Gunrock: A Fast and Programmable Multi-GPU Graph Processing Library

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Why use GPUs for Graph Processing?

Graphs

- Found everywhere
  - Road & social networks, web, etc.
- Require fast processing
  - Memory bandwidth, computing power and GOOD software
- Becoming very large
  - Billions of edges
- Irregular data access pattern and control flow
  - Limits performance and scalability

GPUs

- Found everywhere
  - Data center, desktops, mobiles, etc.
- Very powerful
  - High memory bandwidth (288 GBps) and computing power (4.3 Tflops)
- Limited memory size
  - 12 GB per NVIDIA K40
- Hard to program
  - Harder to optimize

Scalability

Performance

Programmability

What we want to achieve with Gunrock?

Performance

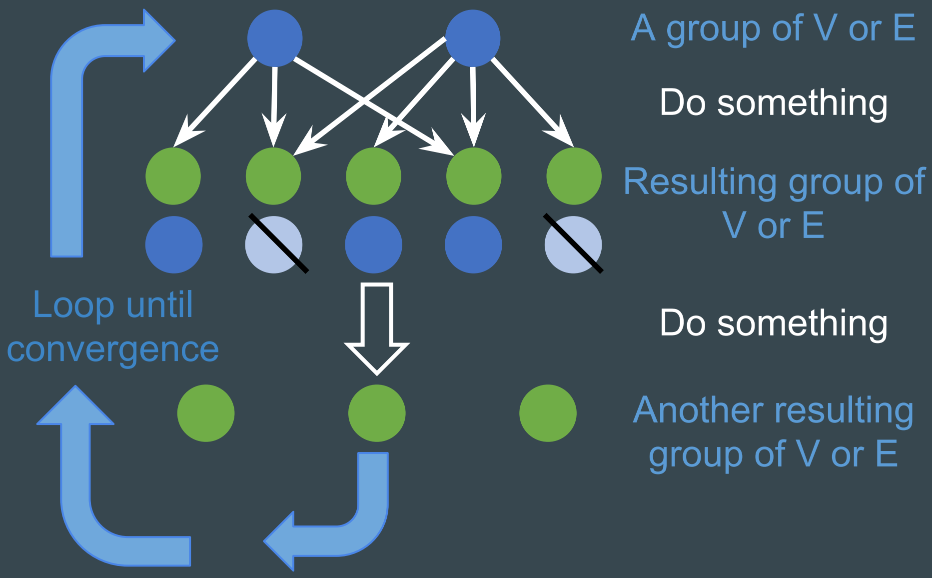
- High performance GPU computing primitives
- High performance framework
- Optimizations
- Multi-GPU capability

Programmability

- A data-centric abstraction designed specifically for the GPU
- Simple and flexible interface to allow user-defined operations
- Framework and optimization details hidden from users, but automatically applied when suitable

Idea: Data-Centric Abstraction & Bulk-Synchronous Programming

A generic graph algorithm:



Data-centric abstraction

- Operations are defined on

  a group of vertices or edges $\stackrel{\text{def}}{=}$ a frontier

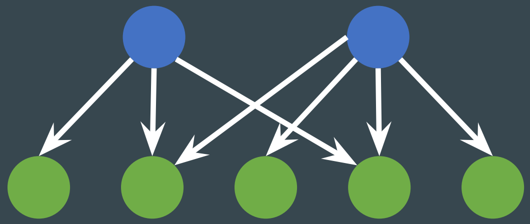
=> Operations = manipulations of frontiers

Bulk-synchronous programming

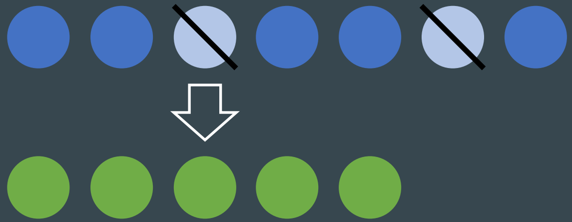
- Operations are done one by one, in order
- Within a single operation, computing on multiple elements can be done in parallel, without order

Gunrock's Operations on Frontiers

Generation

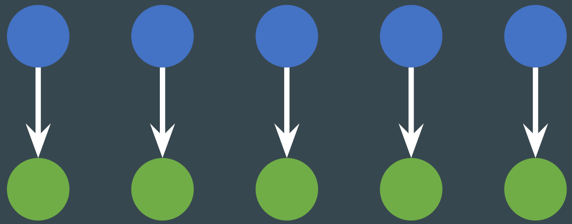


Advance: visit neighbor lists



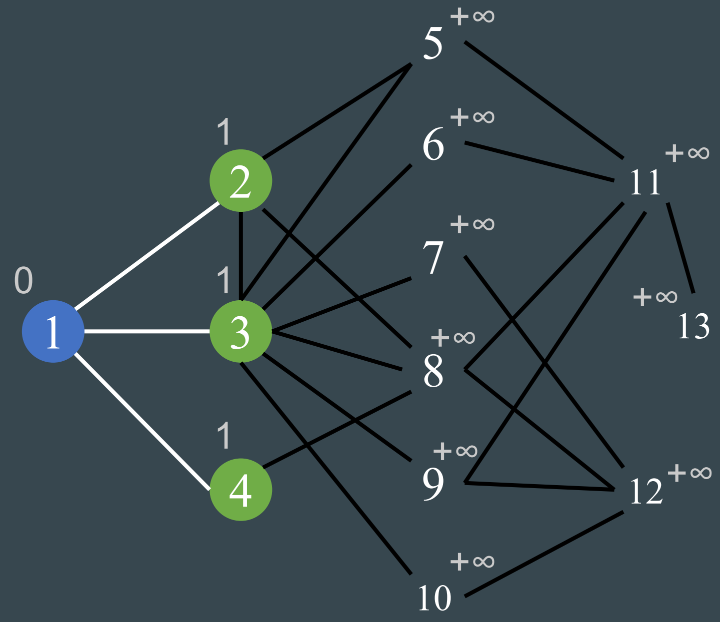
Filter: select and reorganize

Computation



Compute: per-element computation, in parallel
can be combined with advance or filter

