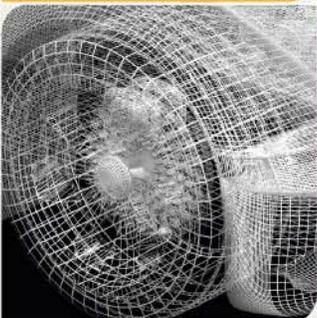


Massive-Scale Analytics of Streaming Social Networks

David A. Bader



Georgia Tech  College of Computing
Computational Science and Engineering

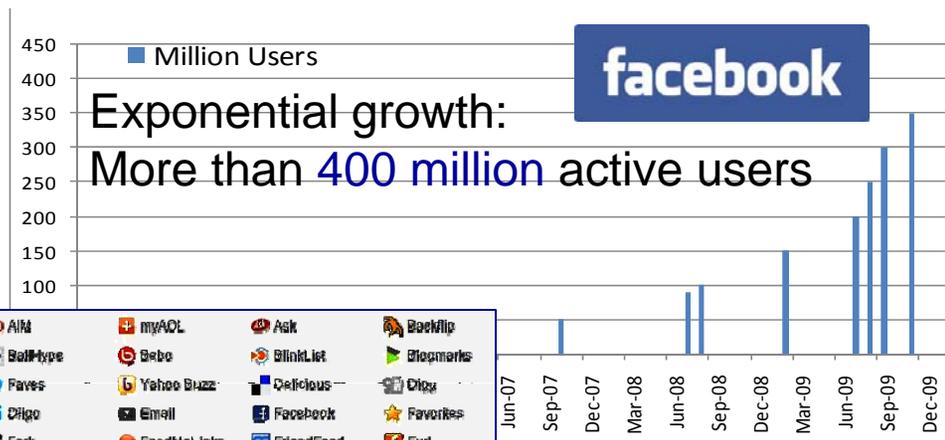
Exascale Streaming Data Analytics:

Real-world challenges



All involve analyzing massive streaming complex networks:

- **Health care** → disease spread, detection and prevention of epidemics/pandemics (e.g. SARS, Avian flu, H1N1 “swine” flu)
- **Massive social networks** → understanding communities, intentions, population dynamics, pandemic spread, transportation and evacuation
- **Intelligence** → business analytics, anomaly detection, security, knowledge discovery from massive data sets
- **Systems Biology** → understanding complex life systems, drug design, microbial research, unravel the mysteries of the HIV virus; understand life, disease,
- **Electric Power Grid** → communication, transportation, energy, water, food supply
- **Modeling and Simulation** → Perform full-scale economic-social-political simulations



Ex: discovered minimal changes in O(billions)-size complex network that could hide or reveal top influencers in the community

Sample queries:

- **Allegiance switching:** identify entities that switch communities.
- **Community structure:** identify the genesis and dissipation of communities
- **Phase change:** identify significant change in the network structure

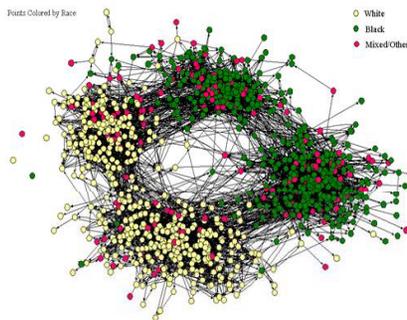
REQUIRES PREDICTING / INFLUENCE CHANGE IN REAL-TIME AT SCALE

Center for Adaptive Supercomputing Software (CASS-MT)

- CASS-MT, launched July 2008
- Pacific-Northwest Lab
 - Georgia Tech, Sandia, WA State, Delaware
- The newest breed of supercomputers have hardware set up not just for speed, but also to better tackle large networks of seemingly random data. And now, a multi-institutional group of researchers has been awarded \$4.0 million to develop software for these supercomputers. Applications include anywhere complex webs of information can be found: from internet security and power grid stability to complex biological networks.



The Social Structure of "Countryside" School District



CRAY

David A. Bader



CASS-MT TASK 7: Analysis of Massive Social Networks

Objective

To design software for the analysis of massive-scale spatio-temporal interaction networks using multithreaded architectures such as the Cray XMT. The Center launched in July 2008 and is led by Pacific Northwest National Laboratory.

Description

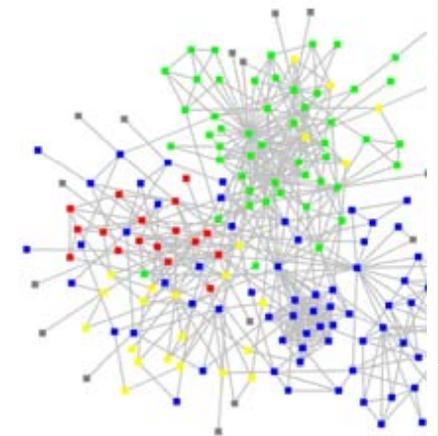
We are designing and implementing advanced, scalable algorithms for static and dynamic graph analysis, including generalized k -betweenness centrality and dynamic clustering coefficients.

Highlights

On a 64-processor Cray XMT, k -betweenness centrality scales nearly linearly (58.4x) on a graph with 16M vertices and 134M edges. Initial streaming clustering coefficients handle around 200k updates/sec on a similarly sized graph.



