# STINGER: Multi-threaded Graph Streaming

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Graph Algorithms Building Blocks (GABB), 19 May 2014

# (insert current prefix here)scale data analysis

| | |
|---|---|
| Health care | Finding outbreaks, population epidemiology |
| Social networks | Advertising, searching, grouping |
| Intelligence | Decisions at scale, regulating algorithms |
| Systems biology | Understanding interactions, drug design |
| Power grid | Disruptions, conservation |
| Simulation | Discrete events, cracking meshes |

- Data analysis runs throughout.
- Many problems can be phrased through *graphs*.
  - Any many are changing and *dynamic*.

# Outline

# General approaches

- High-performance *static graph analysis*
  - Develop techniques that apply to unchanging massive graphs.
  - Provides useful after-the-fact information, starting points.
  - Serves many existing applications well: market research, much bioinformatics, ...
  - Needs to be $O(|E|)$.
- High-performance streaming graph analysis
  - Focus on the dynamic changes within massive graphs.
  - Find trends or new information as they appear.
  - Serves upcoming applications: fault or threat detection, trend analysis, online prediction...
  - Can be $O(|\Delta E|)$? $O(\mathrm{Vol}(\Delta V))$? Less data $\Rightarrow$ faster, efficient

# Streaming graph data

## Data Rates

From `www.statisticsbrain.com`:

- 58M posts per day on Twitter (671 / sec)
- 1M links shared per 20 minutes on Facebook

Other applications (*e.g.* network security) need to respond nearly at line rate, 81k-1.5M pps on gigabit ethernet.

## Opportunities

- Do not need to analyze the entire graph.
- Different domains: Throughput & latency
  - Expose different levels of concurrency
- Can achieve ridiculous “speed ups.”

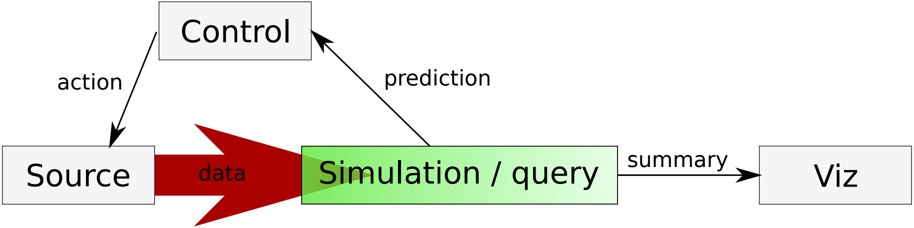
# Streaming Queries

## Different kinds of questions

- How are individual graph metrics (*e.g.* clustering coefficients) changing?
- What are the patterns in the changes?
  - Are there seasonal variations?
  - What are responses to events?
- What are *temporal anomalies* in the graph?
  - Do key members in clusters / communities change?
  - Are there indicators of event responses before they are obvious?

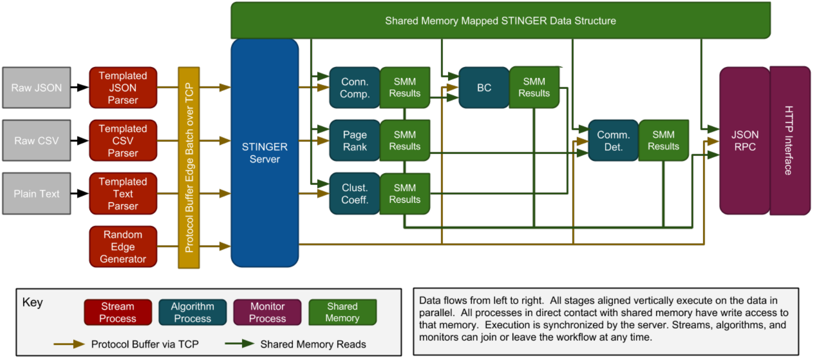
# On to STING...

