Massive-scale analysis of streaming social networks
David A. Bader
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**

REQUIRES PREDICTING / INFLUENCE CHANGE IN REAL-TIME AT SCALE
Ubiquitous High Performance Computing (UHPC)

Goal: develop highly parallel, security enabled, power efficient processing systems, supporting ease of programming, with resilient execution through all failure modes and intrusion attacks

Architectural Drivers:
- Energy Efficient
- Security and Dependability
- Programmability

Program Objectives:
- One PFLOPS, single cabinet including self-contained cooling
- 50 GFLOPS/W (equivalent to 20 pJ/FLOP)
- Total cabinet power budget 57KW, includes processing resources, storage and cooling
- Security embedded at all system levels
- Parallel, efficient execution models
- Highly programmable parallel systems
- Scalable systems – from terascale to petascale

“NVIDIA-Led Team Receives $25 Million Contract From DARPA to Develop High-Performance GPU Computing Systems” –MarketWatch

Echelon: Extreme-scale Compute Hierarchies with Efficient Locality-Optimized Nodes
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 over $14 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.
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. 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
Driving Forces in Social Network Analysis

Facebook has more than 500 million active users.

3 orders of magnitude growth in 3 years!

- Note the graph is **changing** as well as growing.
- What are this graph's properties? *How do they change?*
- Traditional graph partitioning often fails:
  - **Topology:** Interaction graph is low-diameter, and has no good separators
  - **Irregularity:** Communities are not uniform in size
  - **Overlap:** individuals are members of one or more communities
- 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
Example: Mining Twitter for Social Good

ICPP 2010

Massive Social Network Analysis: Mining Twitter for Social Good

David Ediger, Karl Jiang, Jason Ricci, and David A. Bader
Georgia Institute of Technology, Atlanta, GA, USA

Courtenay Corley, Rob Farber, Pacific Northwest National Lab, Richland, WA, USA
William N. Reynolds, Leasqure Software, Inc, Albuquerque, NM, USA

Abstract—Social networks produce an enormous quantity of data. For example, Facebook consists of over 900 million active users sharing over 3 billion pieces of information each month. Analyzing this vast quantity of unstructured data presents challenges for software and hardware. We present GraphCT, a Graph Characterization Toolkit, for massive graphs representing social network data. On a 128-core Cray XE6, GraphCT estimates the betweenness centrality of an artificially generated (8,537,521 vertices, 16 billion-edge graph in 15 minutes and a real-world graph (8,537,521 vertices, 147 billion edges) in 105 minutes. We use GraphCT to analyze public data from Twitter, a microblogging network. Twitter’s message connections appear primary and structured as a news dissemination system. Within the involves over 400 million active users with an average of 120 ‘friendship’ connections each and sharing 5 references to items each month [11]. One analysis approach treats the interactions as graph theory, social analysis, and scale-free networks [9]. However, the volume of data that must be processed to apply these techniques overwhelms current computational capabilities.

Social media provides staggering amounts of information in a short amount of time. Advances in both hardware and software to process these large, dynamic datasets allow us to gain new insights into the ways in which they interact and communicate.

Table 1: Top 15 Users by Betweenness Centrality

<table>
<thead>
<tr>
<th>Rank</th>
<th>H1N1</th>
<th>Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>@CDCFlu</td>
<td>@ajc</td>
</tr>
<tr>
<td>2</td>
<td>@addthis</td>
<td>@driveafaste</td>
</tr>
<tr>
<td>3</td>
<td>@Official_PAX</td>
<td>@ATLCrash</td>
</tr>
<tr>
<td>4</td>
<td>@FluGov</td>
<td>@TWCi</td>
</tr>
<tr>
<td>5</td>
<td>@nytimes</td>
<td>@HelloNorthGA</td>
</tr>
<tr>
<td>6</td>
<td>@tweetmeme</td>
<td>@11AliveNews</td>
</tr>
<tr>
<td>7</td>
<td>@mercola</td>
<td>@WSE_TV</td>
</tr>
<tr>
<td>8</td>
<td>@CNN</td>
<td>@shaunking</td>
</tr>
<tr>
<td>9</td>
<td>@backstreetboys</td>
<td>@Carl</td>
</tr>
<tr>
<td>10</td>
<td>@EllieSmith_X</td>
<td>@SpaceyG</td>
</tr>
<tr>
<td>11</td>
<td>@TIME</td>
<td>@ATLInTownPa</td>
</tr>
<tr>
<td>12</td>
<td>@CDCemergency</td>
<td>@TJS937</td>
</tr>
<tr>
<td>13</td>
<td>@CDC_eHealth</td>
<td>@ATLien</td>
</tr>
<tr>
<td>14</td>
<td>@perez Hilton</td>
<td>@MarshallRamsey</td>
</tr>
<tr>
<td>15</td>
<td>@billmaher</td>
<td>@Kanye</td>
</tr>
</tbody>
</table>

Fig. 3. Subcommunity filtering on Twitter data sets

Image credit: bioethicsinstitute.org
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