Image Courtesy of Cray, Inc.



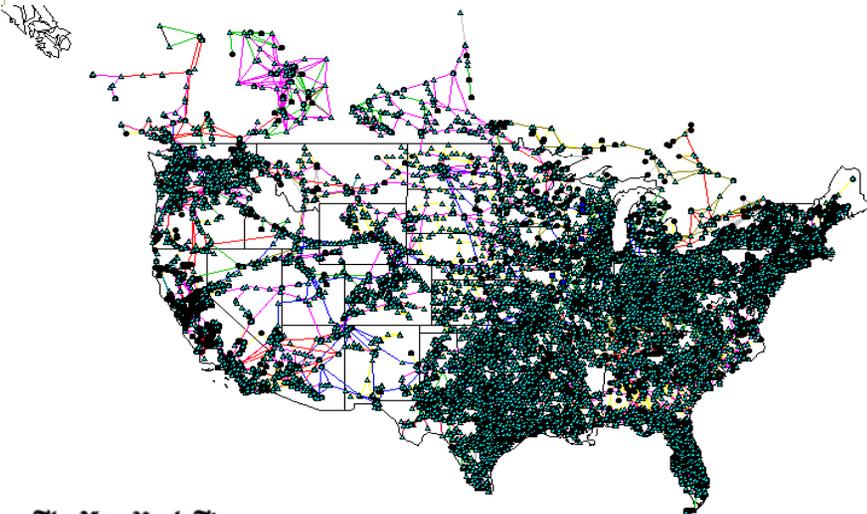
Our research is focusing on temporal analysis, answering questions about changes in global properties (e.g. diameter) as well as local structures (communities, paths).

David A. Bader (CASS-MT Task 7 LEAD)
David Ediger, Karl Jiang, Jason Riedy



Massive Data Analytics: Protecting our Nation

US High Voltage Transmission Grid (>150,000 miles of line)



The New York Times
Thursday, September 4, 2008

Report on Blackout Is Said To Describe Failure to React

By MATTHEW L. WALD
Published: November 12, 2003

A report on the Aug. 14 blackout identifies specific lapses by various parties, including FirstEnergy's failure to react properly to the loss of a transmission line, people who have seen drafts of it say.

A working group of experts from eight states and Canada will meet in private on Wednesday to evaluate the report, people involved in the investigation said Tuesday. The report, which the Energy Department

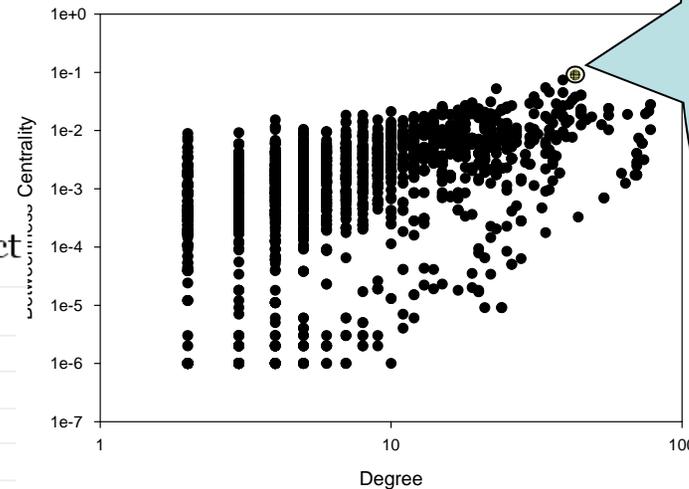
- E-MAIL
- PRINT
- SINGLE-PAGE
- REPRINTS
- SAVE
- SHARE

David A. Bader

Public Health

- CDC / Nation-scale surveillance of public health
- Cancer genomics and drug design
 - computed Betweenness Centrality of Human Proteome

Human Genome core protein interactions
Degree vs. Betweenness Centrality



ENSG0000145332.2
Kelch-like protein 8
implicated in breast cancer



Network Analysis for Intelligence and Surveillance

- [Krebs '04] Post 9/11 Terrorist Network Analysis from public domain information
- Plot masterminds correctly identified from interaction patterns: **centrality**
- A global view of entities is often more insightful
- Detect anomalous activities by exact/approximate **graph matching**

