

# Hybrid Parallel Programming for Massive Graph Analysis

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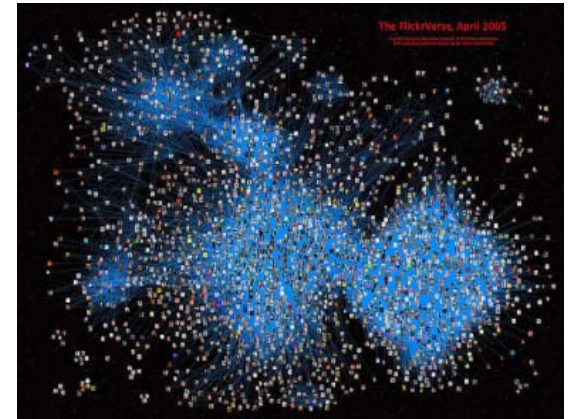
**July 12, 2010**

# Hybrid Parallel Programming

Large-scale graph analysis utilizing

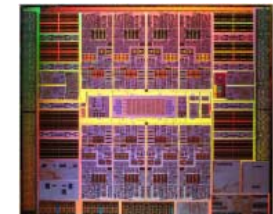
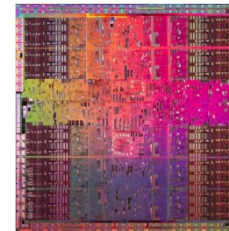
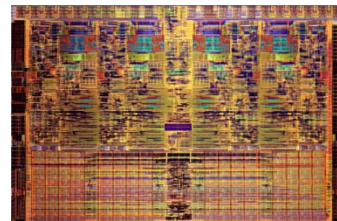
- Clusters of x86 multicore processors

- MPI + OpenMP/UPC



- CPU+GPU

- MPI + OpenCL



- FPGAs, accelerators

- Host code + accelerator code



# Why hybrid programming?

- Traditional sources of performance improvement are flat-lining
- We need new algorithms that exploit large on-chip memory, shared caches, and high DRAM bandwidth

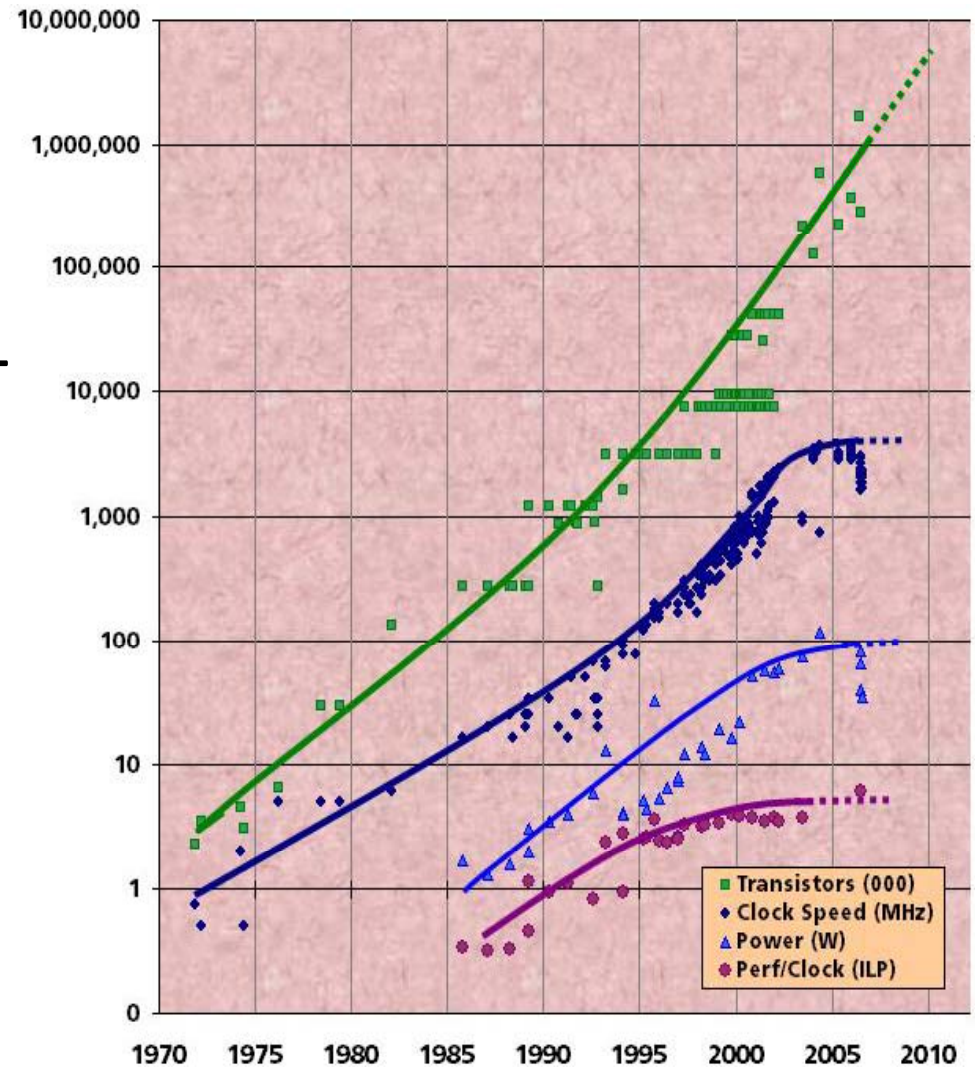
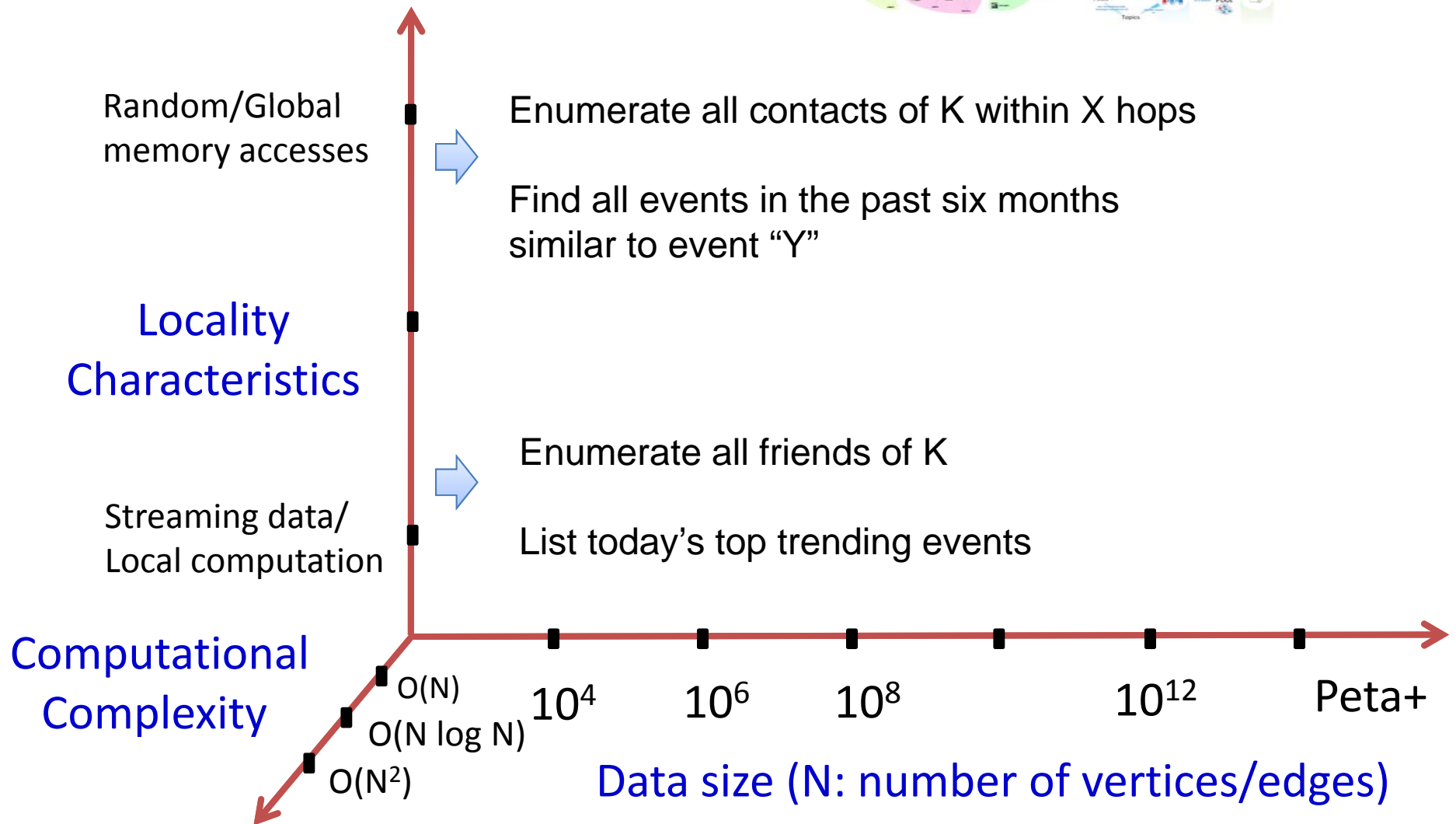
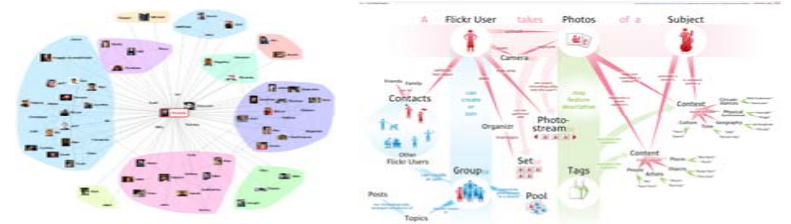