Example: BFS with Gunrock

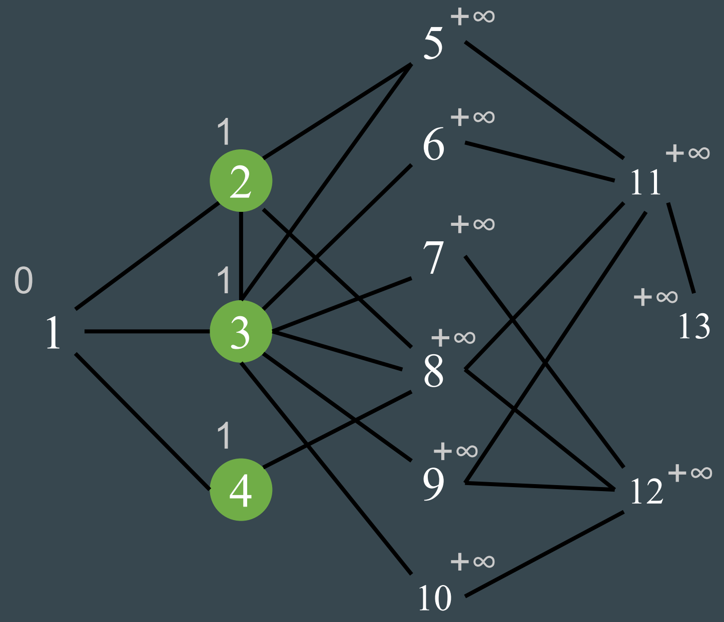


1

Advance + Compute (+1, AtomicCAS)

3 4 2

Example: BFS with Gunrock



1

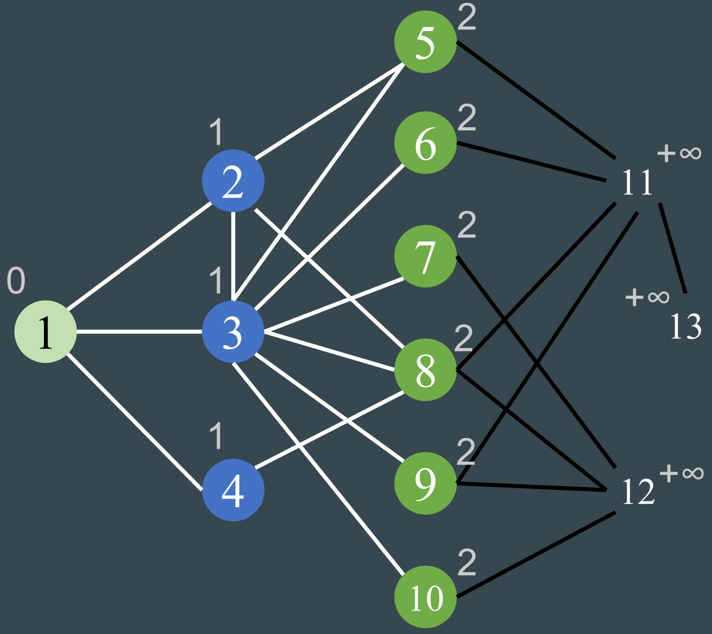
Advance + Compute (+1, AtomicCAS)

3 4 2

Filter

3 4 2

Example: BFS with Gunrock



1

Advance + Compute (+1, AtomicCAS)

3 4 2

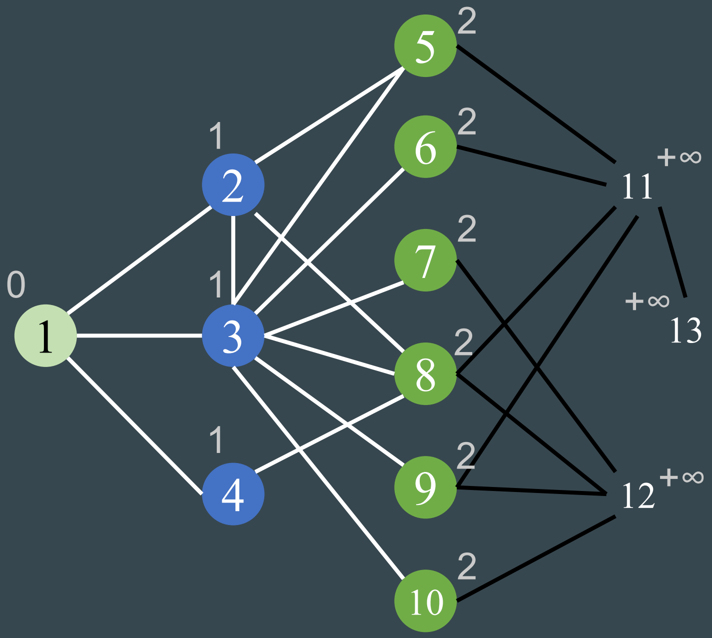
Filter

3 4 2

Advance + Compute (+1, AtomicCAS)

1 2 5 6 7 8 9 10 | 1 8 | 1 3 5 8

Example: BFS with Gunrock



1

Advance + Compute

3 4 2

Filter

3 4 2

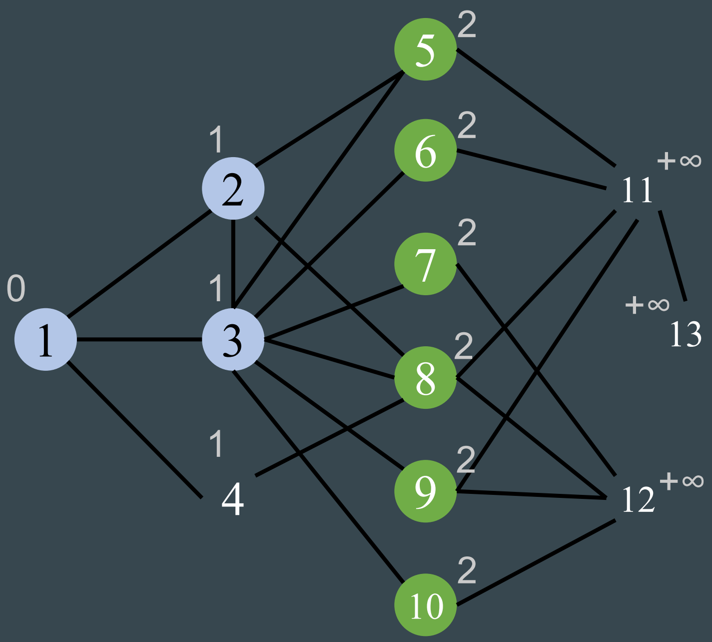
Advance + Compute (+1, AtomicCAS)

1 2 5 6 7 8 9 10 | 1 8 | 1 3 5 8

P: uneven neighbor list lengths (v4 vs. v3)

P: Concurrent discovery conflict (v5,8)

Example: BFS with Gunrock



1

Advance + Compute

3 4 2

Filter

3 4 2

Advance + Compute (+1, AtomicCAS)

