

# GraphChi

Steven Krieg

# Background & Big Idea

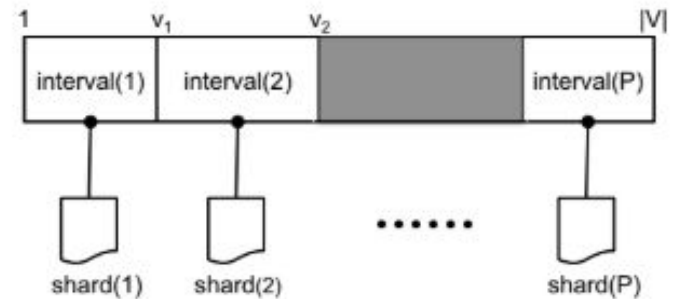
- Carnegie Mellon, 2012
- “Large-Scale Graph Computation on Just a PC”

How do we process graphs that exceed available memory?

# The Solution: Secondary Storage

Graphs are divided into groups of vertices (intervals) and edges (shards).

Intervals are loaded one at a time into memory for processing.

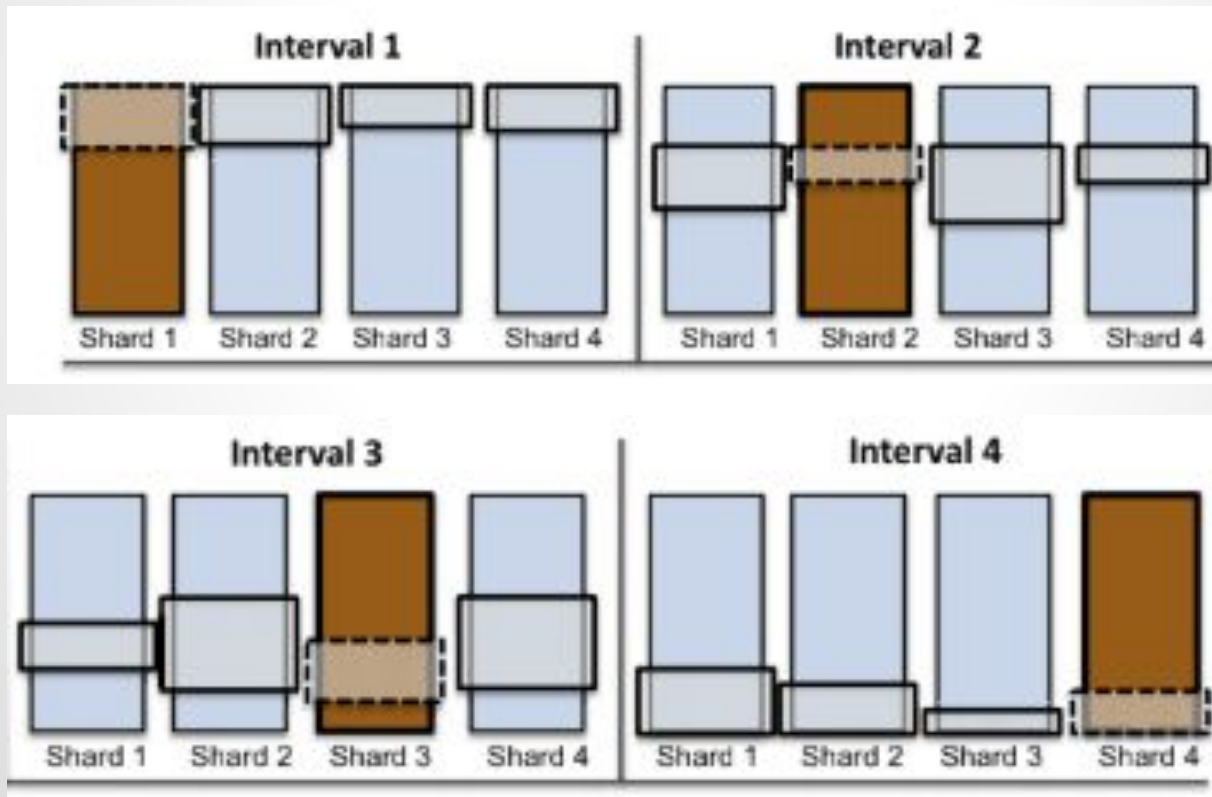


**Interval:** a group of vertices that will be updated in the same execution step

**Shard:** list of edges whose destination vertex is in the interval

1:1 relationship

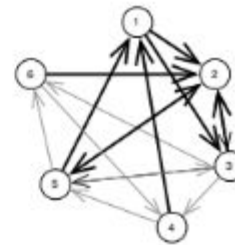
# “Parallel Sliding Windows”