Image source: Herb Sutter, "The Free Lunch is Over", Dr. Dobb's Journal, 2009.

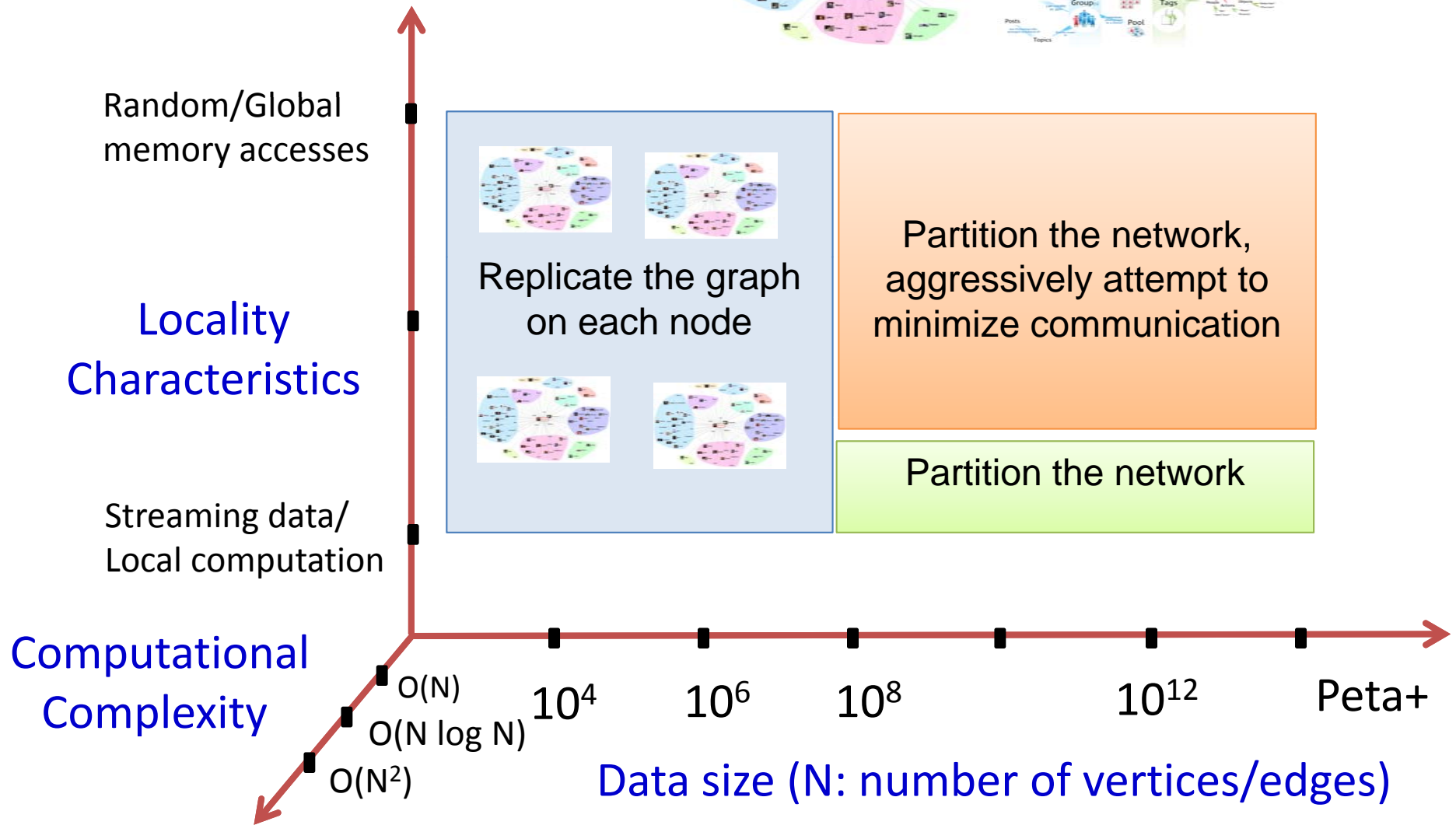
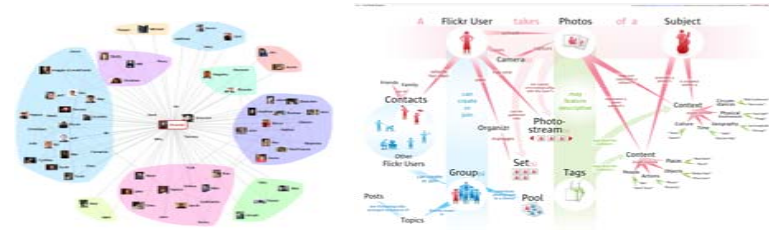
## This talk: Two case studies

