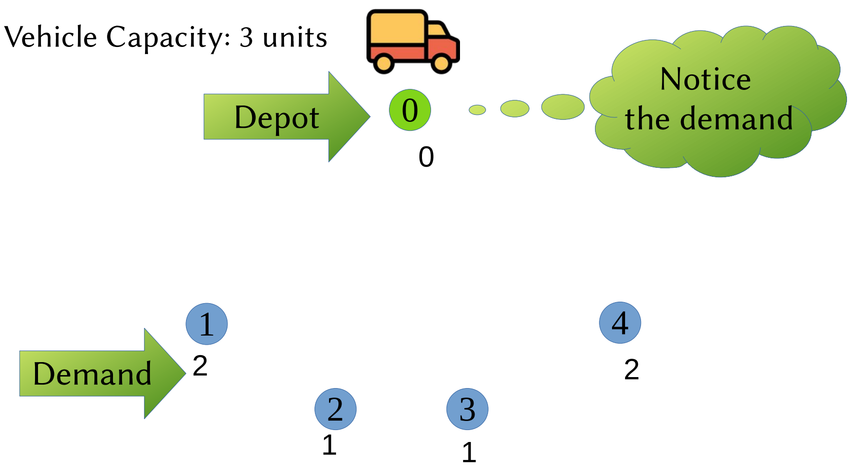
Capacitated Vehicle Routing Problem (CVRP)

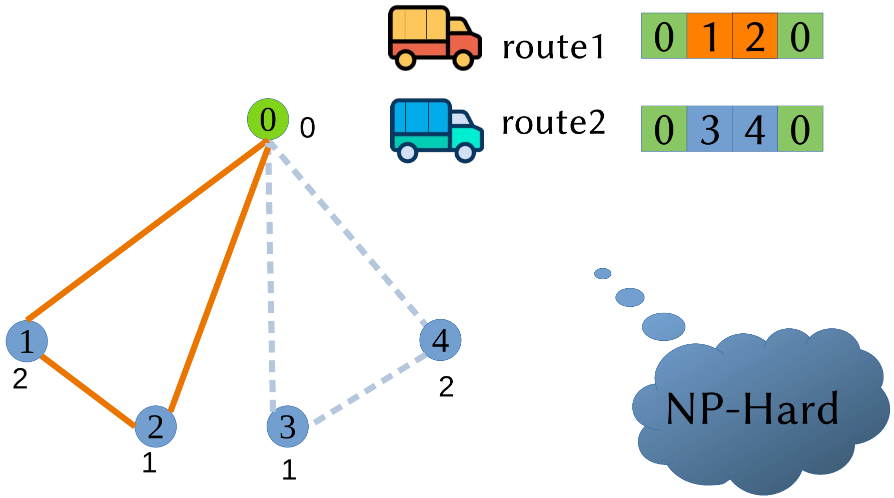
Input : Given n nodes (single Depot and customers) with their coordinates (x_i, y_i) and demands $d_i > 0$ for $i \in n$, Vehicle capacity C. Node 0 is Depot and has zero demand.

Output: Set of routes serving all the customers respecting the vehicle capacity from/to Depot.

Goal : Minimize total distance travelled.

If Capacity = sum of demands d_i ,
CVRP ➜ Travelling Salesman Problem





CVRP Limitations

Current state-of-the-art

- work only on smaller instances
- has a large solution Gap
- takes a lot of time

Instance	Number of customers	Time (s)	
		Base2	Base1
Flanders2	30,000	8,355	2,534
Flanders1	20,000	7,768	2,031
Brussels1	15,000	7,164	871

Table 4: State-of-the-art GPU methods are time-consuming.

RQ1. Can we invent a simpler algorithm?

RQ2. Can we reduce Gap on large instances?

RQ3. Design Parallelization friendly algorithms?