1 2 5 6 7 8 9 10 | 1 8 | 1 3 5 8

Filter

6 7 9 10 8 5

P: uneven neighbor list lengths (v4 vs. v3)

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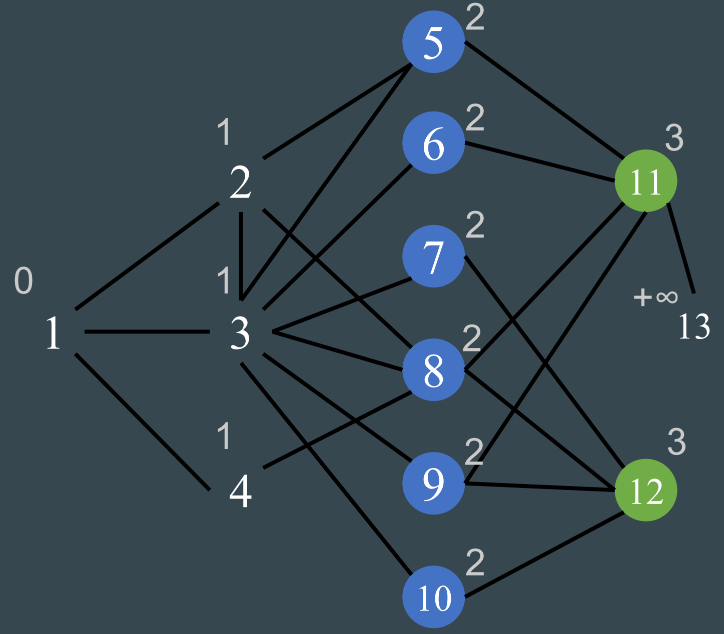
Example: BFS with Gunrock



1

Advance + Compute

3 4 2

Filter

3 4 2

Advance + Compute (+1, AtomicCAS)

1 2 5 6 7 8 9 10 | 1 8 | 1 3 5 8

Filter

6 7 9 10 8 5

Advance + Compute, Filter

11 12

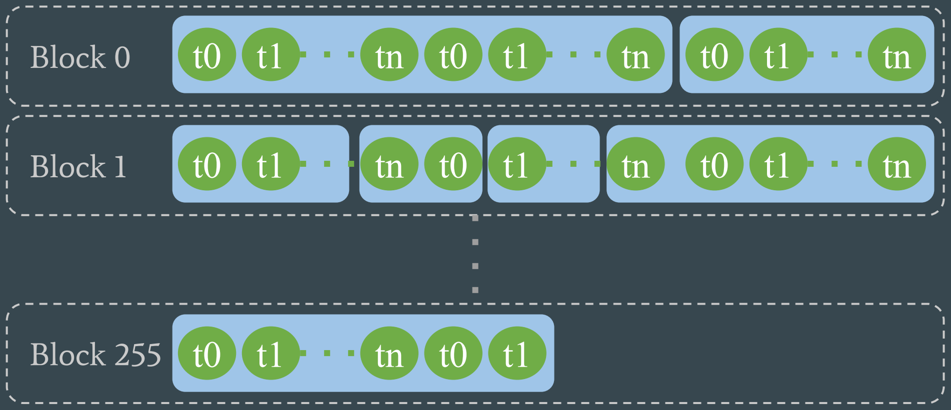
P: uneven neighbor list lengths (v4 vs. v3)

P: Concurrent discovery conflict (v5,8)

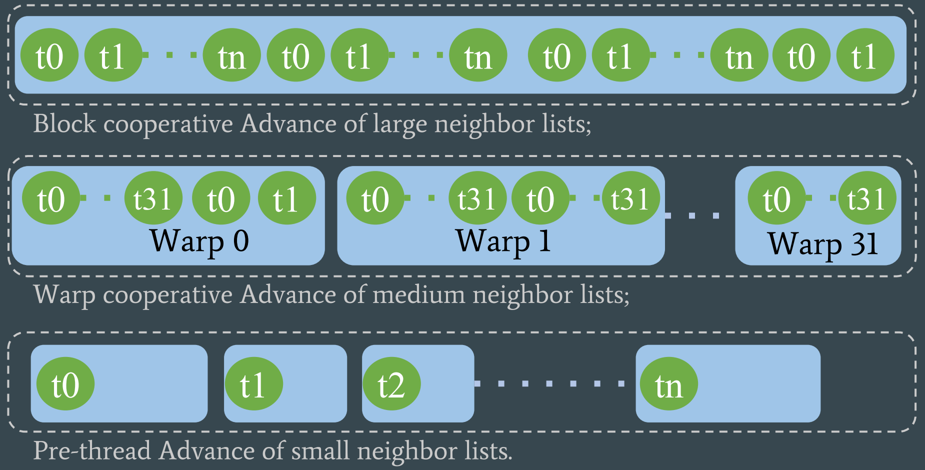
P: From many to very few (v5,6,7,8,9,10 -> v11, 12)

Optimizations: Workload mapping and load-balancing

P: uneven neighbor list lengths
S: trade-off between extra processing and load balancing
First appeared in various BFS implementations, now available for all advance operations



Load-Balanced Partitioning [3]



Per-thread fine-grained, Per-warp and per-CTA coarse-grained [4]

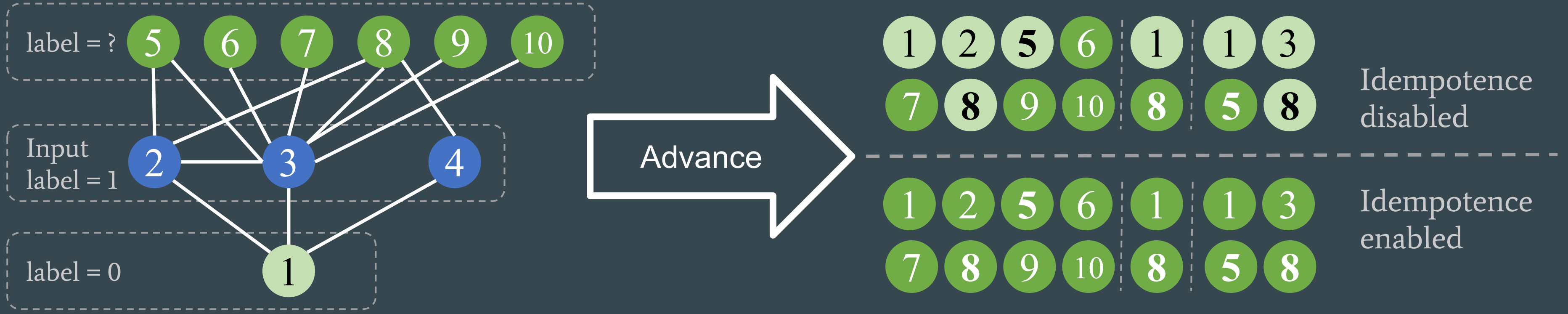
Optimizations: Idempotence

P: Concurrent discovery conflict (v5,8)

