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

Yangzihao Wang and Yuechao Pan with Andrew Davidson, Yuduo Wu, Carl Yang, Leyuan Wang, Andy Riffel and John D. Owens
University of California, Davis
{yzhwang, ychpan}@ucdavis.edu

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

Current Graph Processing Systems

Single-node CPU-based systems: Boost Graph Library

Multi-CPU systems: Ligra, Galois

Distributed CPU-based systems: PowerGraph

Specialized GPU algorithms

GPU-based systems: CuSha, Medusa, Gunrock...

Why Gunrock?

- Data-centric abstraction is designed for GPU
- Our APIs are simple and flexible
- Our optimizations achieve high performance
- Our framework enables multi-GPU integration

What we want to achieve with Gunrock?

Performance

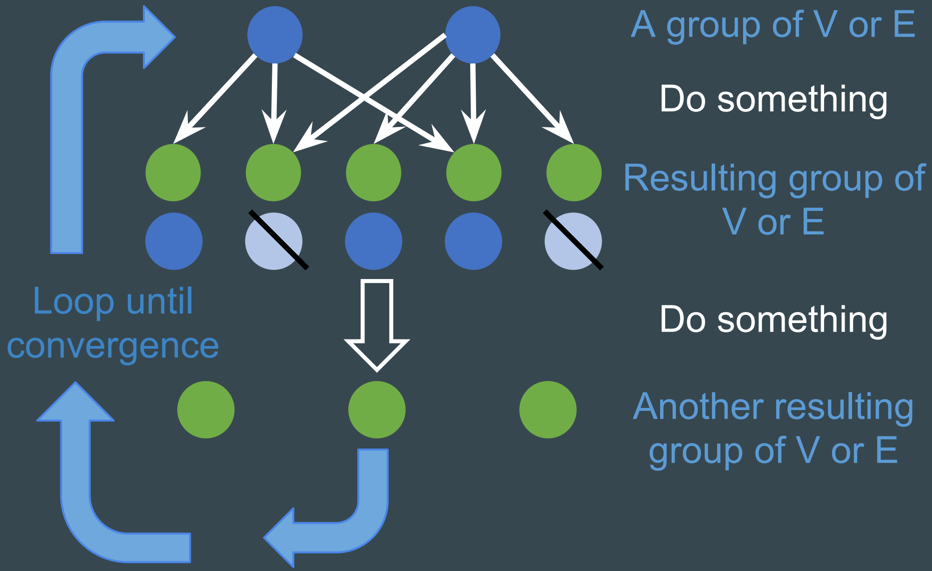
- High performance GPU computing primitives
- High performance framework
- Optimizations
- Multi-GPU capability

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

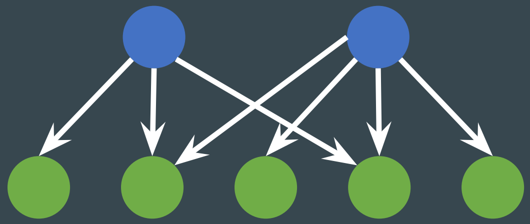
=> Operations = manipulations of frontiers

Bulk-synchronous programming

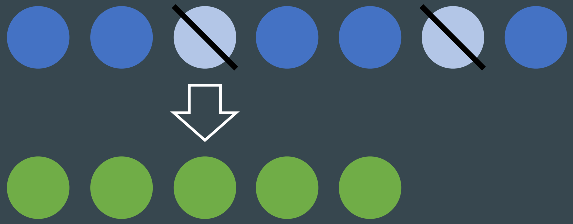
- Operations are done one by one, in order
- Within a single operation, computing on multiple elements can be done in parallel, without order

Gunrock's Operations on Frontiers

Generation

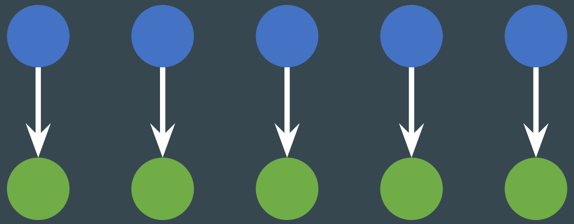


Advance: visit neighbor lists



Filter: select and reorganize

Computation



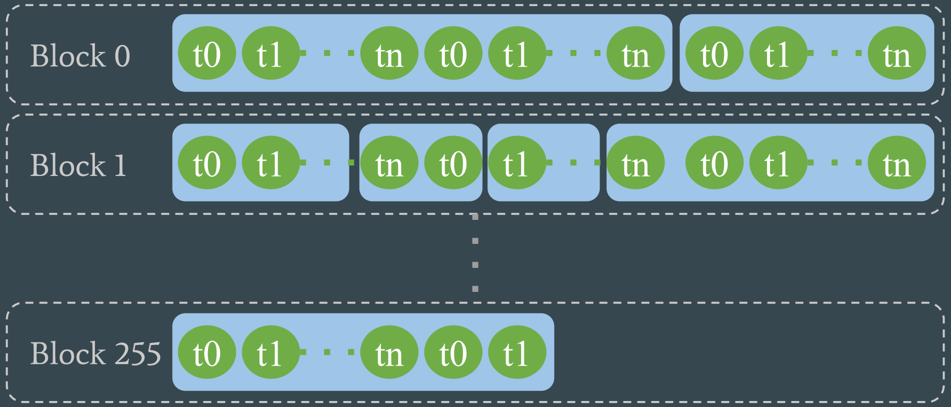
Compute: per-element computation, in parallel
can be combined with advance or filter