- MPI + OpenMP on shared-memory multicore processor clusters
  - Graph analytics on online social network crawls, synthetic “power-law” random graphs
  - Traversal and simplification of a DNA fragment assembly string graph arising in a de novo short-read genome assembly algorithm

# Characterizing Large-scale graph-theoretic computations



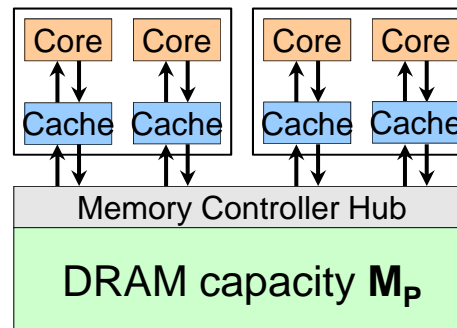
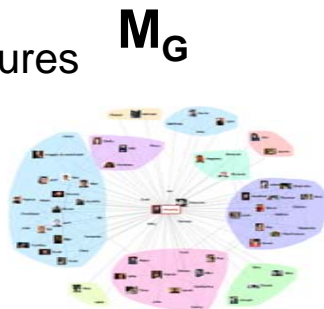
# Parallelization Strategy



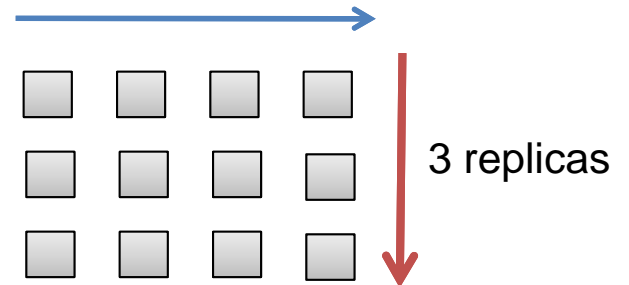
# Minimizing Communication

- Irregular and memory-intensive graph problems: Intra- and Inter-node communication (+ I/O costs, memory latency) costs typically dominate local computational complexity
- Key to parallel performance: Enhance data locality, avoid superfluous inter-node communication
  - **Avoid a P-way partitioning** of the graph
  - Create  $PM_P/M_G$  replicas

Graph + data structures



4-way partitioning



$$P=12, M_G/M_P = 4$$

# Real-world data

Assembled a collection of graphs for algorithm performance analysis, from some of the largest publicly-available network data sets.

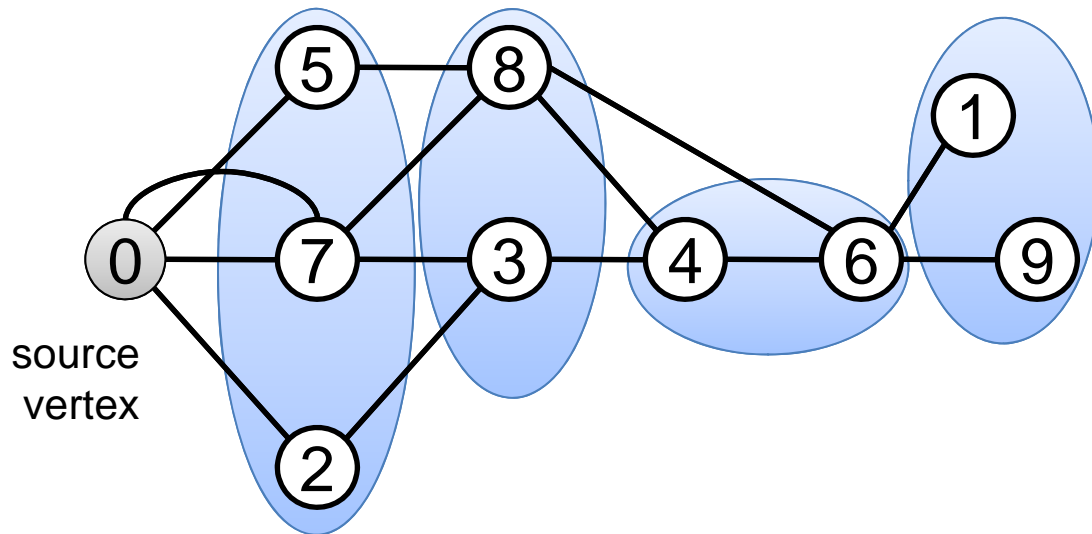
Name	# vertices	# edges	Type
Amazon-2003	473.30 K	3.50 M	co-purchaser
eu-2005	862.00 K	19.23 M	www
Flickr	1.86 M	22.60 M	social
wiki-Talk	2.40 M	5.02 M	collab
orkut	3.07 M	223.00 M	social
cit-Patents	3.77 M	16.50 M	cite
Livejournal	5.28 M	77.40 M	social
uk-2002	18.50 M	198.10 M	www
USA-road	23.90 M	29.00 M	Transp.
webbase-2001	118.14 M	1.02 B	www