Massive Data Analytics: Protecting our Nation

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

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
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

Massive data analytics in Informatics networks

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

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

Emerging applications: dynamic, high-dimensional data

Static networks, Euclidean topologies

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

- SSCA#2 network, SCALE 24 (16.77 million vertices and 134.21 million edges.)
Centrality in Massive Social Network Analysis

- **Centrality metrics**: Quantitative measures to capture the importance of person in a social network
  - *Betweenness* is a global index related to shortest paths that traverse through the person
  - Can be used for community detection as well

- Identifying *central* nodes in large complex networks is the key metric in a number of applications:
  - Biological networks, protein-protein interactions
  - Sexual networks and AIDS
  - Identifying key actors in terrorist networks
  - Organizational behavior
  - Supply chain management
  - Transportation networks

- Current Social Network Analysis (SNA) packages handle 1,000’s of entities, our techniques handle **BILLIONS** (6+ orders of magnitude larger data sets)
Betweenness Centrality (BC)

- Key metric in social network analysis
  [Freeman ’77, Goh ’02, Newman ’03, Brandes ’03]

\[
BC(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}
\]

- \(\sigma_{st}\): Number of shortest paths between vertices s and t
- \(\sigma_{st}(v)\): Number of shortest paths between vertices s and t passing through v

- Exact BC is compute-intensive
BC Algorithms

- Brandes [2003] proposed a faster sequential algorithm for BC on sparse graphs
  - $O(mn + n^2 \log n)$ time and $O(n)$ space for weighted graphs
  - $O(mn)$ time for unweighted graphs
- We designed and implemented the first parallel algorithm:
  - [Bader, Madduri; ICPP 2006]

- Approximating Betweenness Centrality [Bader Kintali Madduri Mihail 2007]
  - Novel approximation algorithm for determining the betweenness of a specific vertex or edge in a graph
  - Adaptive in the number of samples
  - Empirical result: At least 20X speedup over exact BC

Graph: 4K vertices and 32K edges,
System: Sun Fire T2000 (Niagara 1)
An undirected graph of 1.54 million vertices (movie actors) and 78 million edges. An edge corresponds to a link between two actors, if they have acted together in a movie.

Kevin Bacon
HPC Challenges for Massive SNA

- Algorithms that work on complex networks with hundreds to thousands of vertices often disintegrate on real networks with millions (or more) of vertices
  - For example, betweenness centrality is not robust to noisy data (biased sampling of the actual network, missing friendship edges, etc.)
  - Requires niche computing systems that can offer irregular and random access to large global address spaces.
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
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

![Graph Data](image)
![Connected Components](image)
![Betweenness Centrality](image)

Load the Graph Data
Find Connected Components
Run $k$-Betweenness Centrality on the largest component
## GraphCT Functions

<table>
<thead>
<tr>
<th>Name</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMAT graph generator</td>
<td>Modularity Score</td>
</tr>
<tr>
<td>Degree distribution statistics</td>
<td>Conductance Score</td>
</tr>
<tr>
<td>Graph diameter</td>
<td>st-Connectivity</td>
</tr>
<tr>
<td>Maximum weight edges</td>
<td>Delta-stepping SSSP</td>
</tr>
<tr>
<td>Connected components</td>
<td>Bellman-Ford</td>
</tr>
<tr>
<td>Component distribution statistics</td>
<td>GTriad Census</td>
</tr>
<tr>
<td>Vertex Betweenness Centrality</td>
<td>SSCA2 Kernel 3 Subgraphs</td>
</tr>
<tr>
<td>Vertex k-Betweenness Centrality</td>
<td>Greedy Agglomerative Clustering</td>
</tr>
<tr>
<td>Multithreaded BFS</td>
<td>Minimum spanning forest</td>
</tr>
<tr>
<td>Edge-divisive Betweenness-based Community Detection (pBD)</td>
<td>Clustering coefficient</td>
</tr>
<tr>
<td>Lightweight Binary Graph I/O</td>
<td>DIMACS Text Input</td>
</tr>
</tbody>
</table>

**Key**
- Included
- In Progress
- Proposed/Available

David A. Bader
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.
STING Extensible Representation

- Semi-dense edge list blocks with free space
- Compactly stores timestamps, types, weights
- Maps from application IDs to storage IDs
- Deletion by negating IDs, separate compaction
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)

Bader, Related Recent Publications (2009-2010)


- 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.


- 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.
Collaborators and Acknowledgments

- David Ediger (Georgia Tech)
- Karl Jiang (Georgia Tech)
- Jason Riedy (UC Berkeley & Georgia Tech)
- Kamesh Madduri (Lawrence Berkeley National Lab)
- John Feo and Daniel G. Chavarría-Miranda (Pacific Northwest Lab)
- Jon Berry and Bruce Hendrickson (Sandia National Laboratories)
- Guojing Cong (IBM TJ Watson Research Center)
- Jeremy Kepner (MIT Lincoln Laboratory)
Acknowledgment of Support
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.

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

David A. Bader, PI (GA Tech)