Optimizations: Workload mapping and load-balancing

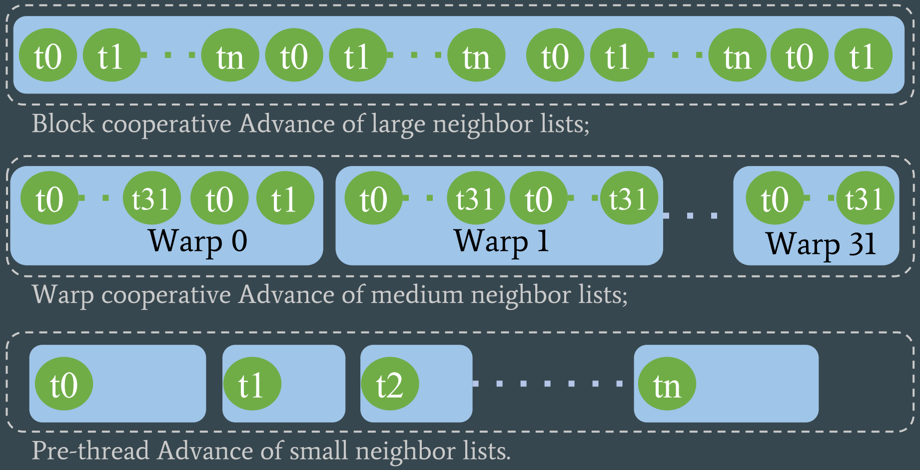
P: uneven neighbor list lengths

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]