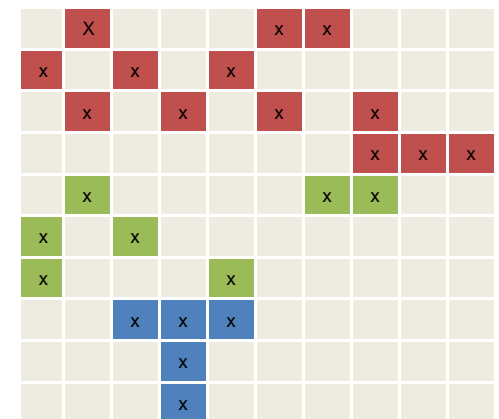
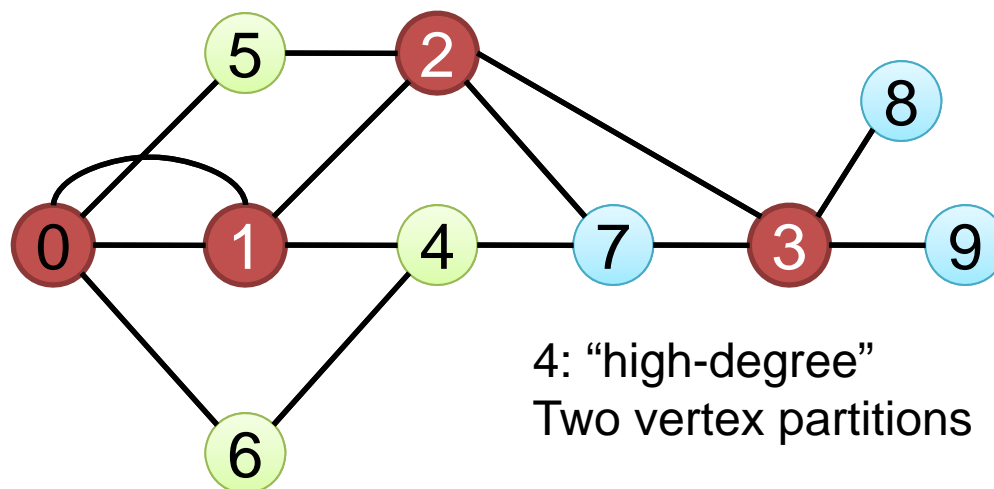
# “2D” Graph Partitioning Strategy

- Tuned for graphs with unbalanced degree distributions and incremental updates
  - Sort vertices by degree
  - Form roughly  $M_G/M_p$  local communities around “high-degree” vertices & partition adjacencies
  - Reorder vertices by degree, assign contiguous chunks to each of the  $M_G/M_p$  nodes
  - Assign ownership of any remaining low-degree vertices to processes
- Comparison: 1D p-way partitioning, 1D p-way partitioning with vertices shuffled

# Parallel Breadth-First Search Implementation



- Expensive preprocessing partitioning + reordering step, currently untimed



# Parallel BFS Implementation

- Concurrency in each phase limited by size of frontier array
- Local computation: inspecting adjacencies, creating a list of unvisited vertices
- Parallel communication step: All-to-all exchange of frontier vertices
  - Potentially  $P^2$  exchanges
  - Partitioning, replication, and reordering significantly reduce number of messages

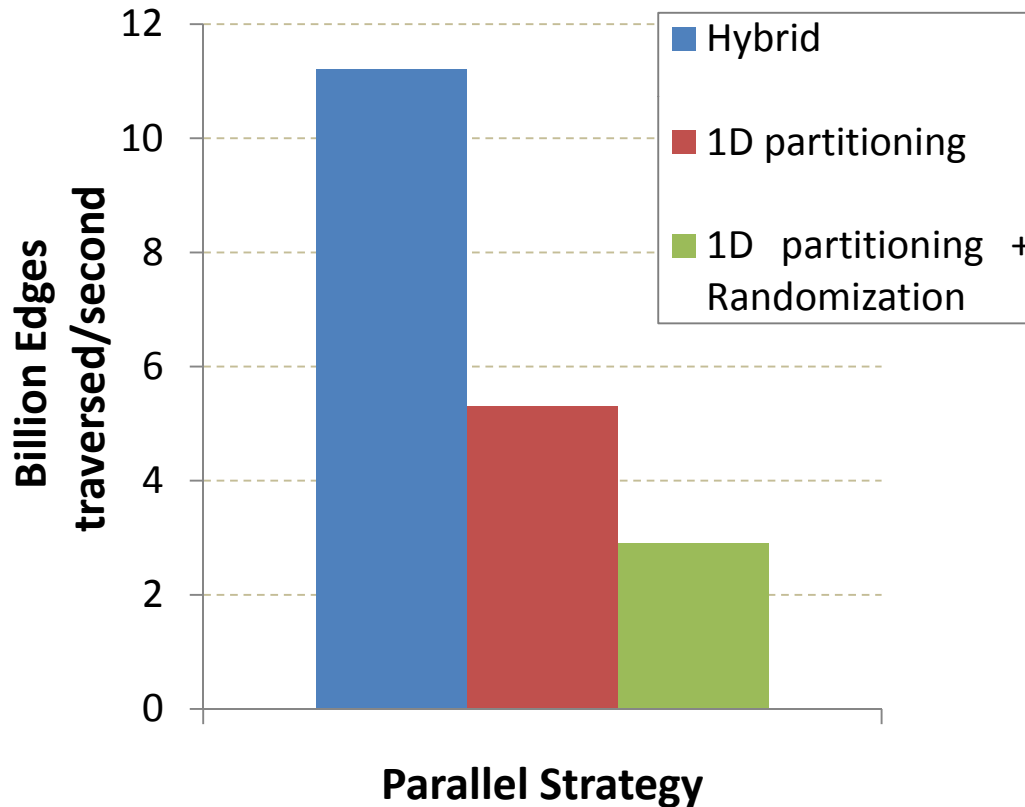
# Single-node Multicore Optimizations

- 1. Software prefetching** on Intel Nehalem (supports 32 loads and 20 stores in flight)
  - Speculative loads of **index array** and **adjacencies of frontier vertices** will reduce compulsory cache misses.
- 2. Aligning adjacency lists** to optimize memory accesses
  - 16-byte aligned loads and stores are faster.
  - Alignment helps reduce cache misses due to fragmentation
  - 16-byte aligned non-temporal stores (during creation of new frontier) are fast.
- 3. SIMD SSE integer intrinsics** to process “high-degree” vertex adjacencies.
- 4. Fast atomics** (BFS is lock-free w/ low contention, and **CAS-based intrinsics** have very low overhead)
- 5. Hugepage** support (significant TLB miss reduction)
- 6. NUMA-aware memory** allocation exploiting first-touch policy