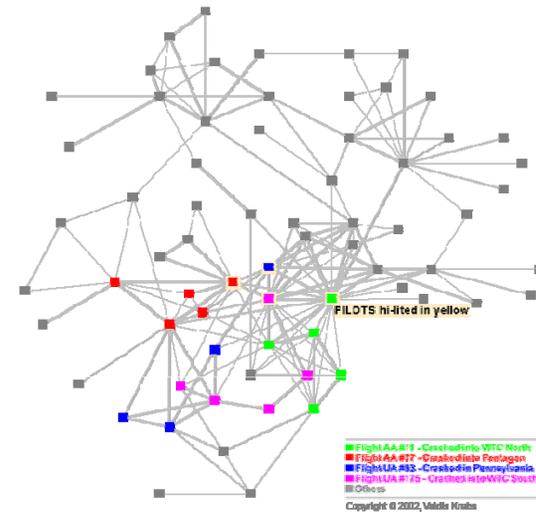


Image Source: <http://www.orgnet.com/hijackers.html>

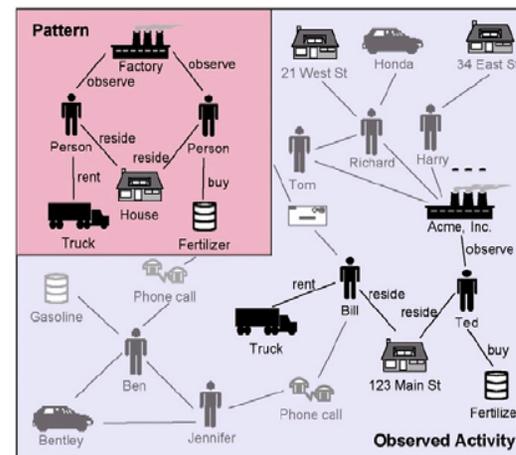
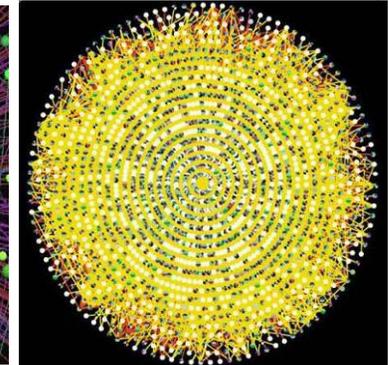
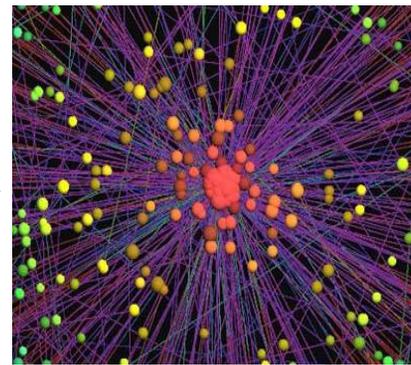
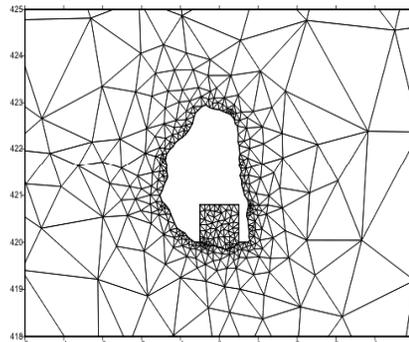


Image Source: T. Coffman, S. Greenblatt, S. Marcus, Graph-based technologies for intelligence analysis, CACM, 47 (3, March 2004): pp 45-47



Massive data analytics in Informatics networks

- Graphs arising in Informatics are very different from topologies in scientific computing.