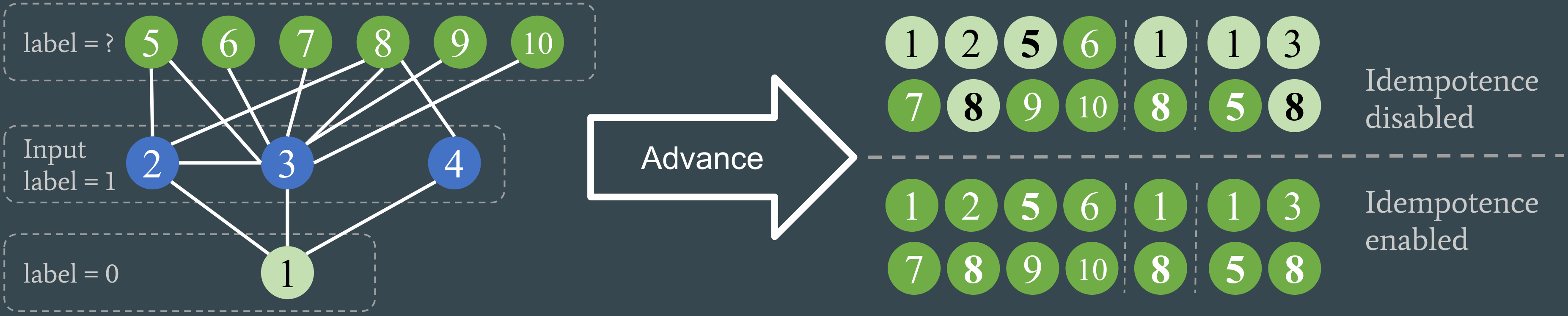
Optimizations: Idempotence

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



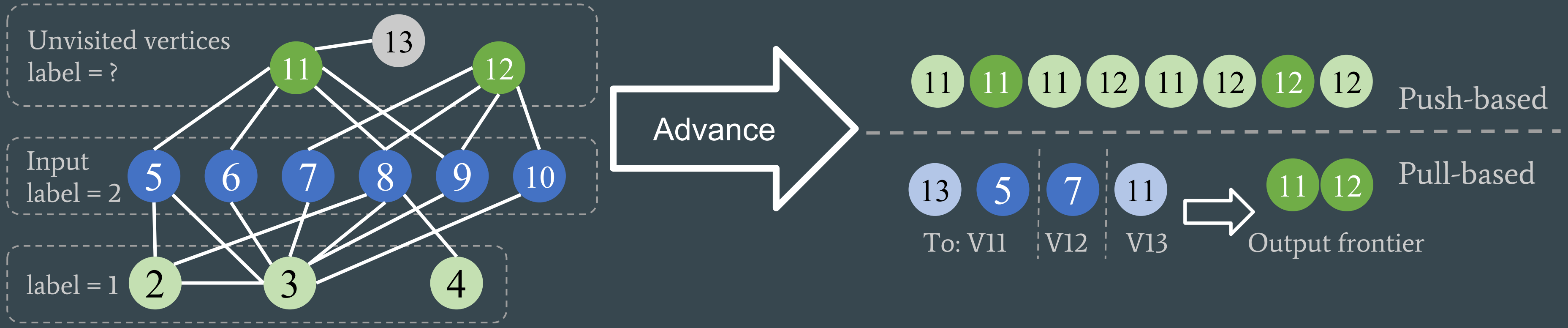
Optimizations: Pull vs. push traversal

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



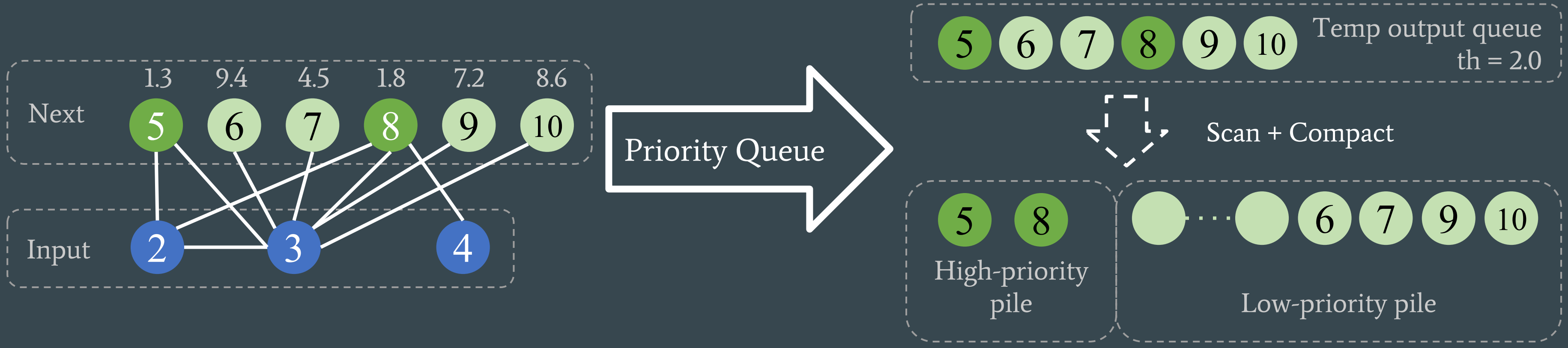
Optimizations: Priority queue

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

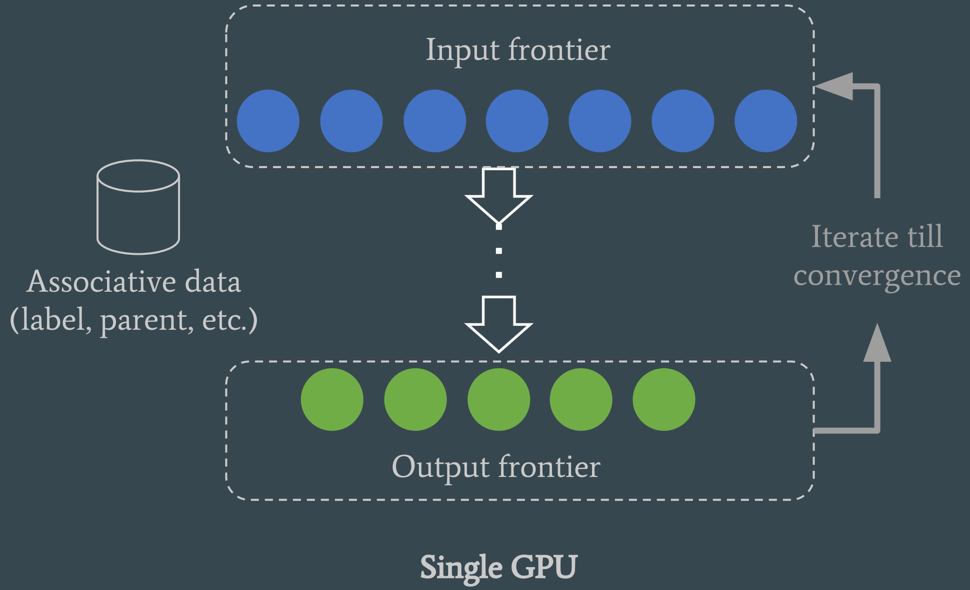
P: Single GPU is not big and fast enough
S: use multiple GPUs
-> larger combined memory space and computing power

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

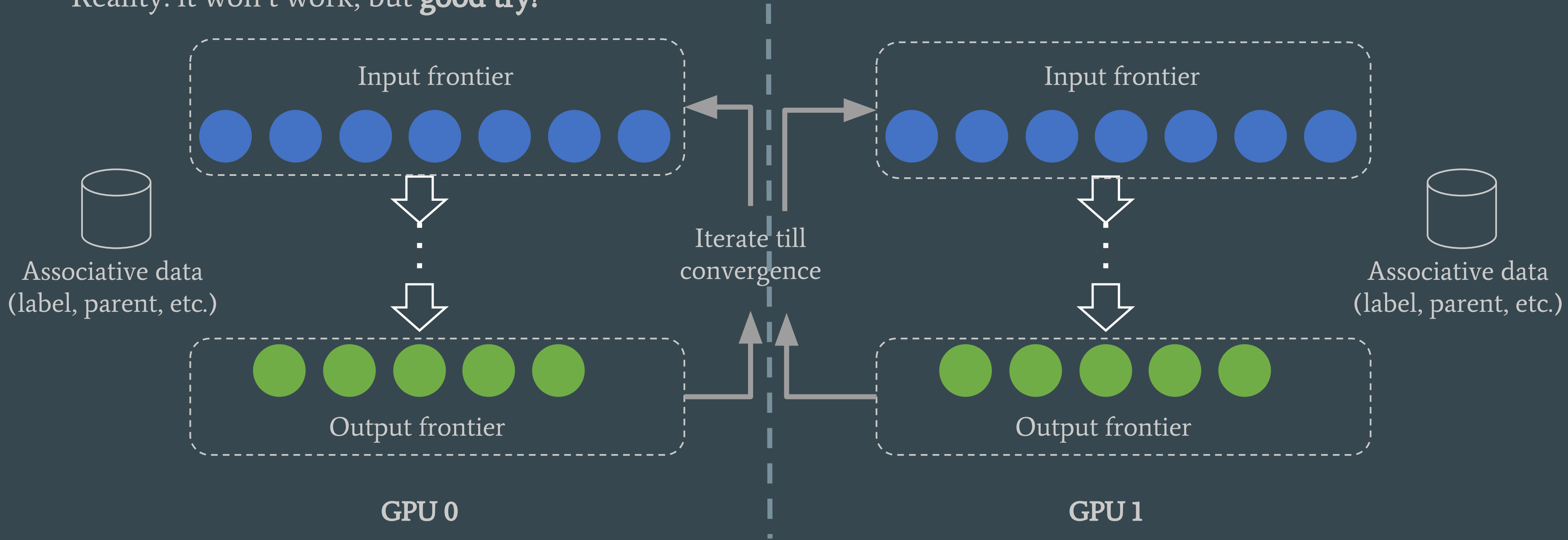
Multi-GPU Framework (for programmers)