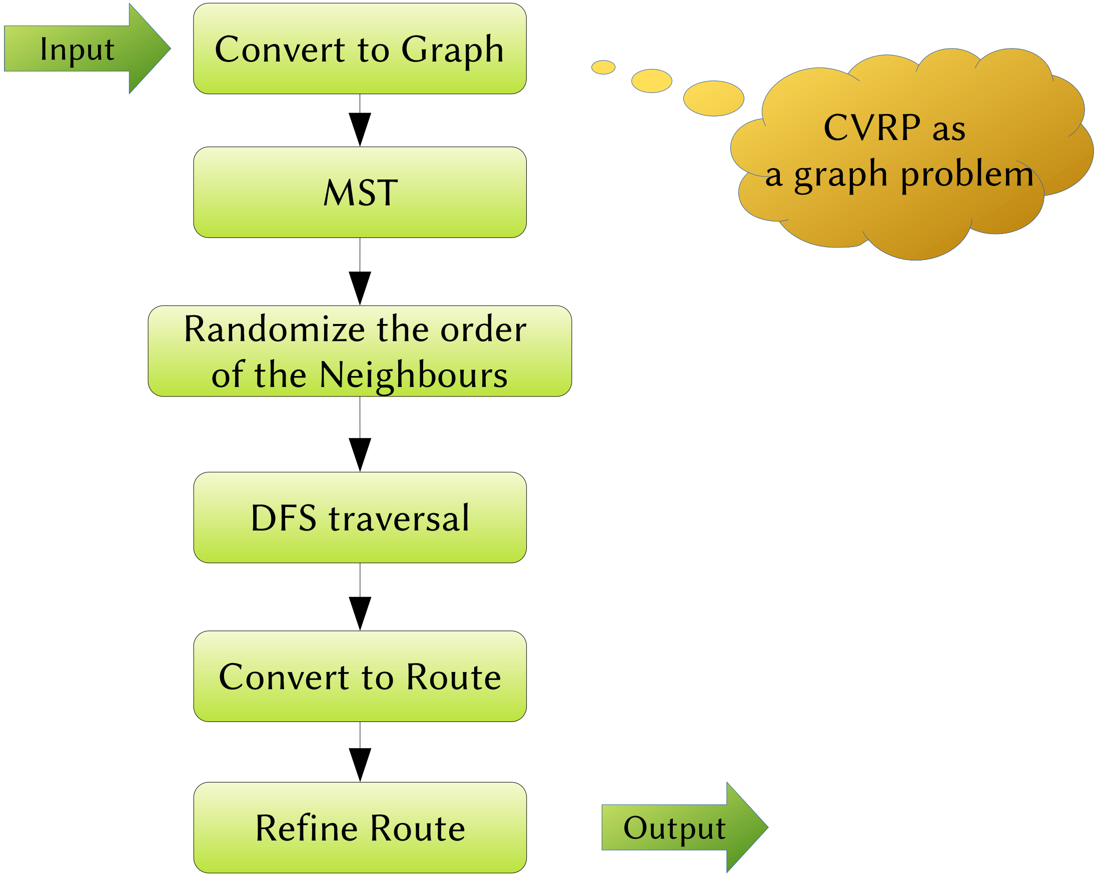
Our **ParMDS**

- Serial and Parallel implementation
- Combining MST and DFS
- Uses Local-search approach
- Uses Randomization approach