# “Parallel Sliding Windows”

Shard 1			Shard 2			Shard 3		
src	dst	value	src	dst	value	src	dst	value
1	2	0.3	1	3	0.4	2	5	0.6
3	2	0.2	2	3	0.3	3	5	0.9
4	1	1.4	3	4	0.8	4	5	0.3
5	1	0.5	5	3	0.2	5	6	1.1
6	2	0.6	6	4	1.9	6	6	1.1
6	2	0.8						

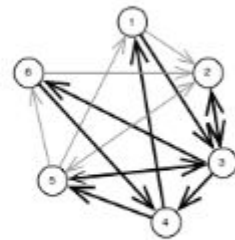
(a) Execution interval (vertices 1-2)



(b) Execution interval (vertices 1-2)

Shard 1			Shard 2			Shard 3		
src	dst	value	src	dst	value	src	dst	value
1	2	0.273	1	3	0.364	2	5	0.545
3	2	0.22	2	3	0.273	3	5	0.9
4	1	1.54	3	4	0.8	4	5	0.3
5	1	0.55	5	3	0.2	5	6	1.1
6	2	0.66	6	4	1.9	6	6	1.1
6	2	0.88						

(c) Execution interval (vertices 3-4)



(d) Execution interval (vertices 3-4)

# A Specific Purpose

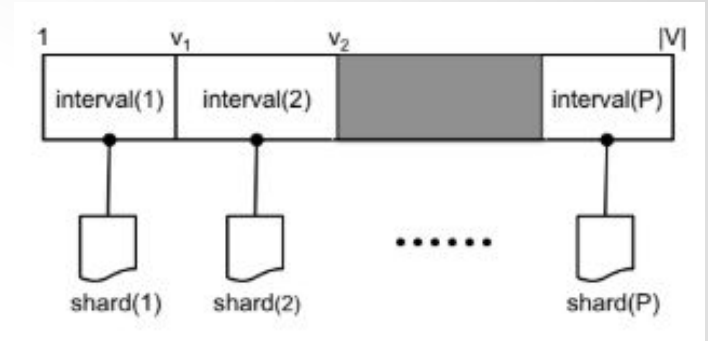
Key performance metric: size (not time).

Use case: large-scale computation (look elsewhere for traversals or queries)

# Graph Expression

Graphs are divided into groups of vertices (intervals) and edges (shards), which are processed as subgraphs.

Programmer can specify interval size, or default is  $\frac{1}{4}$  available memory.



**Interval:** a group of vertices that will be updated in the same execution step

**Shard:** list of edges whose destination vertex is in the interval

1:1 relationship

# Graph Primitives

Weighted, directed graphs.

(You could in theory use unweighted or undirected graphs, but I'm guessing there are better frameworks for those)