Recap: Gunrock on single GPU



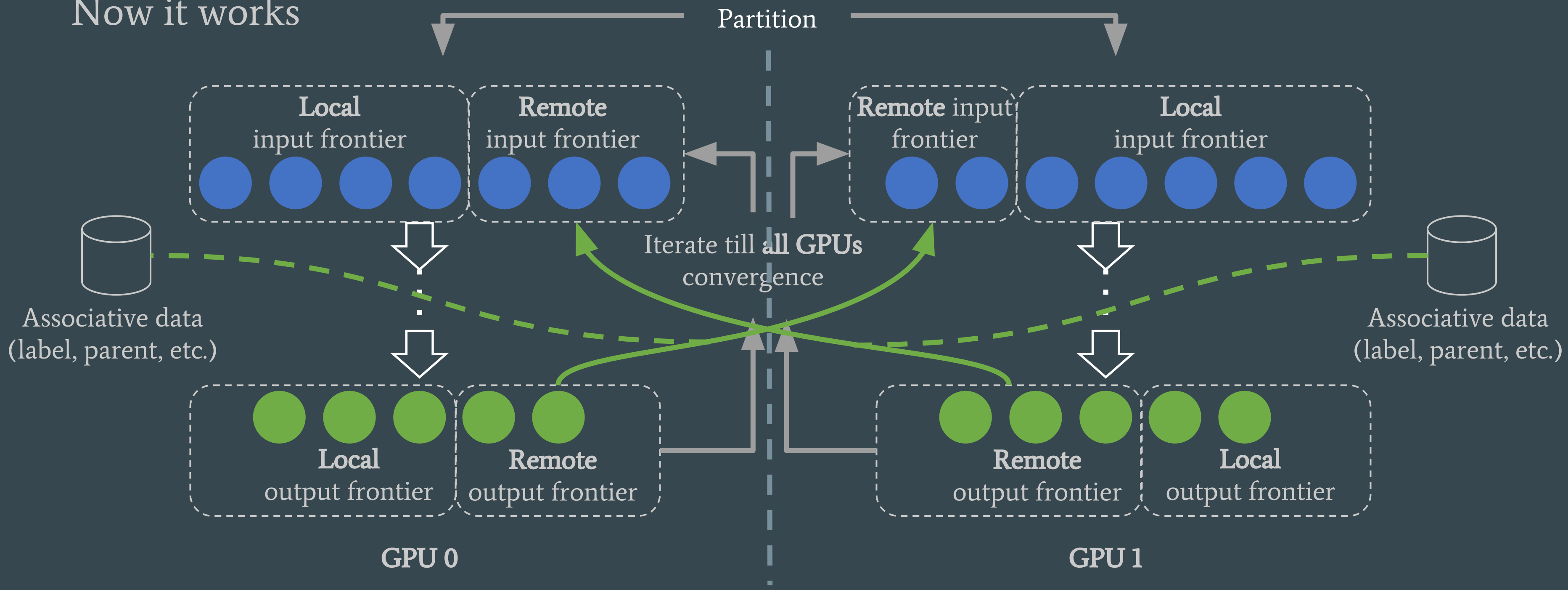
Multi-GPU Framework (for programmers)

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 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 (optional)

-> 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

Optimizations: Multi-GPU Support & Memory Allocation

P: Serialized GPU operation dispatch and execution

S: Multi CPU threads and multiple GPU streams

$\geq$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

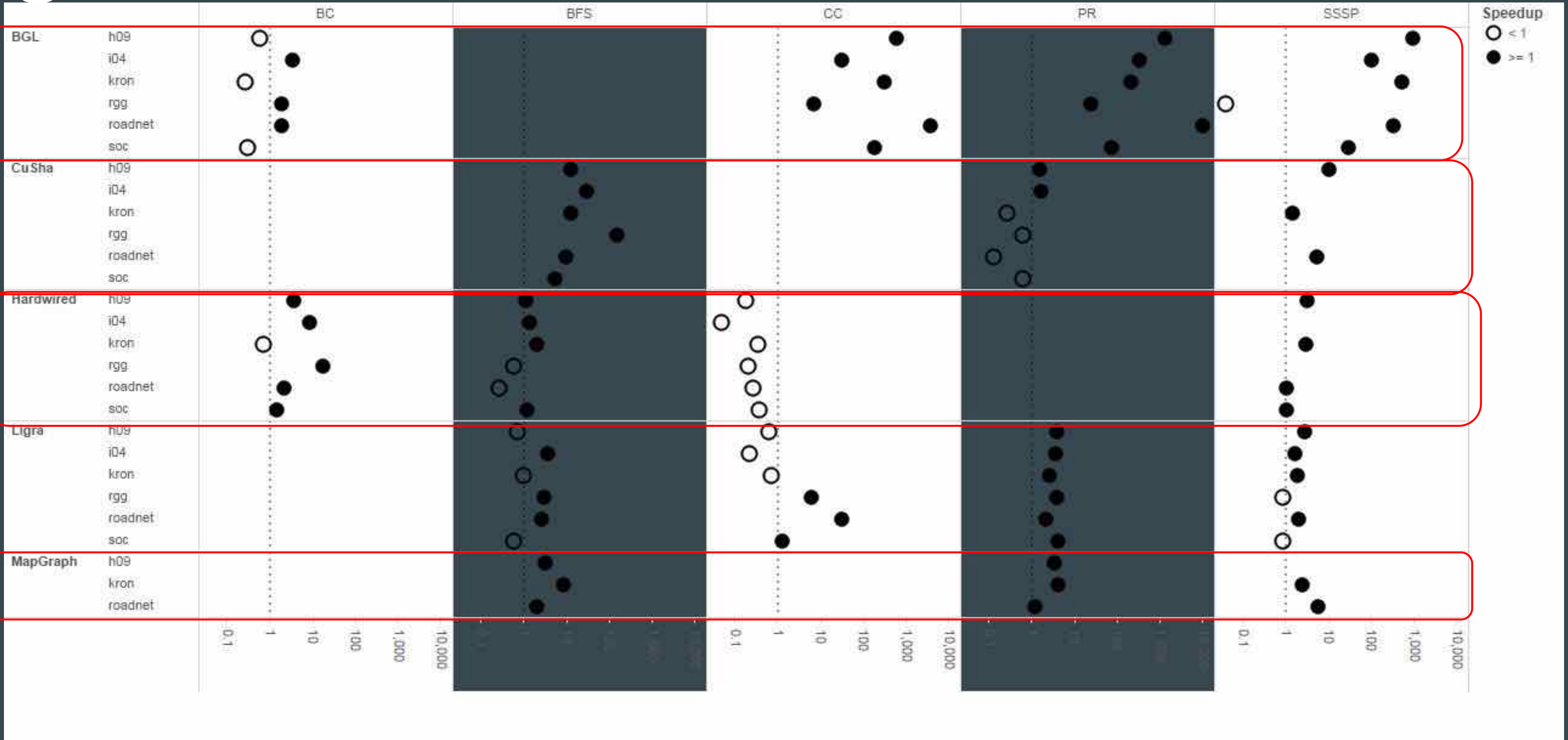
-> can be turned off for performance, if requirements are known (e.g. from previous runs on similar graphs)