S: Idempotent operations (frontier reorganization)

- Allow multiple concurrent discoveries on the same output element
- Avoid atomic operations

First appeared in BFS [4], now available to other primitives



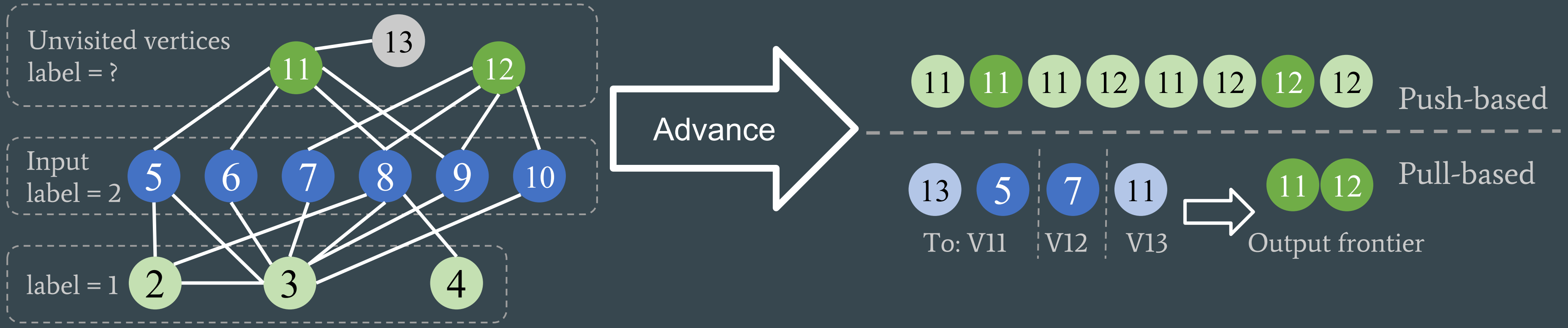
Optimizations: Pull vs. push traversal

P: From many to very few (v5,6,7,8,9,10 -> v11, 12)

S: Pull vs. push operations (frontier generation)

- Automatic selection of advance direction based on ratio of undiscovered vertices

First appeared in DO-BFS [5], now available to other primitives



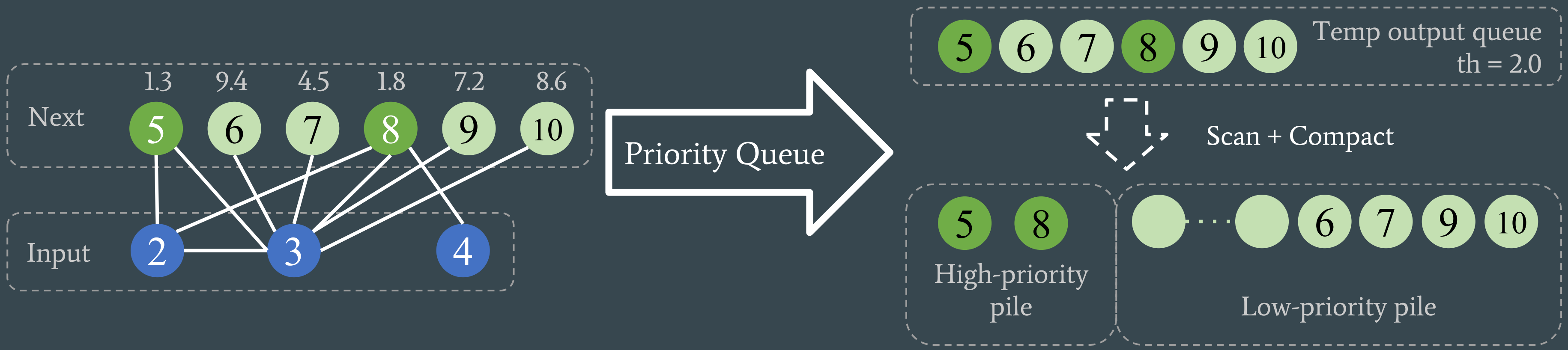
Optimizations: Priority queue

P: A lot of redundant work in SSSP-like primitives

S: Priority queue (frontier reorganization)

- Expand high-priority vertices first

First appeared in SSSP[3], now available to other primitives



Idea: Multiple GPUs

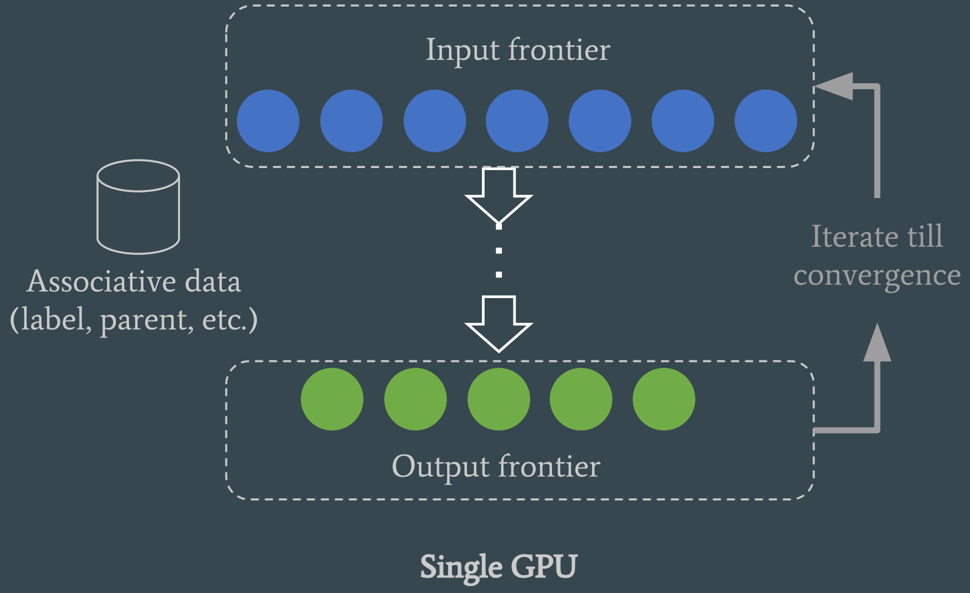
P: Single GPU is not big and fast enough
S: use multiple GPUs
-> larger combined memory space and computing power