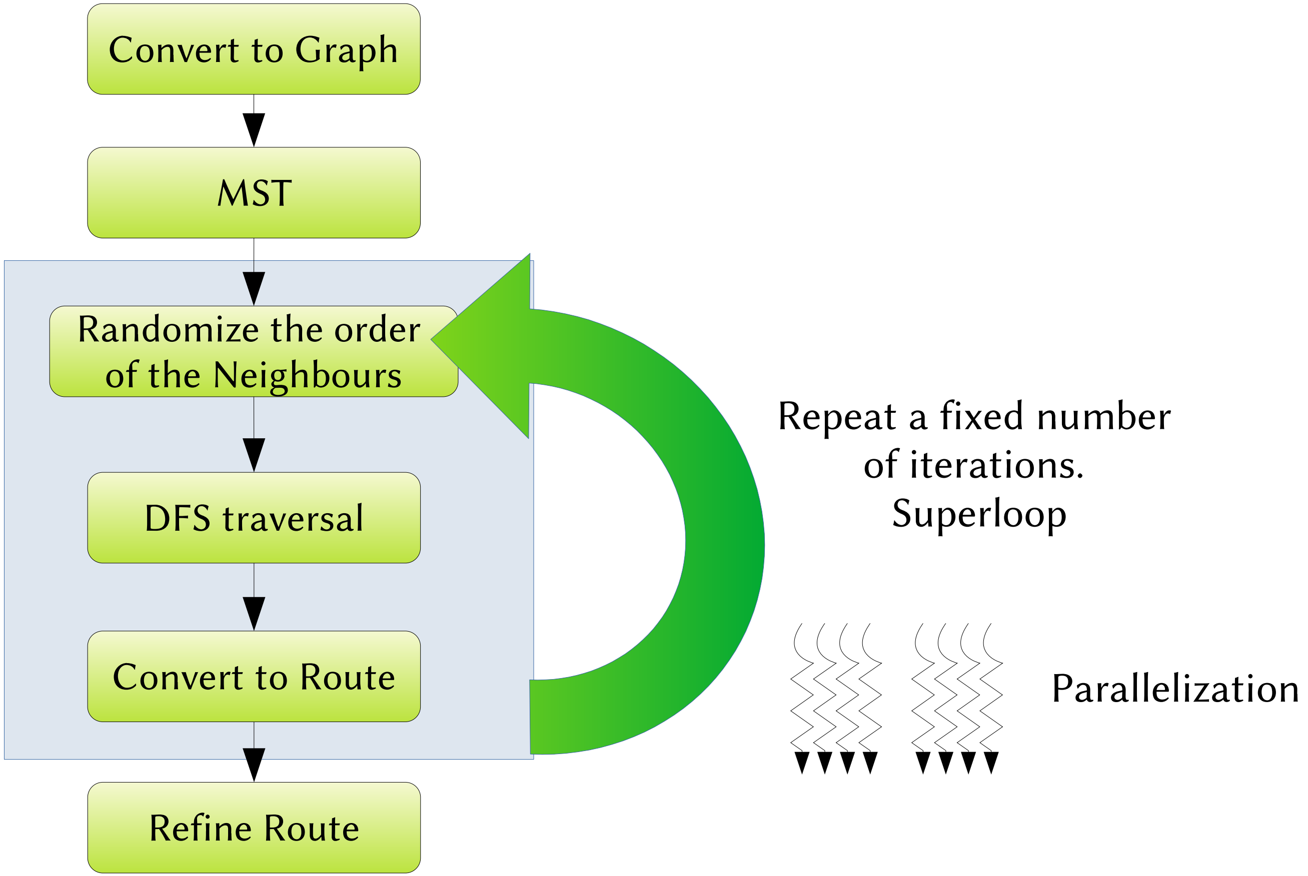
$$Gap = \frac{Z_S - Z_{BKS}}{Z_{BKS}} \times 100$$

Baseline1: P. Yelmewad and B. Talawar. Parallel Version of Local Search Heuristic Algorithm to Solve Capacitated Vehicle Routing Problem, Cluster Computing, 2021.
Baseline2: M. Abdelatti and M. Sodhi. An improved GPU-accelerated heuristic technique applied to the Capacitated Vehicle Routing Problem, GECCO, 2020.