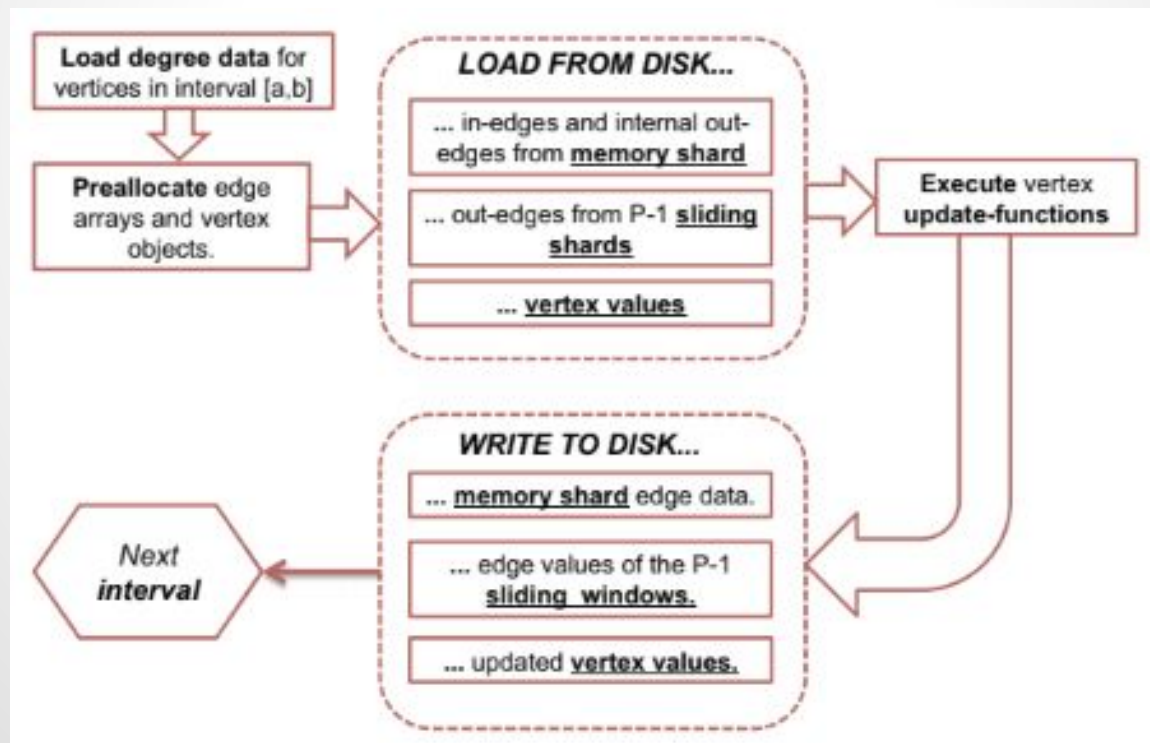


# Preprocessing

1. Divide vertices into intervals such that there is an approximately uniform in-degree distribution
2. Write each edge to a scratch file (shards)
3. Pass through each shard file and order edges
4. Compute a binary “degree file” with in- and out-degrees of each vertex

Can read from several standard graph formats.

# Execution Model



# How to Use (C++)

1. Extend GraphChiProgram class & template functions
2. Define parameters (memory budget, edge/vertex types, number of iterations, etc.)
3. Instantiate custom object and pass it to a graphchi\_engine object

# Sample Functions

```
before_iteration(int iteration, graphchi_context &gcontext)
```

```
after_iteration(int iteration, graphchi_context &gcontext)
```

```
before_exec_interval(vid_t window_st, vid_t window_en, graphchi_context &gcontext)
```

```
after_exec_interval(vid_t window_st, vid_t window_en, graphchi_context &gcontext)
```

```
update(vertex_t &v, graphchi_context &gcontext)
```

# Example (Pagerank)

```
struct PagerankProgram : public GraphChiProgram<VertexDataType, EdgeDataType> {  
...  
void update(graphchi_vertex<VertexDataType, EdgeDataType> &v, graphchi_context &ginfo) {  
...  
    /* Compute the sum of neighbors' weighted pageranks by  
       reading from the in-edges. */  
    for(int i=0; i < v.num_inedges(); i++) {  
        float val = v.inedge(i)->get_data();  
        sum += val;  
    }  
  
    /* Compute my pagerank */  
    float pagerank = RANDOMRESETPROB + (1 - RANDOMRESETPROB) * sum;  
}
```

# Example (Pagerank cont'd)

...

```
/* Write my pagerank divided by the number of out-edges to
   each of my out-edges. */
if (v.num_outedges() > 0) {
    float pagerankcont = pagerank / v.num_outedges();
    for(int i=0; i < v.num_outedges(); i++) {
        graphchi_edge<float> * edge = v.outedge(i);
        edge->set_data(pagerankcont);
    }
}
```

# Performance

Application & Graph	Iter.	Comparative result	GraphChi (Mac Mini)	Ref
Pagerank & domain	3	GraphLab[30] on AMD server (8 CPUs) <b>87 s</b>	<b>132 s</b>	-
Pagerank & twitter-2010	5	Spark [45] with 50 nodes (100 CPUs): <b>486.6 s</b>	<b>790 s</b>	[38]
Pagerank & V=105M, E=3.7B	100	Stanford GPS, 30 EC2 nodes (60 virt. cores), <b>144 min</b>	approx. <b>581 min</b>	[37]
Pagerank & V=1.0B, E=18.5B	1	Piccolo, 100 EC2 instances (200 cores) <b>70 s</b>	approx. <b>26 min</b>	[36]
Webgraph-BP & yahoo-web	1	Pegasus (Hadoop) on 100 machines: <b>22 min</b>	<b>27 min</b>	[22]
ALS & netflix-mm, D=20	10	GraphLab on AMD server: <b>4.7 min</b>	<b>9.8 min</b> (in-mem) <b>40 min</b> (edge-repl.)	[30]
Triangle-count & twitter-2010	-	Hadoop, 1636 nodes: <b>423 min</b>	<b>60 min</b>	[39]
Pagerank & twitter-2010	1	PowerGraph, 64 x 8 cores: <b>3.6 s</b>	<b>158 s</b>	[20]
Triange-count & twitter- 2010	-	PowerGraph, 64 x 8 cores: <b>1.5 min</b>	<b>60 min</b>	[20]

# Further Resources

- [1] Aapo Kyrola, Guy E. Blelloch, & Carlos Guestrin. (2018). GraphChi: Large-Scale Graph Computation on Just a PC.
- [2] <https://github.com/GraphChi>
- [3] Moon, Seunghyeon, Lee, Jae-Gil, Kang, Minseo, Choy, Minsoo, & Lee, Jin-Woo. (2016). Parallel community detection on large graphs with MapReduce and GraphChi. *Data & Knowledge Engineering*, 104, 17-31.
- [5] Lu, J., & Thoma, A. (2016). An experimental evaluation of giraph and GraphChi. *Advances in Social Networks Analysis and Mining (ASONAM)*, 2016 IEEE/ACM International Conference on, 993-996.