P: Multi-GPU program is very difficult to develop and optimize
S: Make algorithm-independent parts into a multi-GPU framework
-> Hide implementation details, and save user's valuable time

P: Single GPU primitives can't run on multi-GPU
S: Partition the graph, renumber the vertices in individual sub-graphs
and do data exchange between super steps
-> Primitives can run on multi-GPUs as it is on single GPU

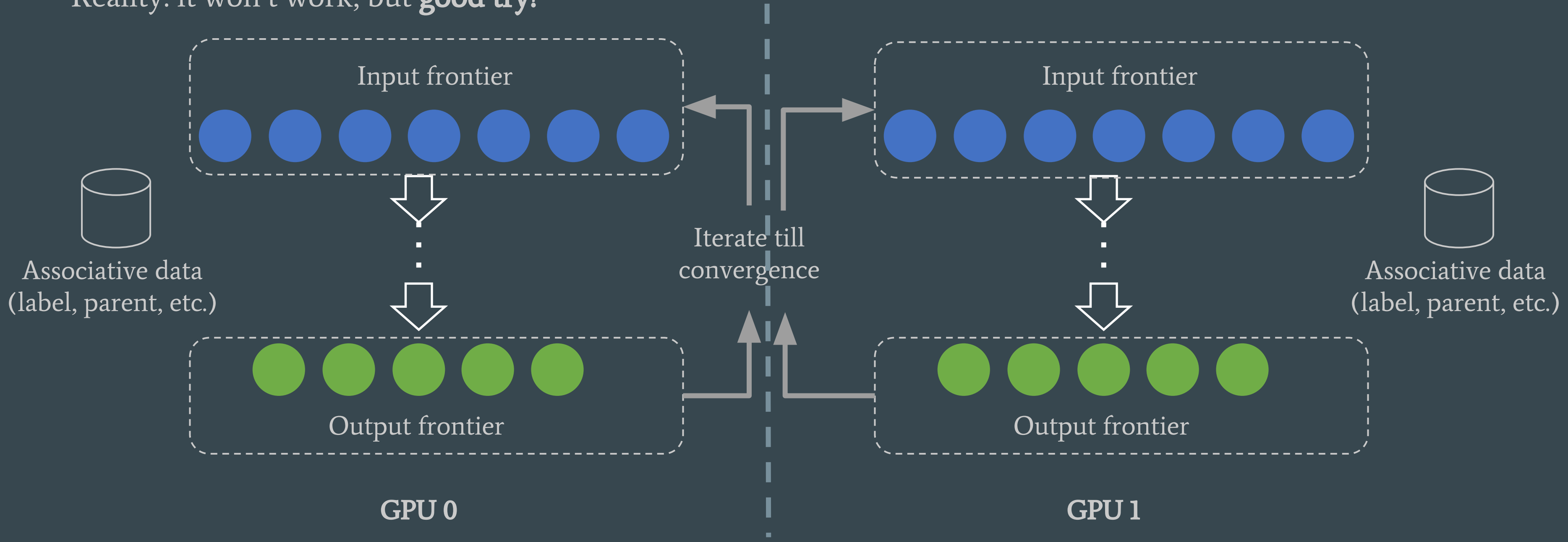
Multi-GPU Framework (for programmers)

Recap: Gunrock on single GPU



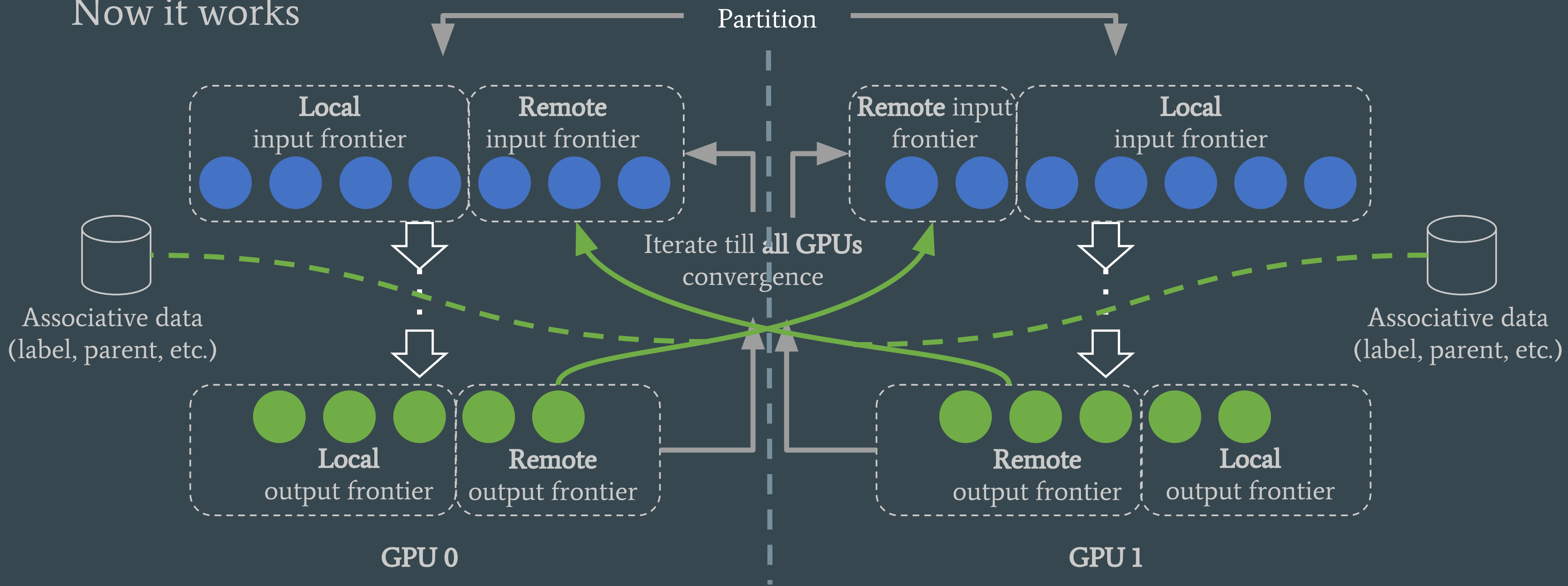
Multi-GPU Framework (for programmers)

Dream: just duplicate the single GPU implementation
Reality: it won't work, but **good try!**