Overview - ParMDS

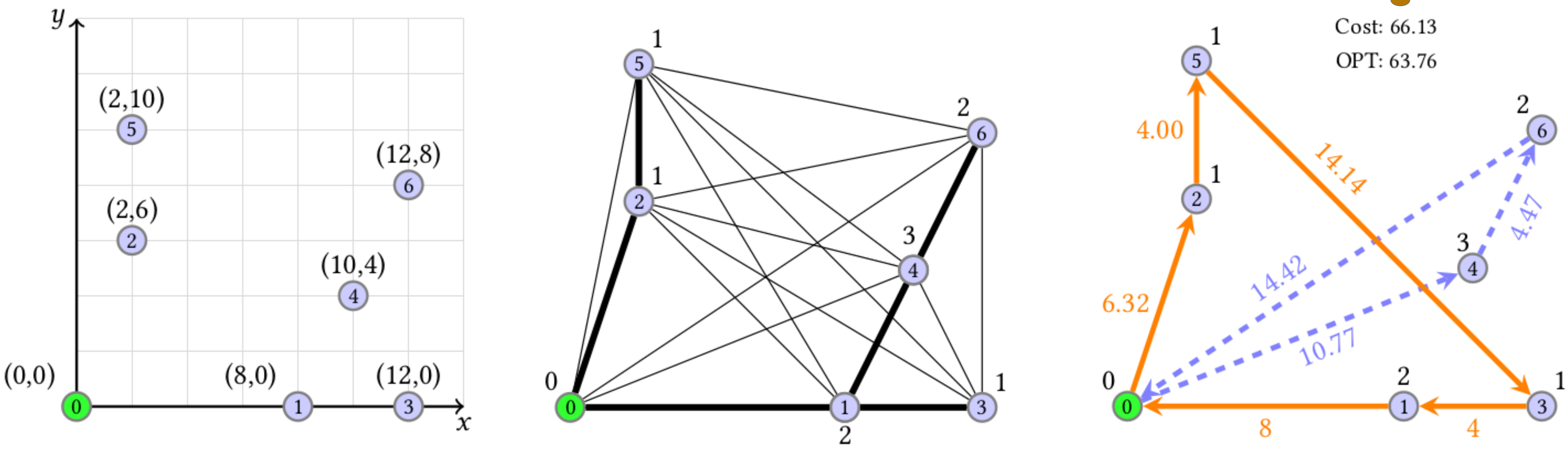


Overview - ParMDS



Example – Overview

Closer to Optimal Cost



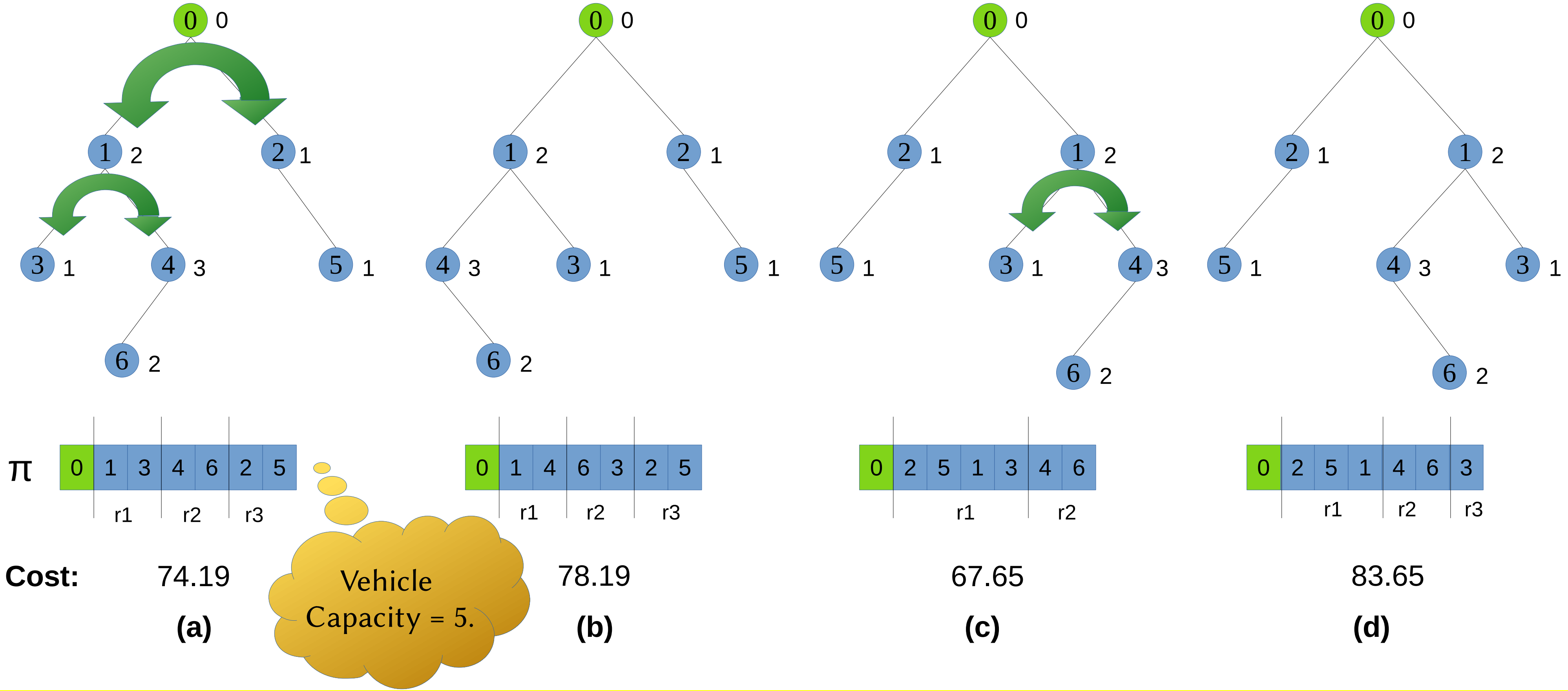
(a) Input instance I

(b) Graph for I, along with node-demands

(c) Final routes generated by ParMDS