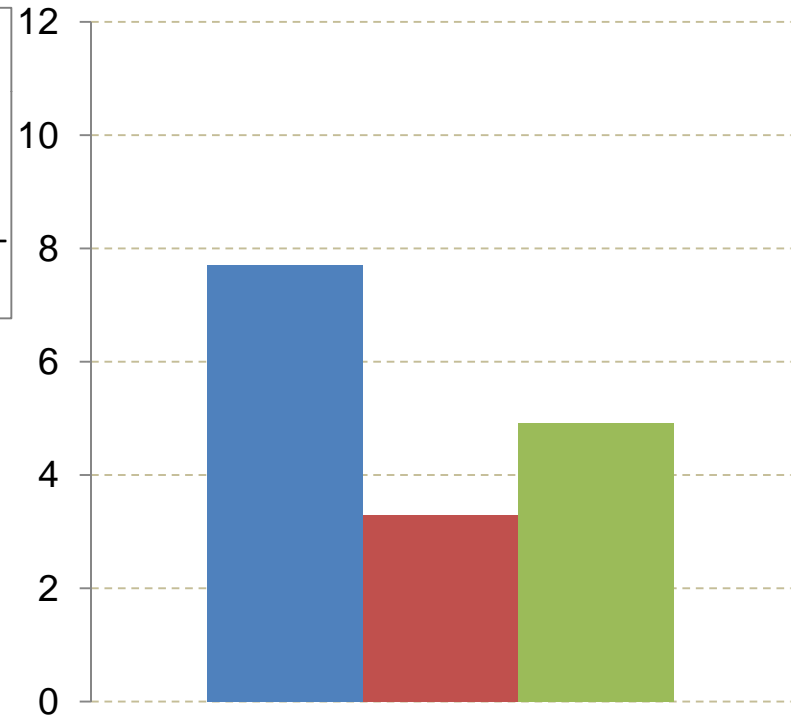
# Parallel Performance

- 32 nodes of NERSC's Carver system
  - dual-socket, quad-core Intel Nehalem 2.67 GHz processor node
  - 24 GB DDR3 1333 MHz memory per node, or roughly 768 TB aggregate memory

**Orkut crawl: 3.07M vertices, 227M edges**



**Synthetic RMAT network: 2 billion vertices, 32 billion edges**

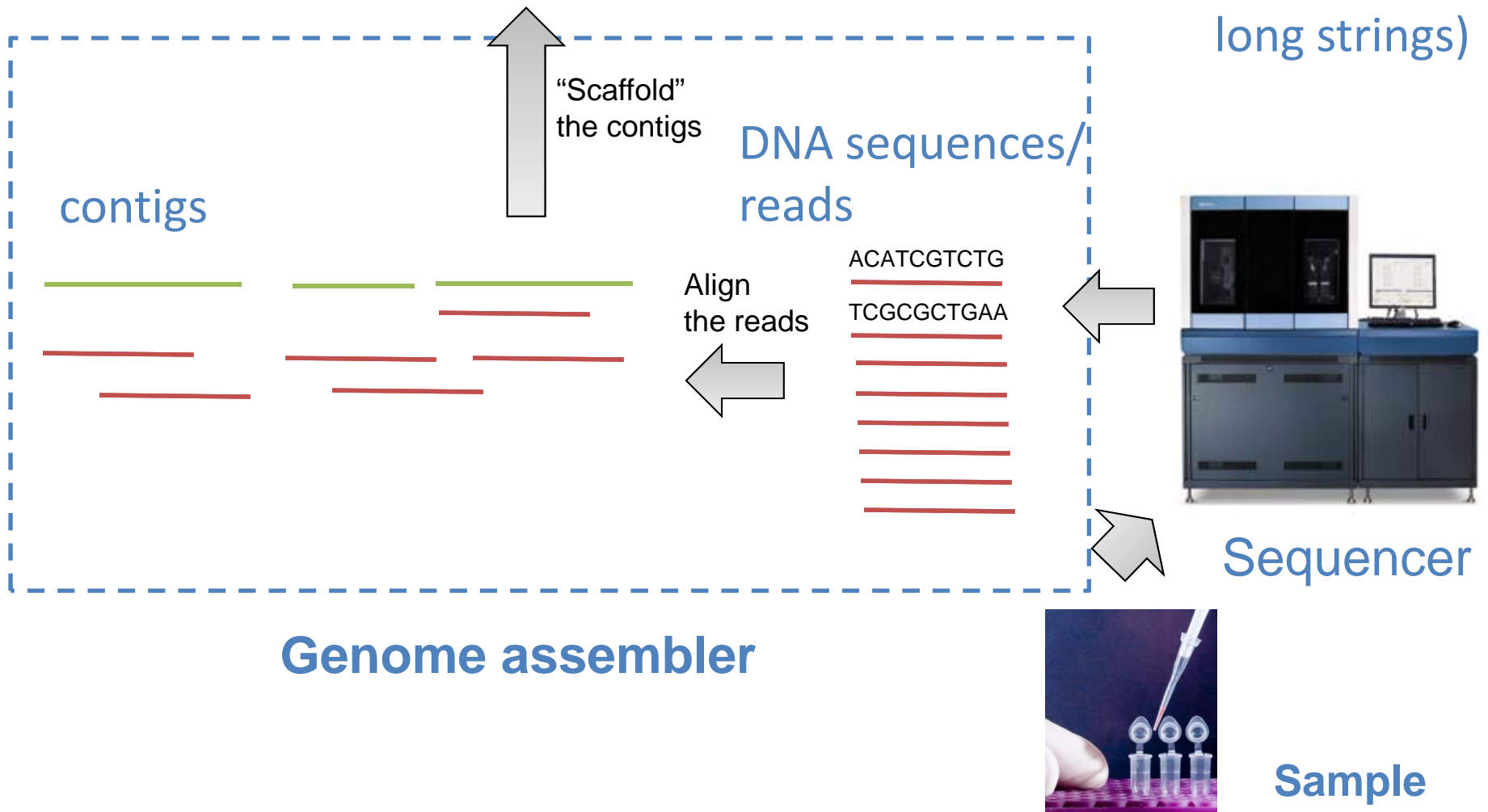


Single-node performance: 300-500 M traversed edges/second.