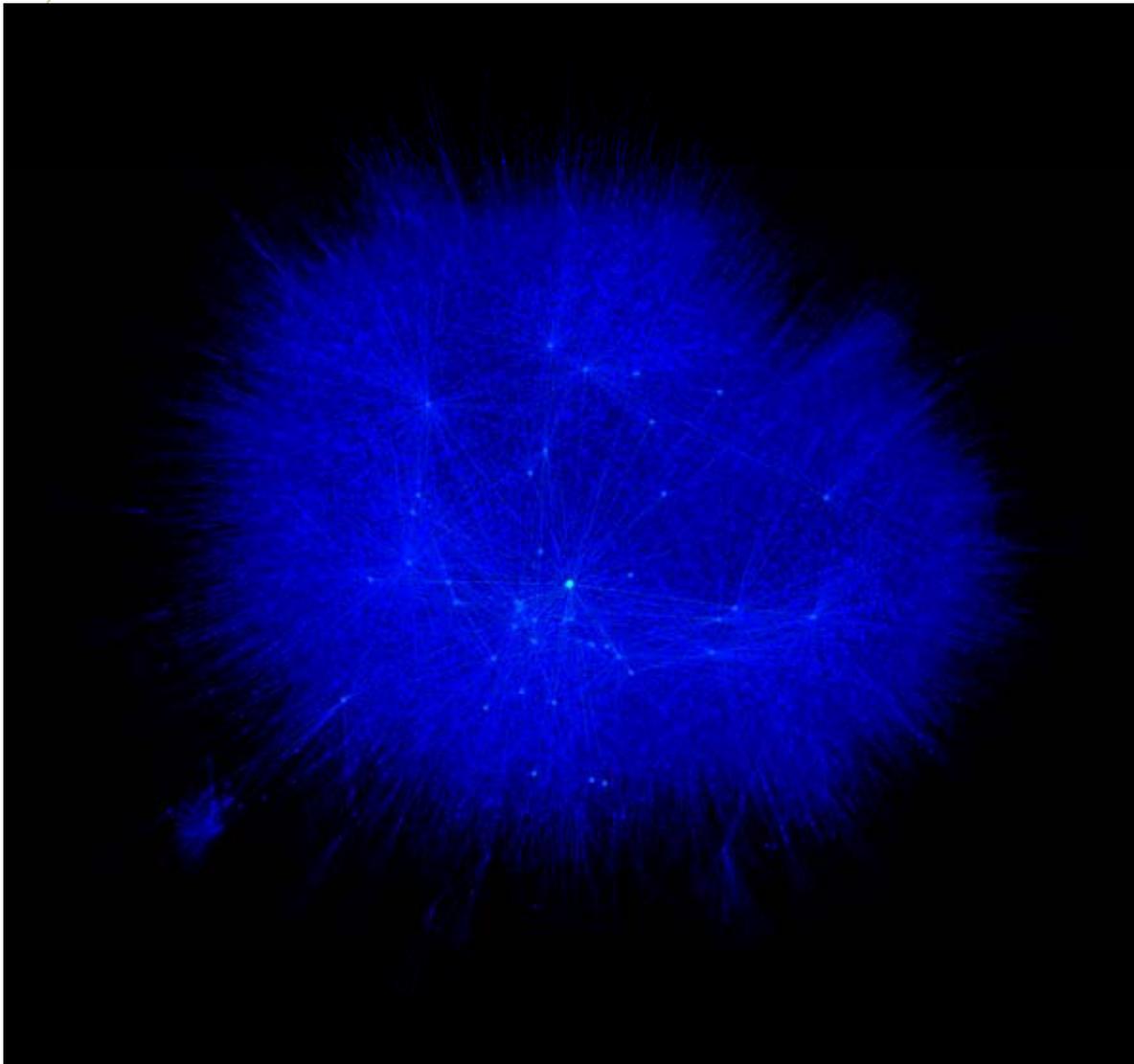
Static networks,
Euclidean topologies

Emerging applications: dynamic,
high-dimensional data

- We need **new data representations** and **parallel algorithms** that exploit topological characteristics of informatics networks.



The Reality



- This image is a visualization of my personal friendster network (circa February 2004) to 3 hops out. The network consists of 47,471 people connected by 432,430 edges.

Credit: Jeffrey Heer, UC Berkeley



Limitations of Current Tools

- ▶ Graphs with millions of vertices are well beyond simple comprehension or visualization: **we need tools to summarize the graphs.**
- ▶ Existing tools: UCINET, Pajek, SocNetV, tnet
- ▶ Limitations:
 - Target workstations, **limited in memory**
 - No parallelism, **limited in performance.**
 - Scale only to low density graphs with a **few million vertices**
- ▶ We need a package that will easily accommodate graphs with several **billion** vertices and deliver results in a timely manner.
 - Need parallelism both for computational speed and memory!
 - The Cray XMT is a natural fit...



The Cray XMT

- **Tolerates latency** by massive multithreading
 - **Hardware support for 128 threads on each processor**
 - Globally hashed address space
 - **No data cache**
 - Single cycle context switch
 - Multiple outstanding memory requests
- Support for fine-grained,
 - word-level synchronization
 - Full/empty bit associated with every
 - memory word
- Flexibly supports dynamic load balancing
- GraphCT currently tested on a 128 processor XMT: **16K threads**
 - **1 TB** of globally shared memory