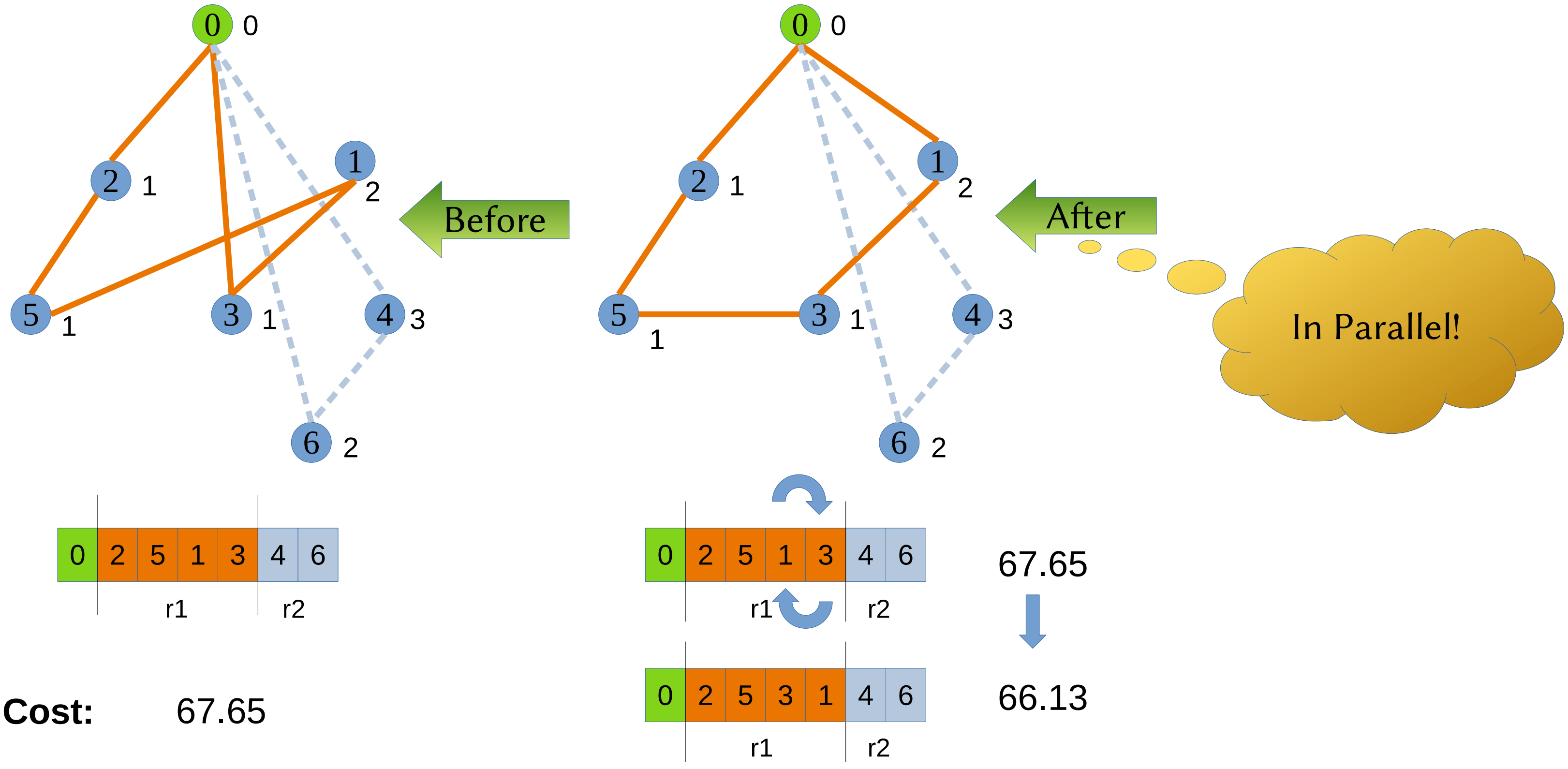
ParMDS on an example input instance with n = 7 and Vehicle Capacity = 5.

Example – DFS and Randomization



Takeaway: Randomizing neighbours of MST may yield a different DFS ordering. Hence, a different route!