# STING's focus




- STING: Spatio-Temporal Interaction Networks and Graphs
- STING manages queries against changing graph data.
  - Visualization and control often are application specific.
- Ideal: Maintain many persistent graph analysis kernels.
  - One current graph snapshot, kernels keep smaller histories.
  - Also (a harder goal), coordinate the kernels' cooperation.

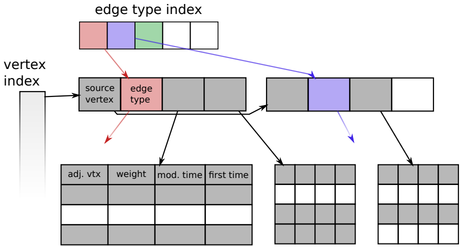
# STING: High-level architecture




Slide credit: Rob McColl and David Ediger

- OpenMP + sufficiently POSIX-ish
- Multiple processes for resilience

# STING Extensible Representation: Core data structure




## Initial considerations [Bader, *et al.*]

- Be useful for the entire “large graph” community
- Permit good performance: No single structure is optimal for all.
- Assume globally addressable memory access and atomic operations
- Not a *graph database*, but supports types, subsets
- Large graph ⇒ rare conflicts

# Building Blocks for Streaming Graph Data

Motivation: Graph Algorithms for Analysis

Graphs and Streaming Data

STING/STINGER Analysis Framework

Building Blocks for Streaming Graph Data
- PageRank
- Triangle Counting
- Agglomerative Communities

Observations

# Incremental PageRank

- PageRank: Well-understood method for ranking vertices based on random walks (related to minimizing conductance).
- Equivalent problem, solve $(I - \alpha A^T D^{-1})x = (1 - \alpha)v$ given initial weights $v$.
- Goal: Use for *seed set expansion*, sparse $v$.
- State-of-the-art for updating $x$ when the graph represented by $A$ changes? Re-start iteration with the previous $x$.
- Can do significantly better for low-latency needs.
- Compute the change $\Delta x$ instead of the entire new $x$.

# Incremental PageRank: Iteration

## Iterative solver

Step $k \rightarrow k+1$:

$$\Delta x^{(k+1)} = \alpha (A + \Delta A)^T (D + \Delta D)^{-1} \Delta x^{(k)} + \alpha \left[ (A + \Delta A)^T (D + \Delta D)^{-1} - A^T D^{-1} \right] x$$

- Additive part: Non-zero only at changes.
- Operator: Pushes changes outward.

# Incremental PageRank: Limiting Expansion

## Iterative solver

Step $k \rightarrow k+1$:

$$\Delta\hat{x}^{(k+1)} = \alpha(A+\Delta A)^T(D+\Delta D)^{-1}\Delta\hat{x}^{(k)}_{|\text{ex}} + \alpha\Delta\hat{x}_{|\text{held}}$$
$$\alpha\left[(A+\Delta A)^T(D+\Delta D)^{-1} - A^T D^{-1}\right]\hat{x}$$

- Additive part: Non-zero only at changes.
- Operator: Pushes sufficiently large changes outward.