Results:
Single GPU Gunrock vs. Others

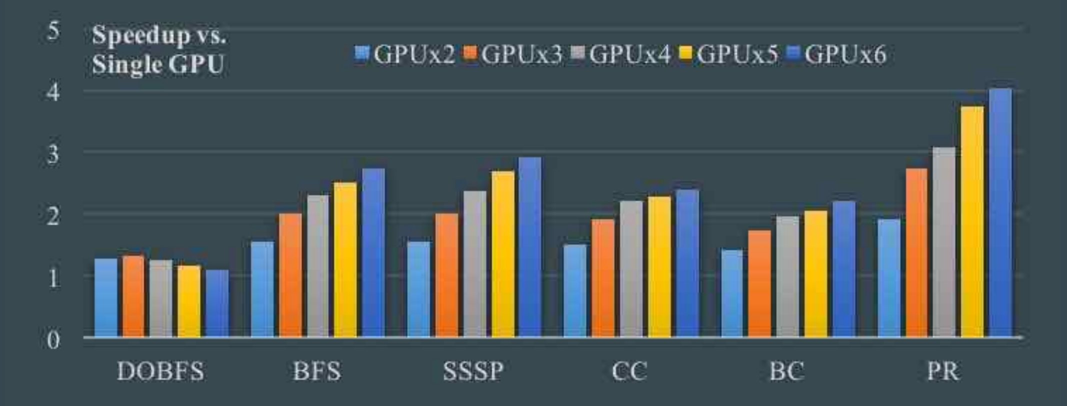
6x-337x speedup on avg over all primitives compared to BGL and PowerGraph.

Outperforms both CuSha and MapGraph.

Comparable to hardwired implementation.



Results: Multi-GPU Scaling



* Primitives (except DOBFS) get good speedups (averaged over 16 datasets of various types)
BFS: 2.74x, SSSP: 2.92x, CC: 2.39x, BC: 2.22x, PR: 4.03x using 6 GPUs

* Peak DOBFS performance: 514 GTEPS with rmat_n20_512

* Gunrock is able to process graph with 3.6B edges (full-friendster graph, undirected, DOBFS in 339ms, 10.7 GTEPS using 4 K40s), 50 PR iterations on the directed version (2.6B edges) took ~51 seconds