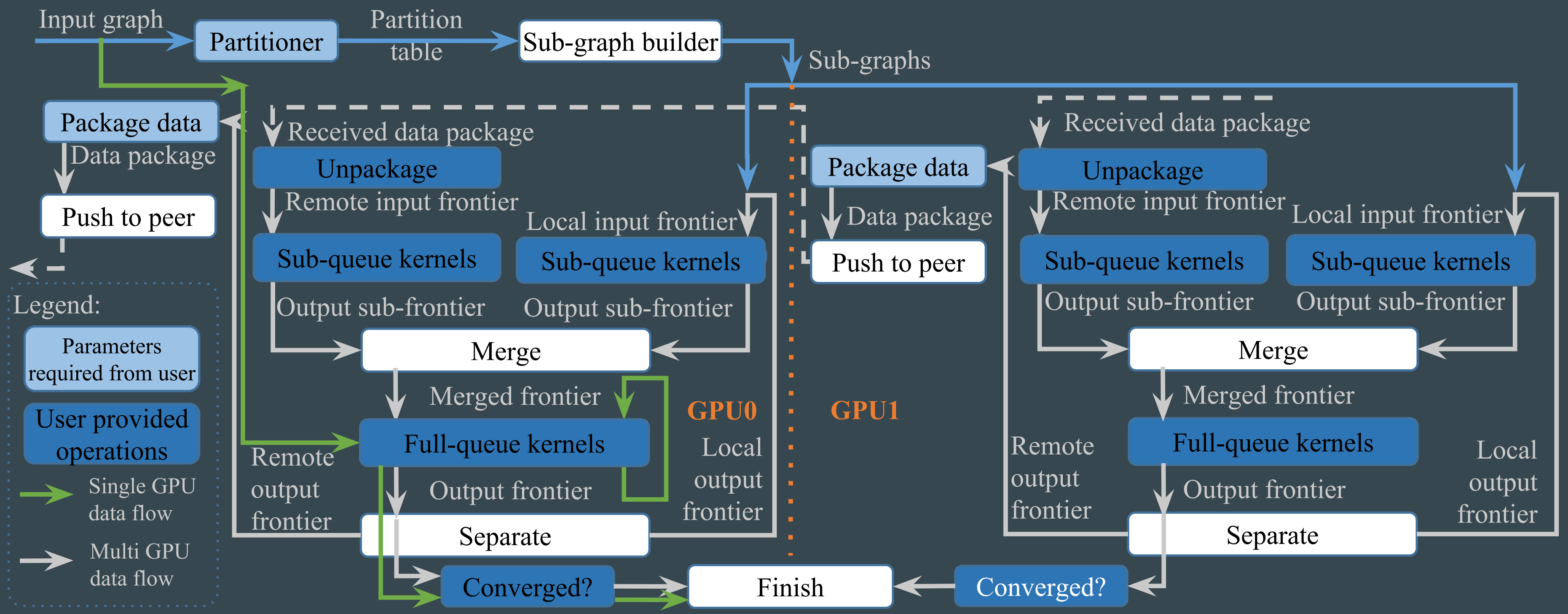


Multi-GPU Framework (for programmers)

Now it works



Multi-GPU Framework (for programmers)



Multi-GPU Framework (for end users)

```
gunrock_executable input_graph --device=0,1,2,3 other_parameters
```

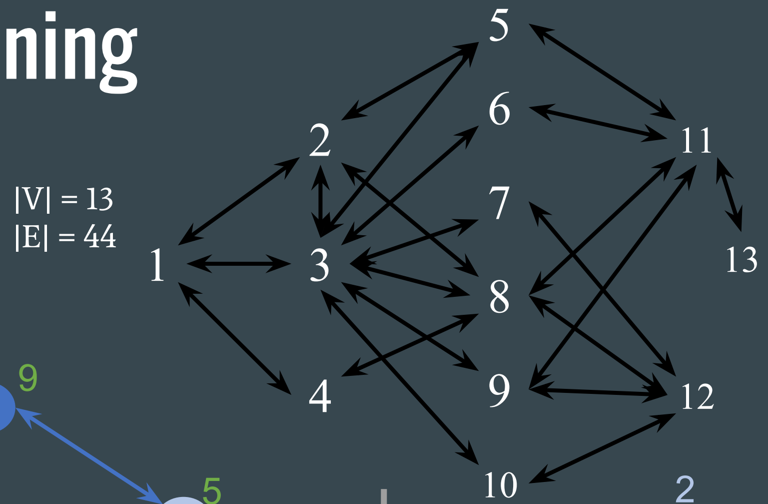
Graph partitioning

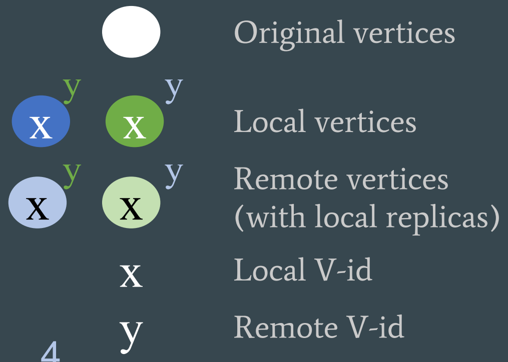
- Distribute the vertices
- Host edges on their sources' host GPU
- Duplicate remote adjacent vertices locally
- Renumber vertices on each GPU

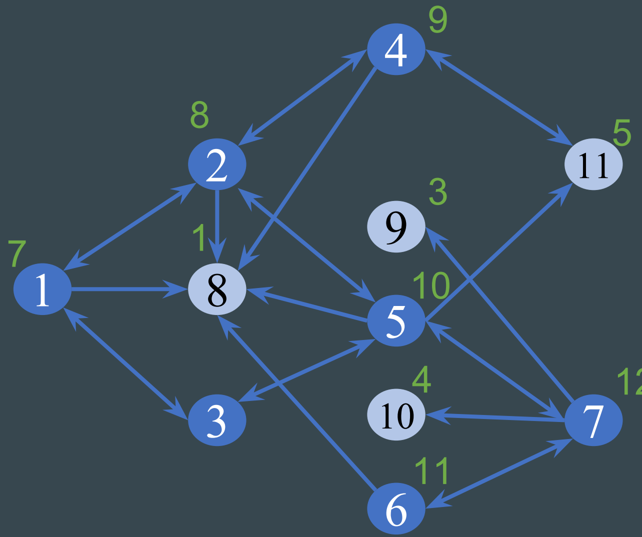
-> Primitives no need to know peer GPUs
-> Local and remote vertices are separated
-> Partitioning algorithm not fixed