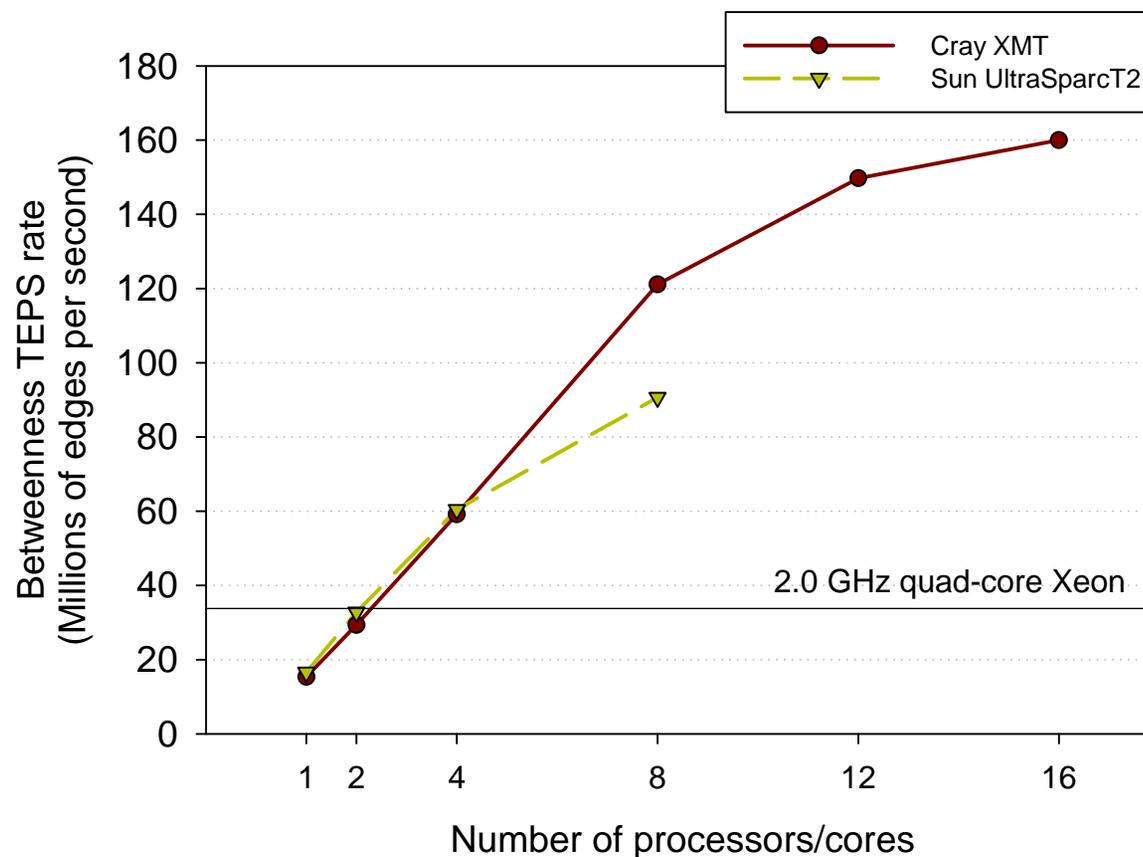


Image Source: cray.com



Graph Analysis Performance: Multithreaded (Cray XMT) vs. Cache-based multicore

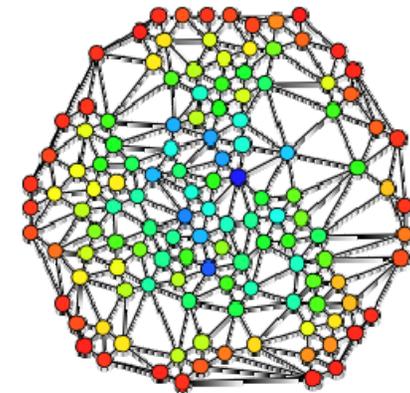
- SSCA#2 network, SCALE 24 (16.77 million vertices and 134.21 million edges.)





What is GraphCT?

- ▶ Graph Characterization Toolkit
- ▶ Efficiently summarizes and analyzes static graph data
- ▶ Built for large multithreaded, shared memory machines like the Cray XMT
- ▶ Increases productivity by decreasing programming complexity
- ▶ Classic metrics & state-of-the-art kernels
- ▶ Works on many types of graphs
 - directed or undirected
 - weighted or unweighted

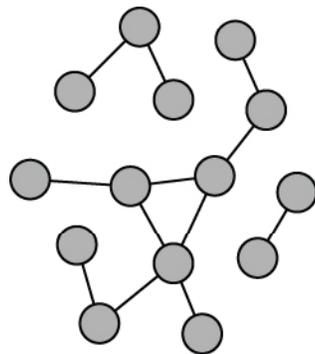


Dynamic spatio-temporal graph

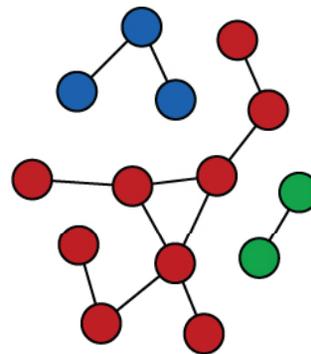
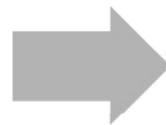


Key Features of GraphCT

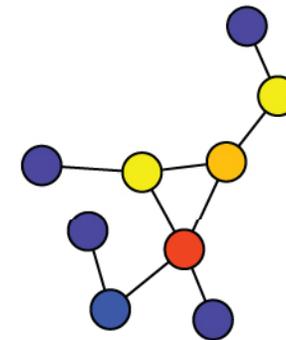
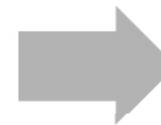
- ▶ Low-level primitives to high-level analytic kernels
- ▶ Common graph data structure
- ▶ Develop custom reports by mixing and matching functions
- ▶ Create subgraphs for more in-depth analysis
- ▶ Kernels are tuned to maximize scaling and performance (up to 128 processors) on the Cray XMT