Intra-route optimization - 2Opt



(a) (b)

ParMDS Algorithm

Input: $G = (V, E)$, Demands $D := \bigcup_{i=1}^{n} d_i$, Capacity Q
Output: R, a collection of routes as a valid CVRP solution
C_R, the cost of R

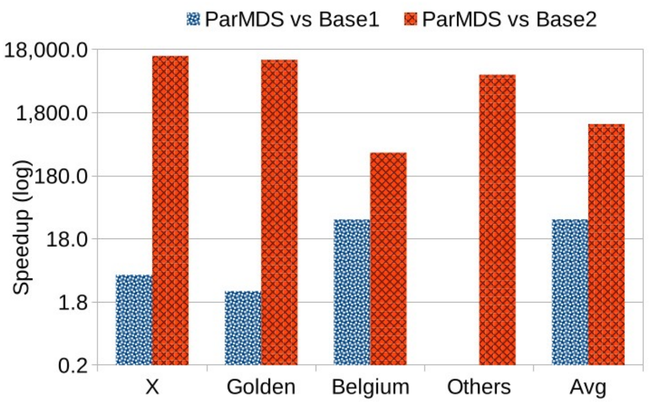
```
T ← PRIMS_MST (G)                                  /* Step 1 */
C_R ← ∞
for i ← 1 to ρ do          /* Superloop */ /* Parallel */
    T_i ← RANDOMIZE (T) /* Shuffle Adjacency List */
    π_i ← DFS_VISIT (T_i, Depot)                   /* Step 2 */
    R_i ← CONVERT_TO_ROUTES (π_i, Q, D)            /* Step 3 */
    C_{R_i} ← CALCULATE_COST (R_i)               /* Parallel */
    if C_{R_i} < C_R then
        C_R ← C_{R_i}                    /* Current Min Cost */
        R′ ← R_i                   /* Current Min Cost Route */
    end
end
R ← REFINE_ROUTES (R′)                             /* Step 4 */
return R, C_R
```

Zoom

```
/* Standard: stride = 1;                                      */
/* Strided : stride = #CPU cores                              */
/* Parallel for loop: Standard/Strided                        */
for i ← 1; i ≤ ρ; i = i + stride do
    for v ∈ V do
        /* seed ← constant or i or rand()                     */
        SHUFFLE-NEIGHBORS(AdjList(v), seed);
    end
    ...
end
...
```

Experiments

- 130 Instances of CVRPLIB
- Intel Xeon CPU E5-2640 v4
- Baselines on GPU
  - NVIDIA's Tesla P100
  - CUDA 11.5

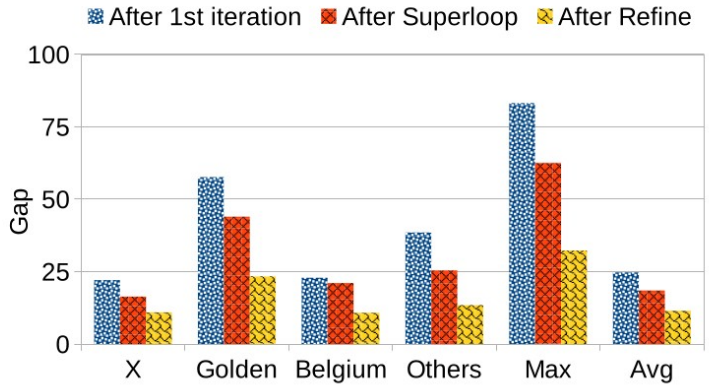


Speedup of ParMDS vs. baselines

Method	Execution Time (s) using Random
SeqMDS	1,722.44
ParMDS-Standard	1,522.26
ParMDS-Strided	186.50

More detailed analysis in our paper

- Our Code uses
  - **SeqMDS:** GCC 9.3.1
  - **ParMDS:** nvc++ compiler NVIDIA's HPC SDK 22.11



Gap at the end of each step

Summary

- Fresh perspective of parallelism-friendly algorithms
- Performance: Algorithmic-, Parallelism- and Platform-Optimizations

- Our techniques are applicable
  - Two-level parallelism technique
  - Strided parallel Local-search

- Future directions
  - Paradigm specific parallelization: Greedy, Dynamic Programming
  - Most STL algorithms run parallel // My Prediction
  - Once source for muti-core and GPU

Thank you!

Questions?