P: Still looking for good partitioning algorithm /scheme

Graph partitioning

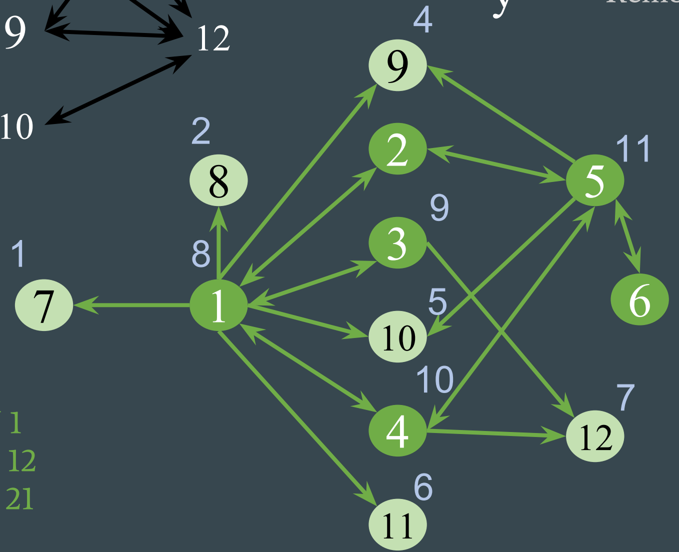






GPU 0
|V| = 11
|E| = 23

GPU 1
|V| = 12
|E| = 21



Optimizations: Multi-GPU Support & Memory Allocation

P: Serialized GPU operation dispatch and execution

S: Multi CPU threads and multiple GPU streams

≥1 CPU threads with multiple GPU streams to control each individual GPUs

-> overlap computation and transmission

-> avoid false dependency

P: Memory requirement only known after advance / filter

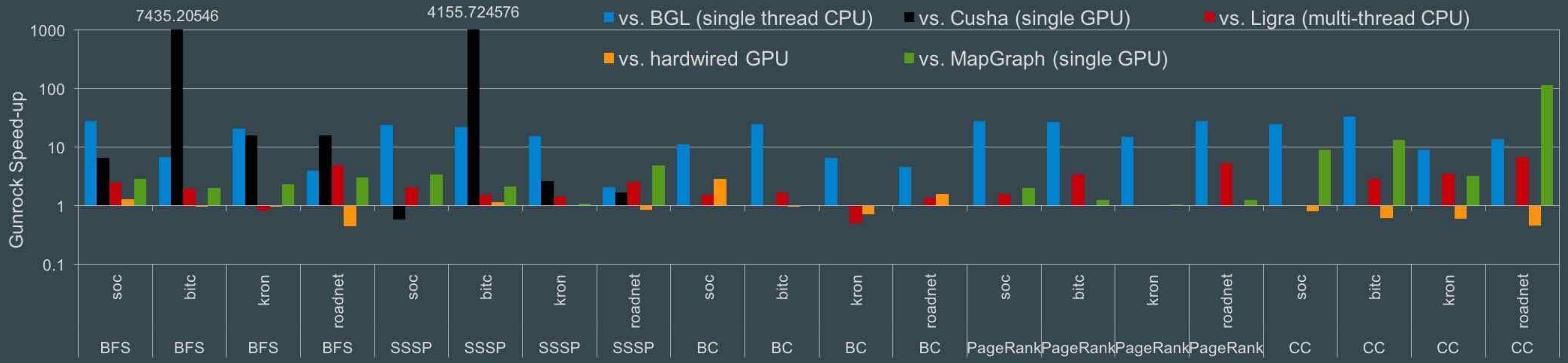
S: Just-enough memory allocation

check space requirement before every possible overflow

-> minimize memory usage

-> can be turned off for performance, if requirements are known (e.g. from previous runs on similar graphs)

Results: Single GPU Gunrock vs. Others



* 17x (avg.) vs. BGL [6], a single thread CPU graph library;
* 2.4x (avg.) vs. Ligra [8], a multi-thread CPU graph library;
* beats Cusha [7] with bitcoin dataset;
* comparable with hardwired GPU implementations,
  some speed-up from applying optimizations across primitives;
* 10x (avg.) vs. MapGraph [9], especially for CC

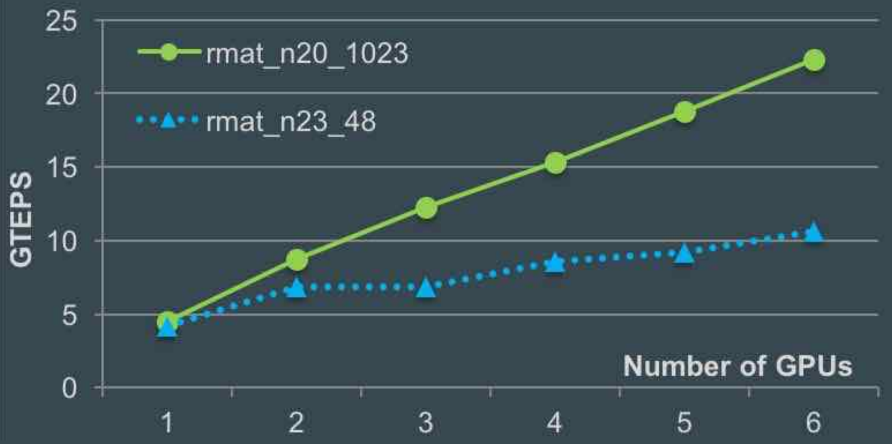
Results: Multi-GPU Gunrock vs. Others (BFS)

	Ref.	Ref. hardware	Ref. performance	Our hardware	Our performance
rmat_n20_128	Merrill et al. [4]	4x Tesla C2050	8.3 GTEPS	4x Tesla K40	11.2 GTEPS
rmat_n20_16	Zhong et al. [10]	4x Tesla C2050	15.4 ms	4x Tesla K40	9.29 ms
peak performance	Fu et al. [9]	16x Tesla K20	15 GTEPS	6x Tesla K40	22.3 GTEPS
peak performance	Fu et al. [11]	16x Tesla K20	29.1 GTEPS	6x Tesla K40	22.3 GTEPS

* ~ 35% faster than Merrill et al.'s results. Their results on > 3-year-old hardware are impressive, though only customized to BFS.
* > 50% faster than Medusa (Zhong et al.), another programmable graph framework.
* 6 GPU peak performance comparable to MapGraph (Fu et al.) using 16 GPU cluster