# Genome Assembly Preliminaries

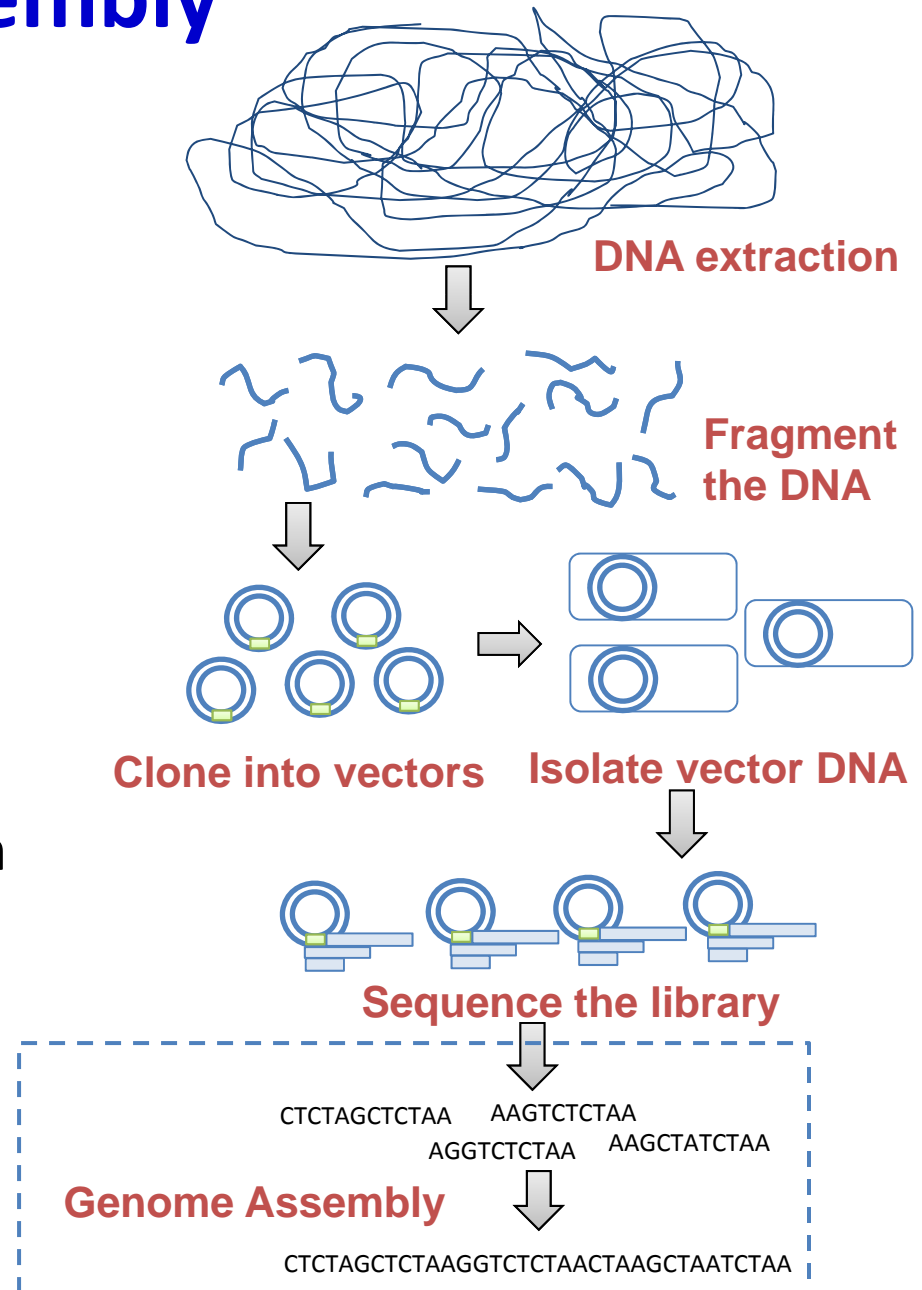
ACACGTGTGCACTACTGCACTCTACTCCACTGACTA

nucleotide  
Genome  
(collection of long strings)



# De novo Genome Assembly

- Genome Assembly: “a big jigsaw puzzle”
- *De novo*: Latin expression meaning “from the beginning”
  - No prior reference organism
  - Computationally falls within the **NP-hard** class of problems



## Eulerian path-based strategies

- Break up the (short) reads into overlapping strings of length  $k$ .