Load the Graph Data



Find Connected Components



Run k -Betweenness Centrality
on the largest component

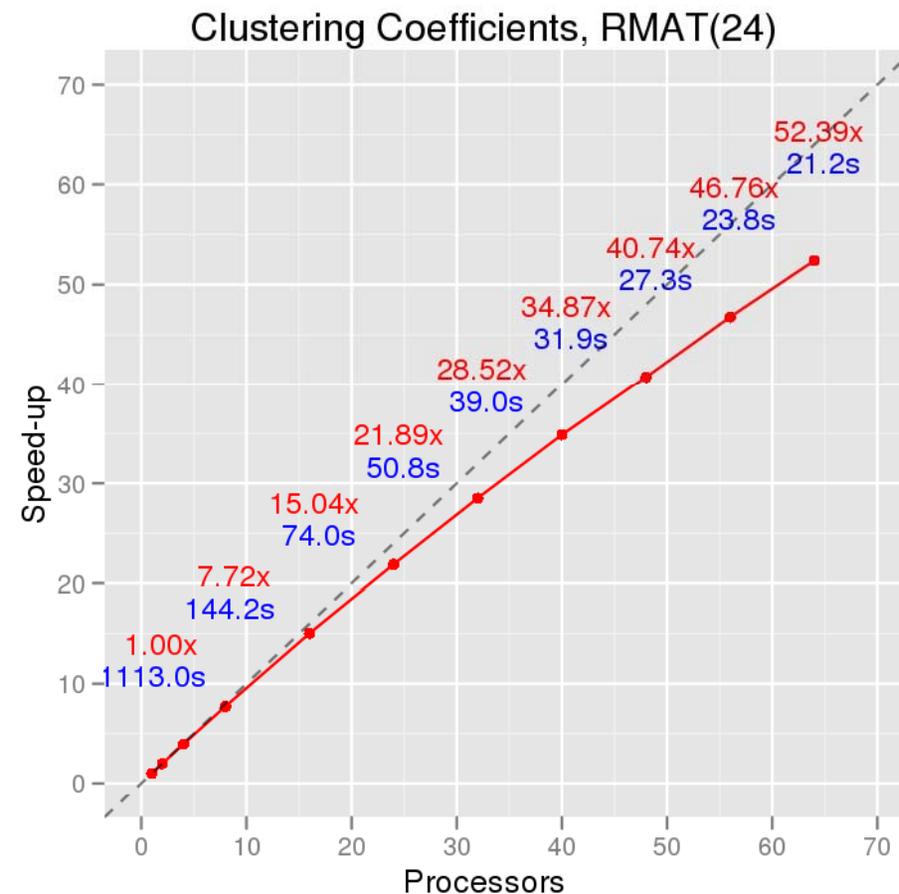
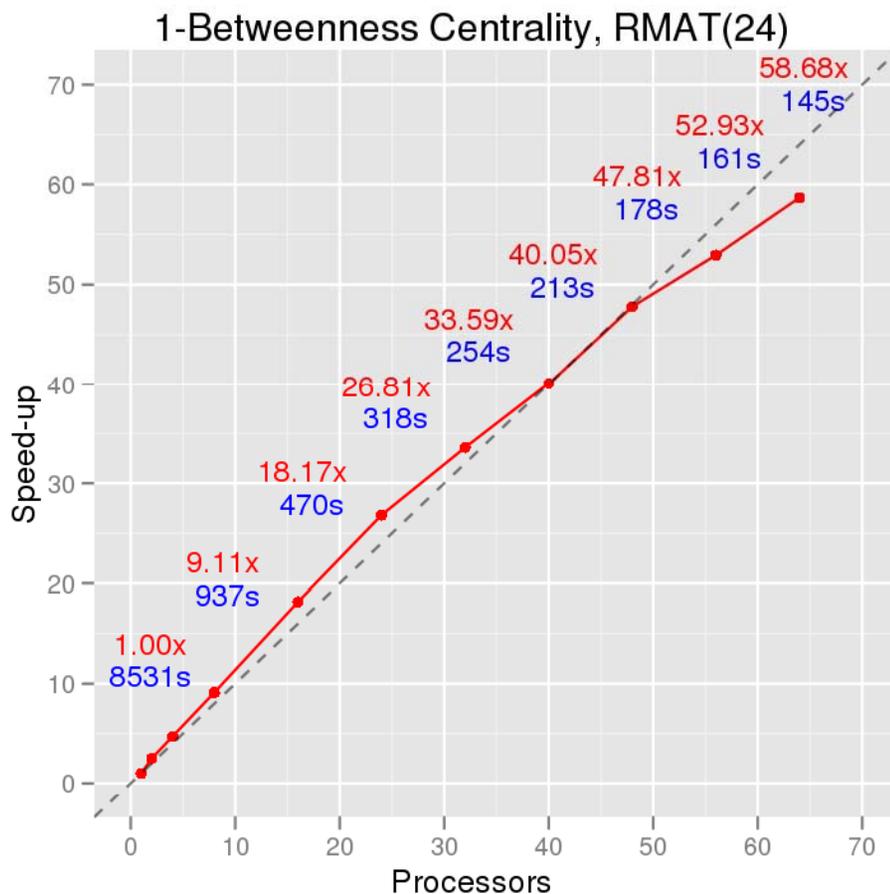


GraphCT Functions

Name	Name	
RMAT graph generator	Modularity Score	
Degree distribution statistics	Conductance Score	
Graph diameter	st-Connectivity	
Maximum weight edges	Delta-stepping SSSP	
Connected components	Bellman-Ford	
Component distribution statistics	GTriad Census	
Vertex Betweenness Centrality	SSCA2 Kernel 3 Subgraphs	
Vertex k-Betweenness Centrality	Greedy Agglomerative Clustering	Key
Multithreaded BFS	Minimum spanning forest	Included
Edge-divisive Betweenness-based Community Detection (pBD)	Clustering coefficients	In Progress
Lightweight Binary Graph I/O	DIMACS Text Input	Proposed/Available



GraphCT Performance



- RMAT(24) : 16.7M vertices, 134M edges
- RMAT(28) : 268M vertices, 2.1B edges
 - BC₁ : 2800s on 64P
 - CC : 1200s on 64P



Analysis of Graphs with Streaming Updates

- ▶ **STINGER: A Data Structure for Changing Graphs**
 - Light-weight data structure that supports efficient iteration *and* efficient updates.
- ▶ **Experiments with Streaming Updates to Clustering Coefficients**
 - Working with bulk updates, can handle almost 200k per second