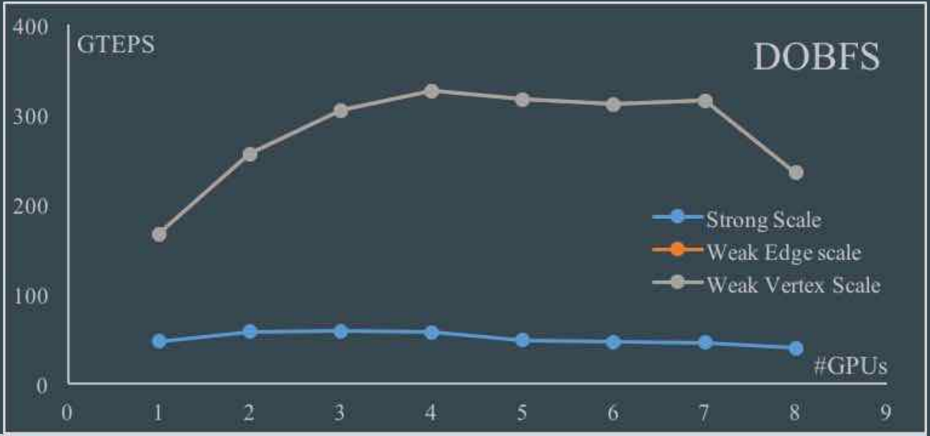
Results: Multi-GPU Scaling

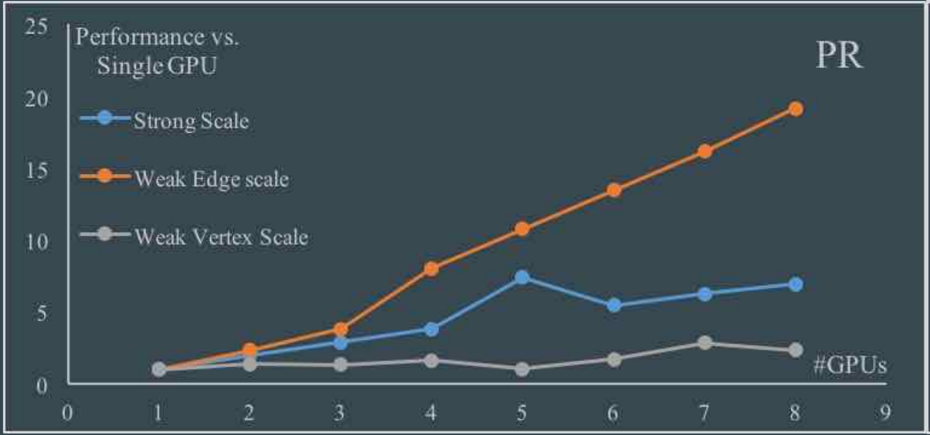
*Strong: Rmat_n24_32

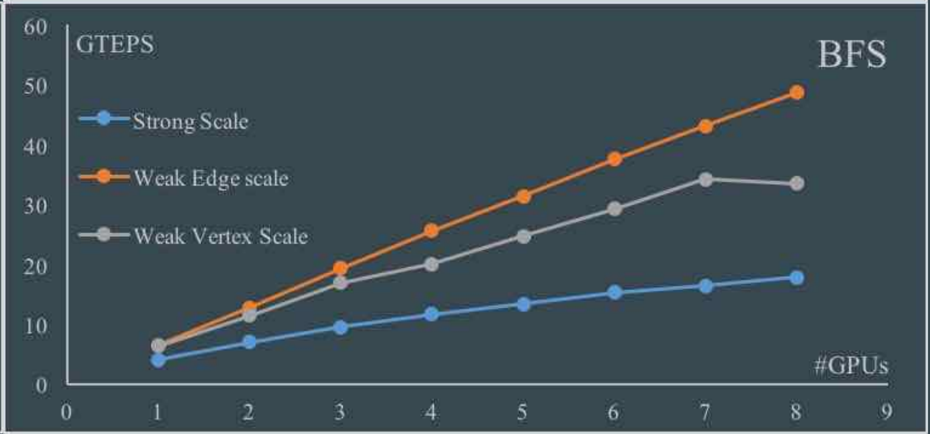
*Weak edge: Rmat_n19_256 * #GPUs

*Weak vertex: Rmat_2^{19} * #GPUs_256

Mostly linear, except for DOBFS strong scaling







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

graph	algo	ref.	ref. hw.	ref. perf.	our hw.	our perf.	comp.
com-orkut (3M, 117M, UD)	BFS	Bisson [5]	1×K20X×4	2.67 GTEPS	4×K40	14.22 GTEPS	5.33X
com-Friendster (66M, 1.81B, UD)	BFS	Bisson [5]	1×K20X×64	15.68 GTEPS	4×K40	14.1 GTEPS	0.90X
kron_n23_16 (8M, 256M, UD)	BFS	Bernaschi [4]	1×K20X×4	~1.3 GTEPS	4×K40	30.8 GTEPS	23.7X
kron_n25_16 (32M, 1.07G, UD)	BFS	Bernaschi [4]	1×K20X×16	~3.2 GTEPS	6×K40	31.0 GTEPS	9.69X
kron_n25_32 (32M, 1.07G, D)	BFS	Fu [13]	2×K20×32	22.7 GTEPS	4×K40	32.0 GTEPS	1.41X
kron_n23_32 (8M, 256M, D)	BFS	Fu [13]	2×K20×2	6.3 GTEPS	4×K40	27.9 GTEPS	4.43X
kron_n24_32 (16.8M, 1.07G, UD)	BFS	Liu [23]	2×K40	15 GTEPS	2×K40	77.7 GTEPS	5.18X
kron_n24_32 (16.8M, 1.07G, UD)	BFS	Liu [23]	8×k40	18.4 GTEPS	4×K80	40.2 GTEPS	2.18X
twitter-mpi (52.6M, 1.96G, D)	BFS	Bebee [3]	1×K40×16	0.2242 sec	3×K40	94.31 ms	2.38X

* graph format: name (|V|, |E|, directed (D) or undirected (UD))
* ref. hw. format: #GPU per node x GPU model x #nodes
* Gunrock out-performs or close to small GPU clusters using 4 ~ 64 GPUs, on both real and generated graphs
* a few times faster than Enterprise (Liu et al., SC15), a dedicated multi-GPU DOBFS implementation

Current Status

Open source, available @

http://gunrock.github.io/

It has over 10 graph primitives

* traversal-based, node-ranking, global (CC, MST)
* LOC ≤ 10 to use a primitive
* LOC ≤ 300 to program a new primitive
* Good balance between performance and programmability

Multi-GPU framework going to support multi-node GPU cluster

* 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
* ...

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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 ≥ 7.5, GPU compute capability ≥ 3.0, Linux || Mac OS

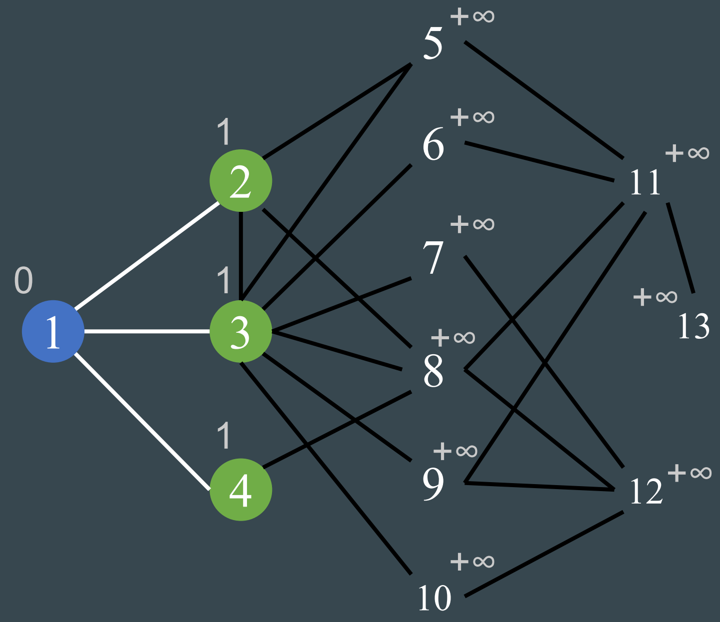
Q: Language?
A: C/C++, with a simple wrapper connects to Python