$k = 5$

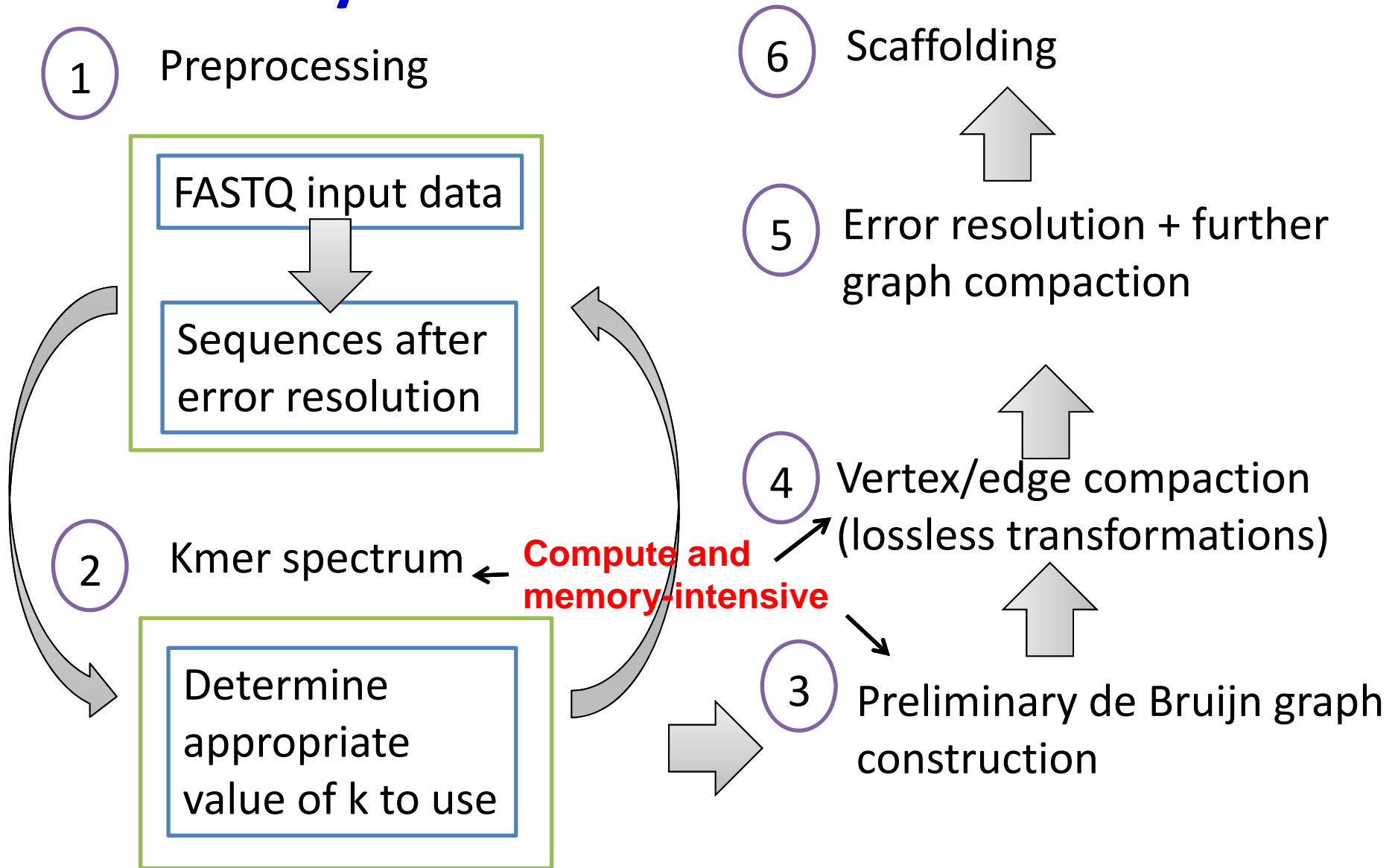
ACGTTATATATTCTA	➔	ACGTT	CGTTA	GTTAT
		TTATA	.....	TTCTA
CCATGATATATTCTA	➔	CCATG	CATGA	ATGAT
		TGATA	.....	TTCTA

- Construct a de Bruijn graph (a directed graph representing overlap between strings)



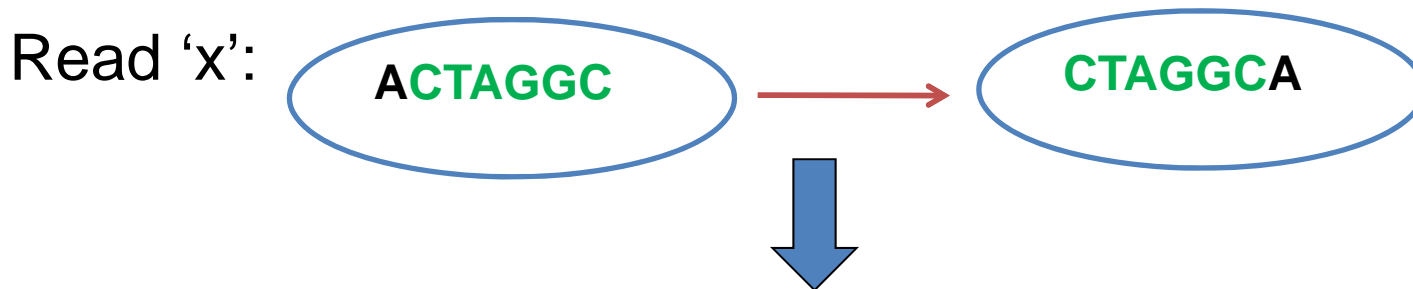


# Steps in the de Bruijn graph-based assembly scheme



# Graph construction

- Store edges only, represent vertices (kmers) implicitly.
- Distributed graph representation
- Sort by start vertex
- Edge storage format:

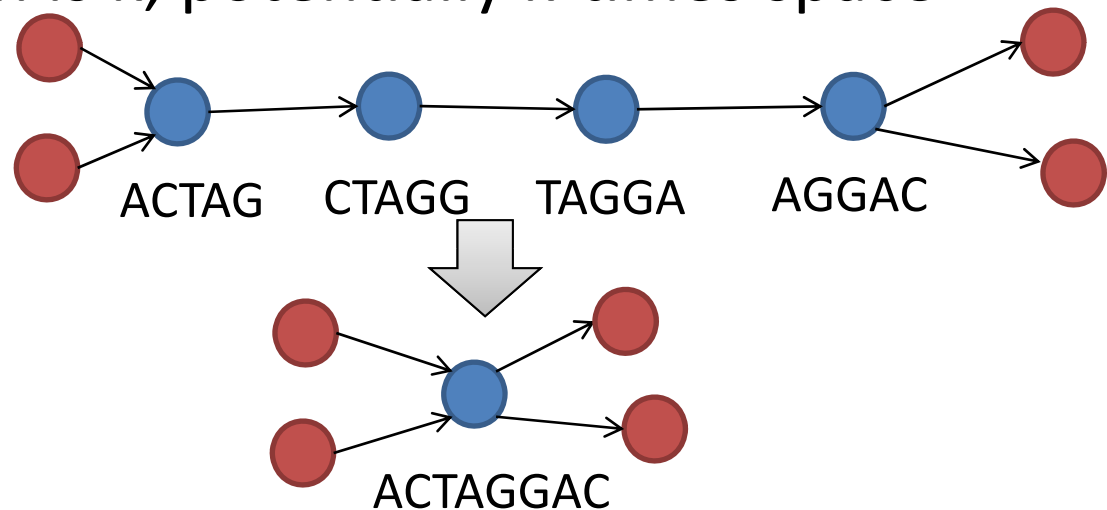


Store edge (ACTAGGCA), orientation,  
edge direction, edge id (y), originating read id (x), edge count

2 bits per nucleotide

# Vertex compaction

- High percentage of unique kmers
  - ⇒ Try compacting kmers from same read first
  - If kmer length is  $k$ , potentially  $k$ -times space reduction!