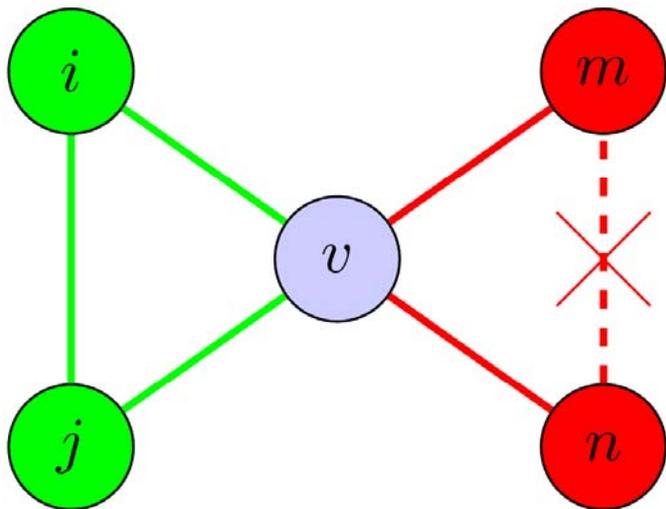


STING Extensible Representation (STINGER)

- ▶ Enhanced representation developed for dynamic graphs developed in consultation with David A. Bader, Johnathan Berry, Adam Amos-Binks, Daniel Chavarría-Miranda, Charles Hastings, Kamesh Madduri, and Steven C. Poulos.
- ▶ Design goals:
 - Be useful for the entire “large graph” community
 - Portable semantics and high-level optimizations across multiple platforms & frameworks (XMT C, MTGL, etc.)
 - Permit good performance: No single structure is optimal for all.
 - Assume globally addressable memory access
 - Support multiple, parallel readers and a single writer
- ▶ Operations:
 - Insert/update & delete both vertices & edges
 - Aging-off: Remove old edges (by timestamp)
 - Serialization to support checkpointing, etc.

Testbed: Clustering Coefficients

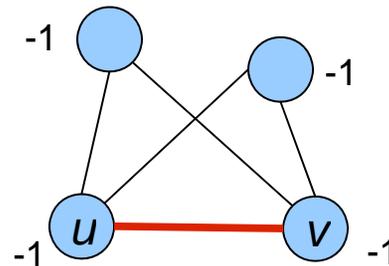
- ▶ Roughly, the ratio of actual triangles to possible triangles around a vertex.



- ▶ Defined in terms of **triplets**.
- ▶ $i-j-v$ is a **closed triplet** (triangle).
- ▶ $m-v-n$ is an **open triplet**.
- ▶ Clustering coefficient
closed triplets / # all triplets
- ▶ Locally, count those around v .
- ▶ Globally, count across entire graph.
 - Multiple counting cancels ($3/3=1$)

Streaming updates to clustering coefficients

- ▶ Monitoring clustering coefficients could identify anomalies, find forming communities, *etc.*
- ▶ Computations stay **local**. A change to edge $\langle u, v \rangle$ affects only vertices u, v , and their neighbors.



- ▶ Need a fast method for updating the triangle counts, degrees when an edge is inserted or deleted.
 - Dynamic data structure for edges & degrees: STINGER
 - Rapid triangle count update algorithms: exact and **approximate**
- ▶ “Massive Streaming Data Analytics: A Case Study with Clustering Coefficients.” Ediger, David, Karl Jiang, E. Jason Riedy, and David A. Bader. MTAAP 2010, Atlanta, GA, April 2010.

Updating clustering coefficients

- ▶ Using RMAT as a graph and edge stream generator.
 - Mix of insertions and deletions
- ▶ Result summary for single actions
 - Exact: from 8 to 618 actions/second
 - Approx: from 11 to 640 actions/second
- ▶ Alternative: Batch changes
 - Lose some temporal resolution within the batch
 - Median rates for batches of size B:

Algorithm	B = 1	B = 1000	B = 4000
Exact	90	25 100	50 100
Approx.	60	83 700	193 300

- ▶ STINGER overhead is minimal; most time is spent metric.

Hierarchy of Interesting Analytics

- ▶ **Extend single-shot graph queries to include time.**
 - Are there s - t paths between time T_1 and T_2 ?
 - What are the important vertices at time T ?
- ▶ **Use persistent queries to monitor properties.**
 - Does the path between s and t shorten drastically?
 - Is some vertex suddenly very central?
- ▶ **Extend persistent queries to fully dynamic properties.**
 - Does a small community stay independent rather than merge with larger groups?
 - When does a vertex jump between communities?
- ▶ **New types of queries, new challenges...**

Bader, Related Recent Publications (2005-2008)