Q: ... (continue)

Example python interface - breadth-first search

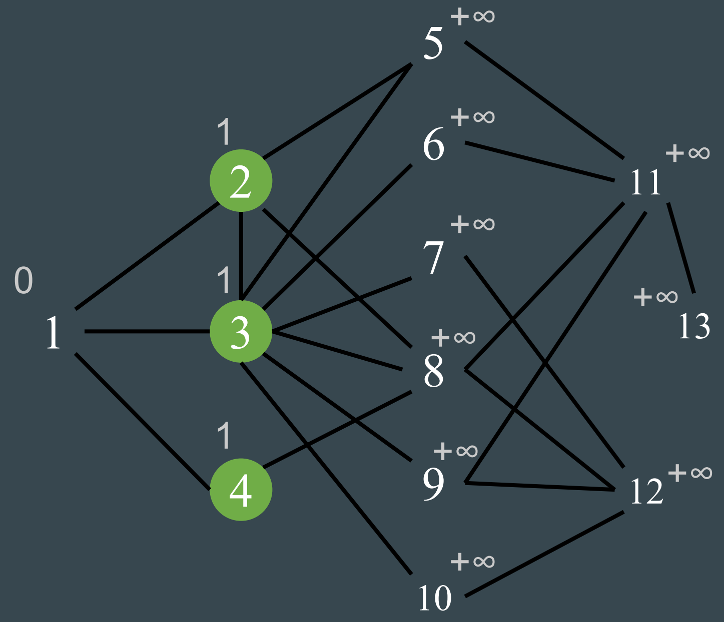
```
from ctypes import *
### load gunrock shared library - libgunrock
gunrock = cdll.LoadLibrary('../../build/lib/libgunrock.so')

### 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],
```

Example: BFS with Gunrock



Advance + Compute (+1, AtomicCAS)

Example: BFS with Gunrock



1

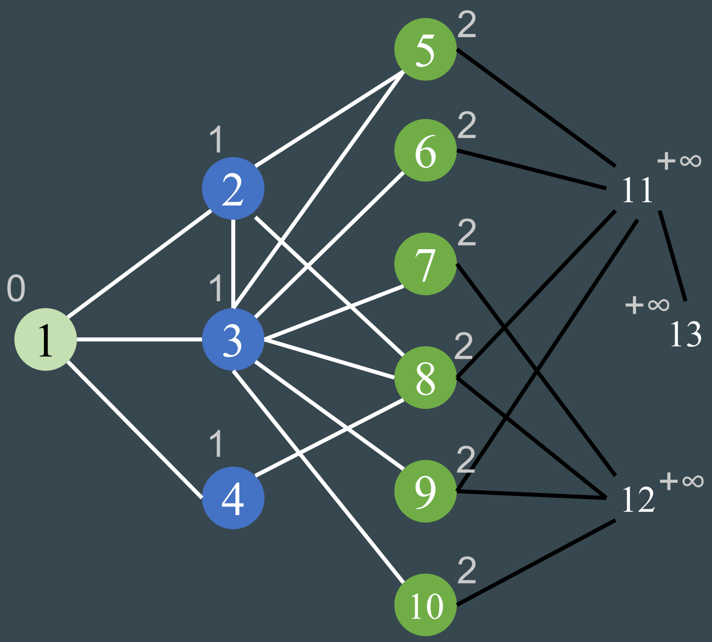
Advance + Compute (+1, AtomicCAS)

3 4 2

Filter

3 4 2

Example: BFS with Gunrock



1

Advance + Compute (+1, AtomicCAS)