- Parallelization: computation can be done locally by sorting by read ID, traversing unit-cardinality kmers.

# Summary of various steps and Analysis

A metagenomic data set (140 million reads, 20G bp),  $k = 45$ .

Step	Memory footprint	Approach used	Parallelism & Computational kernels
1. Preprocessing	minimal	Streaming file read and write, kmer merging	“Pleasantly parallel”, I/O-intensive
2. Kmer spectrum	~ 200 GB	3 local sorts, 1 AlltoAll communication steps.	Parallel sort, AlltoAllv
3. Graph construction	~ 320 GB	Two sorts	Fully local computation
4. Graph compaction	~ 60 GB	3+ local sorts, 2 AlltoAll communication steps + local graph traversal	AlltoAllv + local computation
5. Error detection	~ 35 GB	Connected components + AlltoAll	Intensive communication
6. Scaffolding	? GB	Euler tours over components	Mostly local computation

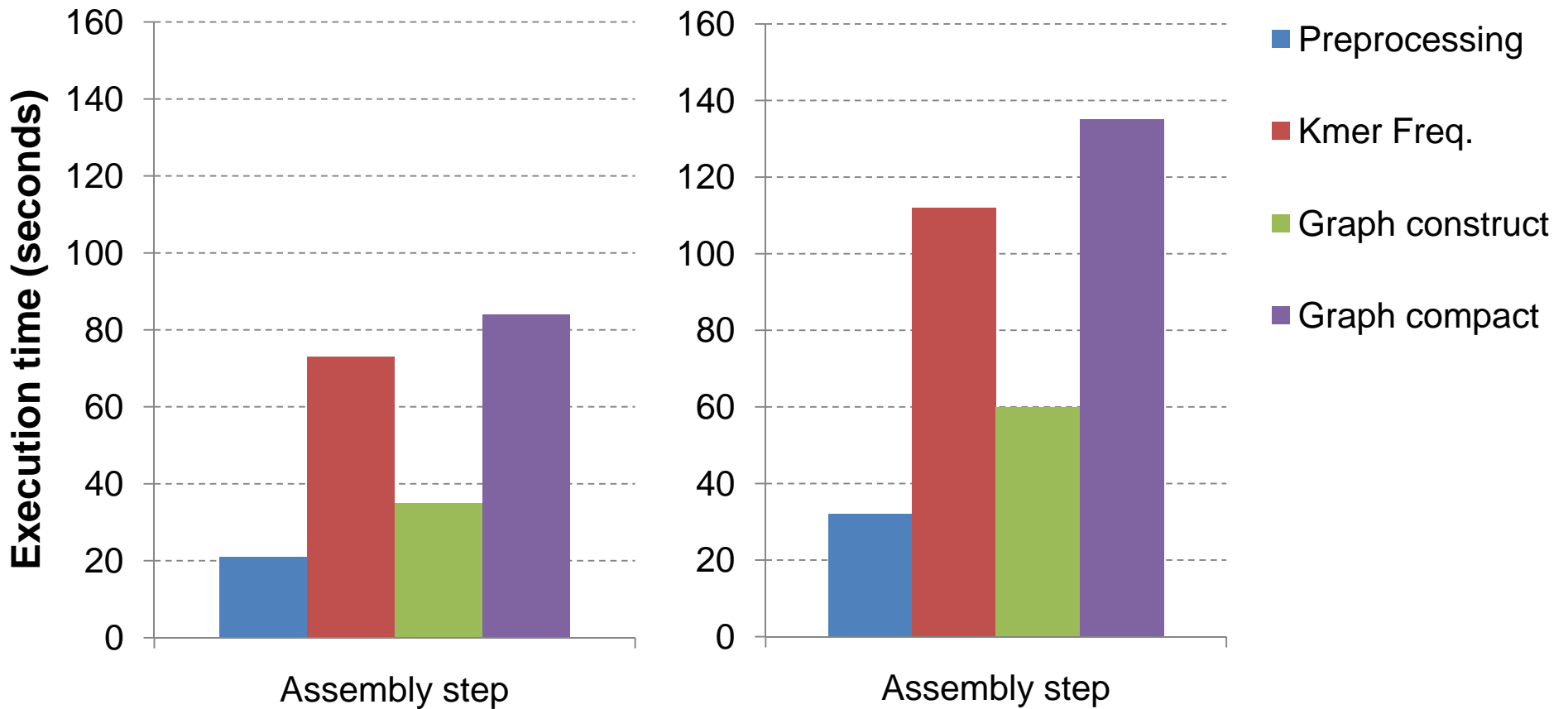
# Parallel Implementation Details

- Data set under consideration requires 320 GB for in-memory processing
  - NERSC Franklin system [Cray XT4, 2.3 GHz quad-core Opterons, 8 GB memory per node]
  - Experimented with 64 nodes (256-way parallelism) and 128 nodes (512-way)
- MPI across nodes + OpenMP within a node
- Local sort: multicore-parallel radix sort
- Global sort: bin data in parallel + AlltoAll comm. + local sort + AlltoAll comm.

# Parallel Performance

128 nodes: 213 seconds

64 nodes: 340 seconds



- Comparison: *Velvet* (open-source serial code) takes ~ 12 hours on a 500 GB machine.

# Talk Summary

- Two examples of “hybrid” parallel programming for analyzing large-scale graphs
  - Up to 3x faster with hybrid approaches on 32 nodes
- Two different types of graphs, the strategies to achieve high performance differs
  - Social and information networks: low diameter, difficult to generate balanced partitions with low edge cuts
  - DNA fragment string graph:  $O(N)$  diameter, multiple connected components
- Single-node multicore optimizations + communication optimization (reducing data volume and number of messages in All-to-all exchange).



# Acknowledgments



**Thank you!**

**Questions?**

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