- D.A. Bader, G. Cong, and J. Feo, “**On the Architectural Requirements for Efficient Execution of Graph Algorithms,**” *The 34th International Conference on Parallel Processing (ICPP 2005)*, pp. 547-556, Georg Sverdrups House, University of Oslo, Norway, June 14-17, 2005.
- D.A. Bader and K. Madduri, “**Design and Implementation of the HPCS Graph Analysis Benchmark on Symmetric Multiprocessors,**” *The 12th International Conference on High Performance Computing (HiPC 2005)*, D.A. Bader et al., (eds.), Springer-Verlag LNCS 3769, 465-476, Goa, India, December 2005.
- D.A. Bader and K. Madduri, “**Designing Multithreaded Algorithms for Breadth-First Search and st-connectivity on the Cray MTA-2,**” *The 35th International Conference on Parallel Processing (ICPP 2006)*, Columbus, OH, August 14-18, 2006.
- D.A. Bader and K. Madduri, “**Parallel Algorithms for Evaluating Centrality Indices in Real-world Networks,**” *The 35th International Conference on Parallel Processing (ICPP 2006)*, Columbus, OH, August 14-18, 2006.
- K. Madduri, D.A. Bader, J.W. Berry, and J.R. Crobak, “**Parallel Shortest Path Algorithms for Solving Large-Scale Instances,**” *9th DIMACS Implementation Challenge – The Shortest Path Problem*, DIMACS Center, Rutgers University, Piscataway, NJ, November 13-14, 2006.
- K. Madduri, D.A. Bader, J.W. Berry, and J.R. Crobak, “**An Experimental Study of A Parallel Shortest Path Algorithm for Solving Large-Scale Graph Instances,**” *Workshop on Algorithm Engineering and Experiments (ALENEX)*, New Orleans, LA, January 6, 2007.
- J.R. Crobak, J.W. Berry, K. Madduri, and D.A. Bader, “**Advanced Shortest Path Algorithms on a Massively-Multithreaded Architecture,**” *First Workshop on Multithreaded Architectures and Applications (MTAAP)*, Long Beach, CA, March 30, 2007.
- D.A. Bader and K. Madduri, “**High-Performance Combinatorial Techniques for Analyzing Massive Dynamic Interaction Networks,**” *DIMACS Workshop on Computational Methods for Dynamic Interaction Networks*, DIMACS Center, Rutgers University, Piscataway, NJ, September 24-25, 2007.
- D.A. Bader, S. Kintali, K. Madduri, and M. Mihail, “**Approximating Betweenness Centrality,**” *The 5th Workshop on Algorithms and Models for the Web-Graph (WAW2007)*, San Diego, CA, December 11-12, 2007.
- David A. Bader, Kamesh Madduri, Guojing Cong, and John Feo, “**Design of Multithreaded Algorithms for Combinatorial Problems,**” in S. Rajasekaran and J. Reif, editors, *Handbook of Parallel Computing: Models, Algorithms, and Applications*, CRC Press, Chapter 31, 2007.
- Kamesh Madduri, David A. Bader, Jonathan W. Berry, Joseph R. Crobak, and Bruce A. Hendrickson, “**Multithreaded Algorithms for Processing Massive Graphs,**” in D.A. Bader, editor, *Petascale Computing: Algorithms and Applications*, Chapman & Hall / CRC Press, Chapter 12, 2007.
- D.A. Bader and K. Madduri, “**SNAP, Small-world Network Analysis and Partitioning: an open-source parallel graph framework for the exploration of large-scale networks,**” *22nd IEEE International Parallel and Distributed Processing Symposium (IPDPS)*, Miami, FL, April 14-18, 2008.

Bader, Related Recent Publications (2009-2010)



- ▶ S. Kang, D.A. Bader, “An Efficient Transactional Memory Algorithm for Computing Minimum Spanning Forest of Sparse Graphs,” 14th ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming (PPoPP), Raleigh, NC, February 2009.
- ▶ Karl Jiang, David Ediger, and David A. Bader. “Generalizing k-Betweenness Centrality Using Short Paths and a Parallel Multithreaded Implementation.” The 38th International Conference on Parallel Processing (ICPP), Vienna, Austria, September 2009.
- ▶ Kamesh Madduri, David Ediger, Karl Jiang, David A. Bader, Daniel Chavarría-Miranda. “A Faster Parallel Algorithm and Efficient Multithreaded Implementations for Evaluating Betweenness Centrality on Massive Datasets.” Third Workshop on Multithreaded Architectures and Applications (MTAAP), Rome, Italy, May 2009.
- ▶ David A. Bader, et al. “STINGER: Spatio-Temporal Interaction Networks and Graphs (STING) Extensible Representation.” 2009.
- ▶ David Ediger, Karl Jiang, E. Jason Riedy, and David A. Bader. “Massive Streaming Data Analytics: A Case Study with Clustering Coefficients,” Fourth Workshop in Multithreaded Architectures and Applications (MTAAP), Atlanta, GA, April 2010.
- ▶ Seunghwa Kang, David A. Bader. “Large Scale Complex Network Analysis using the Hybrid Combination of a MapReduce cluster and a Highly Multithreaded System:,” Fourth Workshop in Multithreaded Architectures and Applications (MTAAP), Atlanta, GA, April 2010.



Acknowledgment of Support



NSF Computing Research Infrastructure: Development of a Research Infrastructure for Multithreaded Computing Community Using Cray Eldorado Platform



- The Cray XMT system serves as an ideal platform for the research and development of algorithms, data sets, libraries, languages, tools, and simulators for applications that benefit from large numbers of threads, massively data intensive, sparse-graph problems that are difficult to parallelize using conventional message-passing on clusters.
 - A shared community resource capable of efficiently running, in experimental and production modes, complex programs with thousands of threads in shared memory;
 - Assembling software infrastructure for developing and measuring performance of programs running on the hardware; and
 - Building stronger ties between the people themselves, creating ways for researchers at the partner institutions to collaborate and communicate their findings to the broader community.



CRAY

FACULTY

David A. Bader, PI (GA Tech)

Collaborators include: Univ of Notre Dame, Univ. of Delaware, UC Santa Barbara, CalTech, UC Berkeley, Sandia National Laboratories

<http://www.nsf.gov/awardsearch/showAward.do?AwardNumber=0708307>