3 4 2

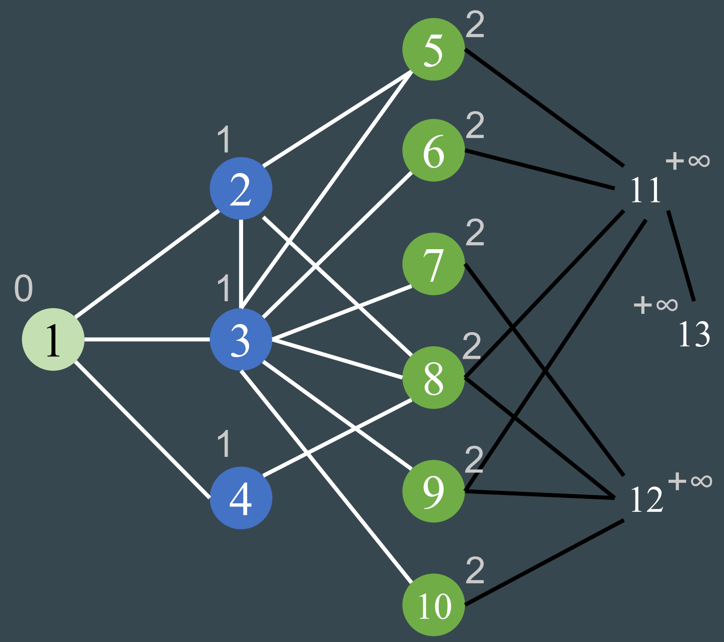
Filter

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

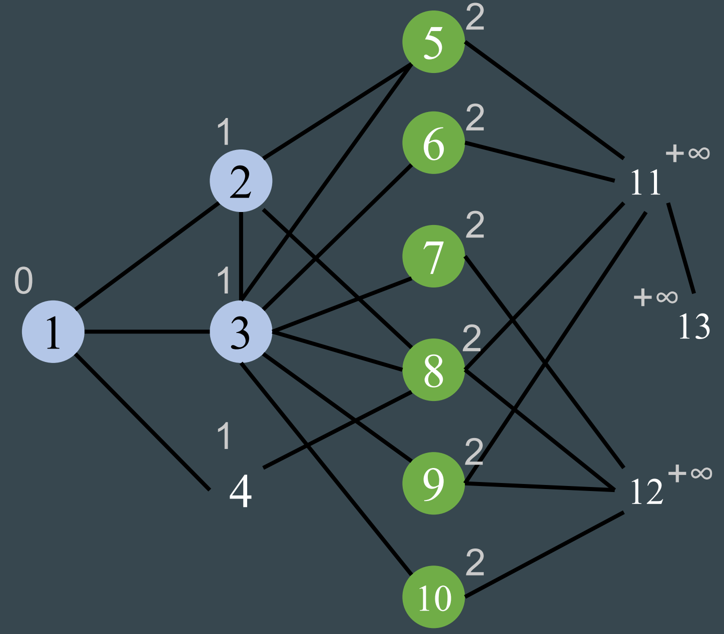
Advance + Compute (+1, AtomicCAS)

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

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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

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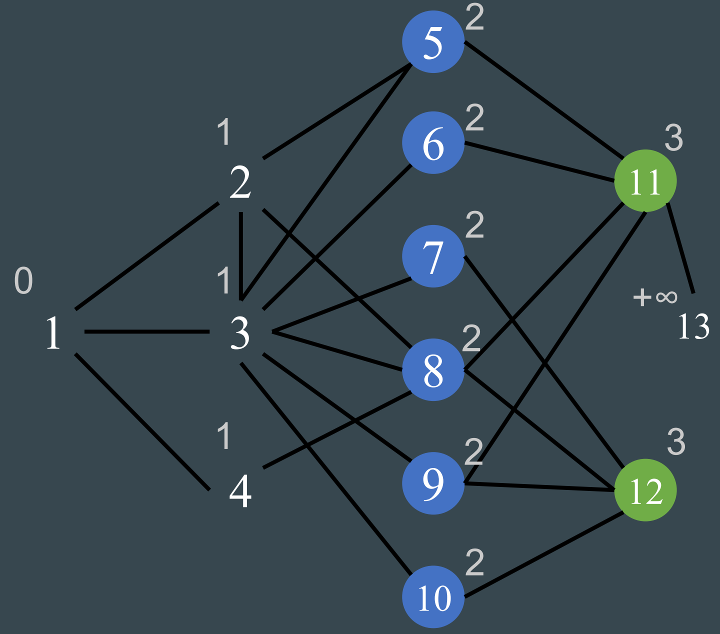
Example: BFS with Gunrock



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

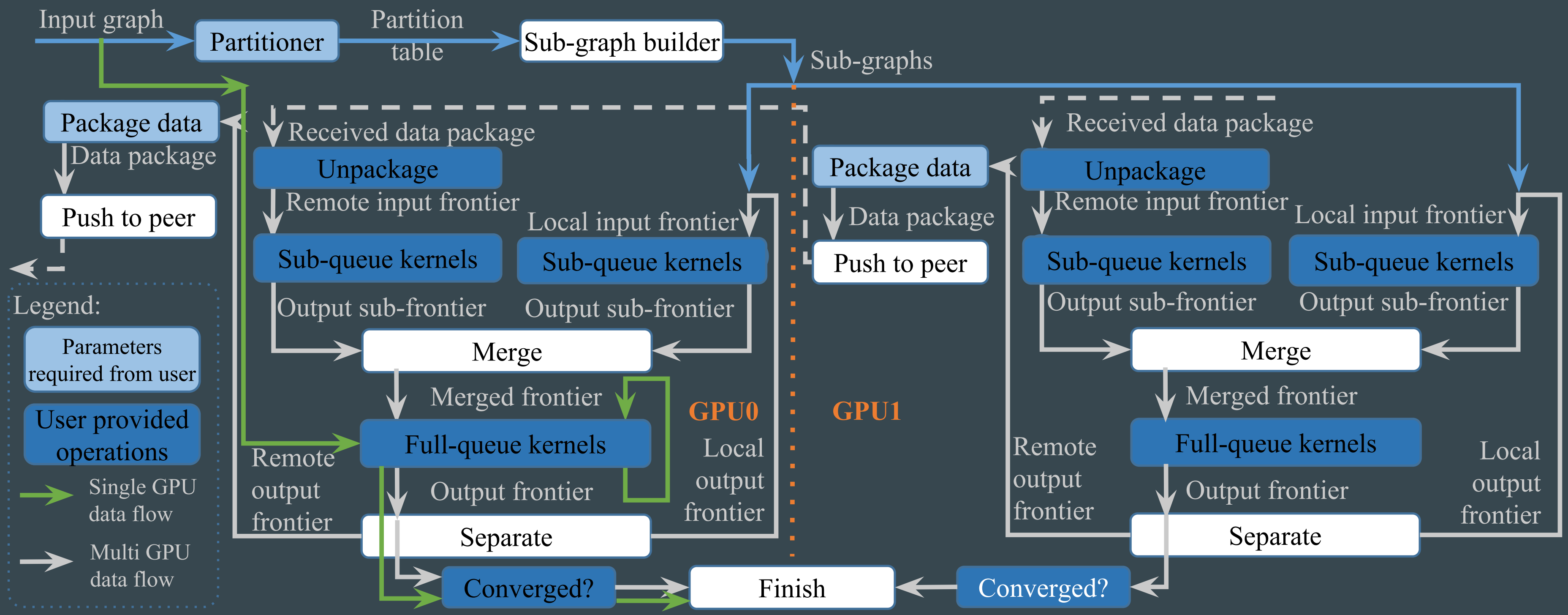
11 12

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)

Multi-GPU Framework (for programmers)



Graph partitioning