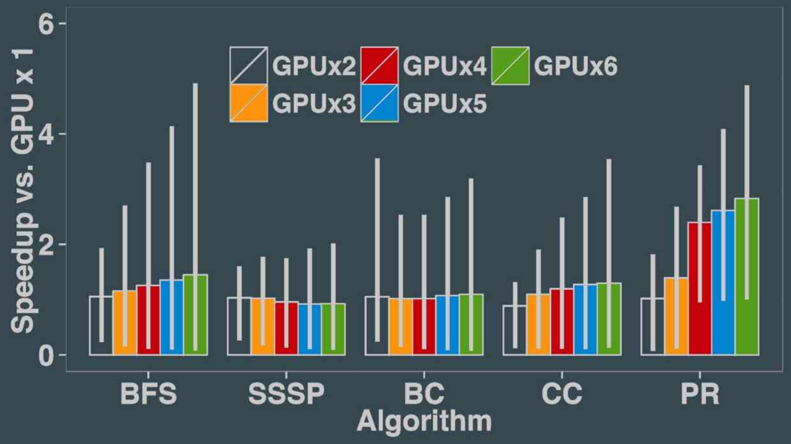
Results: Multi-GPU Scaling

* Traversed edges per sec (TEPS) for BFS→
* Strong scaling on rmat_n22_48 ↓
* Weak scaling on R-MAT graphs (scale 48, each GPU hosting ~180M edges) ↘

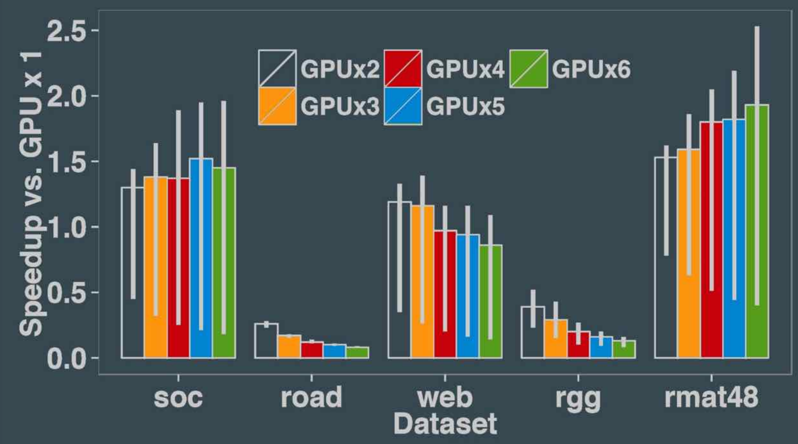


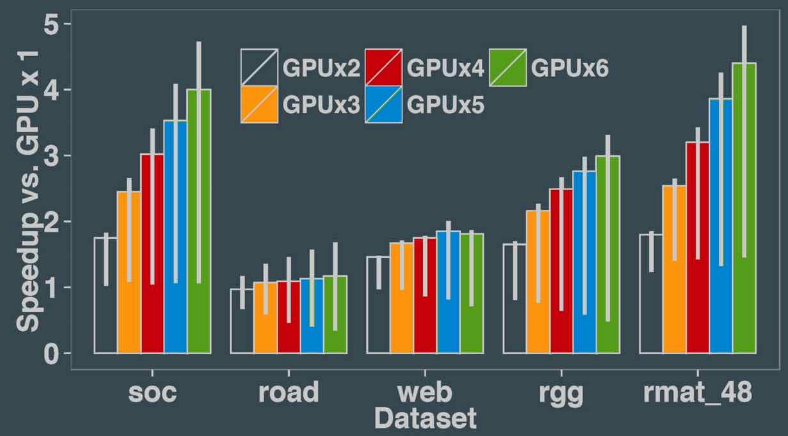
Things that we can improve on

* Partitioning
* Inter-iteration overhead
* Long tail / small frontier issue



Speedup of 5 algorithms (→), BFS (↙) and PR (↘)





Current Status

Open source, available @
http://gunrock.github.io/

It has over 10 graph primitives
* traversal-based, node-ranking, global (CC, MST)
* LOC $\leq$ 10 to use a primitive
* LOC $\leq$ 300 to program a new primitive
* Good balance between performance and programmability

Multi-GPU framework under major revision
* use circular-queue for better scheduling and smaller overhead
* extendable onto multi-node usage

More graph primitives are coming
* graph coloring, maximum independent set, community detection, subgraph matching

Future Work

* Multi-node support with NVLink
* Performance analysis and optimization
* Graph BLAS
* Asynchronized graph algorithms
* Fixed partitioning / 2D partitioning
* Global, neighborhood, and sampling operations
* More graph primitives
* Dynamic graphs
* Kernel fusion
* ...

Acknowledgment

The Gunrock team

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For their discussion on library development and dataset generating code

All code contributors to the Gunrock library

NVIDIA

For hardware support, GPU cluster access, and all other supports and discussions

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* DARPA STTR award D14PC00023

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[11] Z. Fu, H. K. Dasari, B. Bebee, M. Berzins, and B. Thompson. Parallel breadth first search on GPU clusters. In IEEE International Conference on Big Data, pages 110-118, Oct. 2014.

Questions?

Q: How can I find Gunrock?
A: http://gunrock.github.io/

Q: Is it free and open?
A: Absolutely (under Apache License v2.0)

Q: Papers, slides, etc.?
A: https://github.com/gunrock/gunrock#publications

Q: Requirements?
A: CUDA ≥ 5.5, GPU compute capability ≥ 3.0, Linux || Mac OS

Q: Language?
A: C/C++, with a simple wrapper connects to Python

Q: ... (continue)

Example python interface - breadth-first search

```
from ctypes import *
### load gunrock shared library - libgunrock
gunrock = cdll.LoadLibrary('../../build/lib/libgunrock.so')

### read in input CSR arrays from files
row_list = [int(x.strip()) for x in open('toy_graph/row.txt')]
col_list = [int(x.strip()) for x in open('toy_graph/col.txt')]

### convert CSR graph inputs for gunrock input
row = pointer((c_int * len(row_list))(*row_list))
col = pointer((c_int * len(col_list))(*col_list))
nodes = len(row_list) - 1
edges = len(col_list)

### output array
labels = pointer((c_int * nodes)())

### call gunrock function on device
gunrock.bfs(labels, nodes, edges, row, col, 0)

### sample results
print ' bfs labels (depth):',
for idx in range(nodes): print labels[0][idx],
```