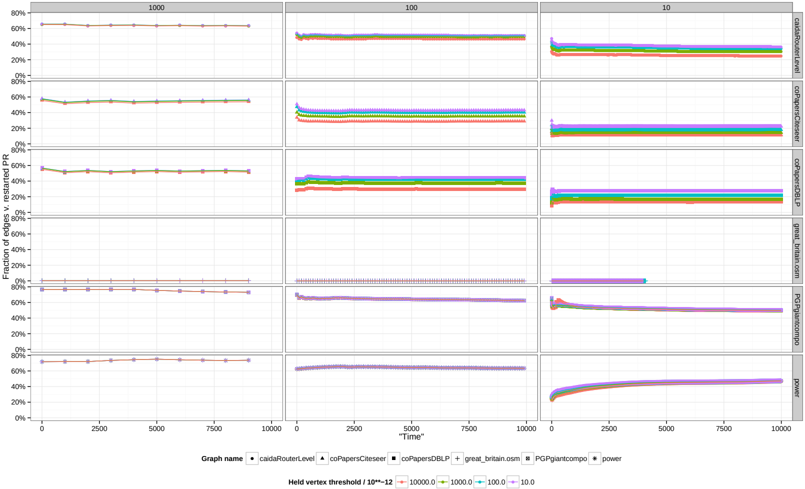
# Incremental PageRank: Test Cases

- Initial, high-level implementation via sparse matrices in Julia.
- Test graphs from the $10^{\text{th}}$ DIMACS Implementation Challenge.
- Add uniformly random edges... worst case.
- Up to 100k in different batch sizes.
- One sequence of edge actions per graph shared across experiments.
- Conv. & hold base threshold: $10^{-12}$

| Graph | $\lvert V\rvert$ | $\lvert E\rvert$ | Avg. Deg. | Size (MiB) |
|---|---|---|---|---|
| caidaRouterLevel | 192 244 | 609 066 | 3.17 | 5.38 |
| coPapersCiteseer | 434 102 | 1 603 6720 | 36.94 | 124.01 |
| coPapersDBLP | 540 486 | 15 245 729 | 28.21 | 118.38 |
| great-britain.osm | 7 733 822 | 8 156 517 | 1.05 | 91.73 |
| PGPgiantcompo | 10 680 | 24 316 | 2.28 | 0.23 |
| power | 4 941 | 6 594 | 1.33 | 0.07 |

# Incremental PageRank: Throughput v. latency

Percent of edge traversals relative to re-started iteration:



# Triangle Counting

## Current version

- Count all the triangles around each graph vertex.
- Used in clustering coefficients (numerator), *etc*.
  - Up to 130 000 graph updates per second on X5570 (Nehalem-EP, 2.93GHz)
  - 2000× speed-up over static recomputation
- Main algorithm, for each vertex $v$:
  - Sort its adjacency list.
  - For each neighbor $w$,
    - search for $w$'s neighbors in the sorted list.
- *Could* compute $\mathrm{diag}(A^3)$, more or less...

# Triangle Counting: Small Batches

## Low-latency case

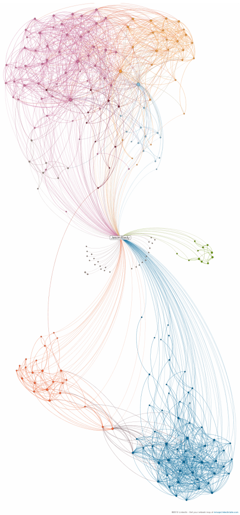
- In generall, diag($A^3$) is a silly option.
- But $A^3 \Delta x$, a BFS, to count around a few vertices...
- Brute force (MTAAP10)
  - Roughly 4× slower with moderate batches, and
  - less than 2× slower with small batches.
- Could be reasonable for a quick hack.

Small changes (low latency) may find more applications of linear algebra-like primitives.

# Community Detection

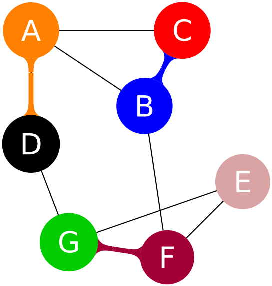
What do *we* mean?

- Partition a graph's vertices into disjoint communities.
- Locally optimize some metric, *e.g.* modularity, conductance
- Try to capture that vertices are *more similar* within one community than between communities.
- *Modularity*: More internal edges than expected.



Jason's network via LinkedIn Labs

# Parallel Agglomerative Method




- Use a matching to avoid a serializing queue.
  - Simple greedy algorithm.
  - *Would require smuggling data and communication in through element operators...*
- Highly scalable, $5.8 \times 10^6 - 7 \times 10^6$ edges/sec, $8\times - 16\times$ speed-up on 80-thread E7-8870 (thanks Intel!)
- Extends to dynamic community maintenance
  - Extract vertices from communities, re-agglomerate
  - *Matrix triple product-ish*

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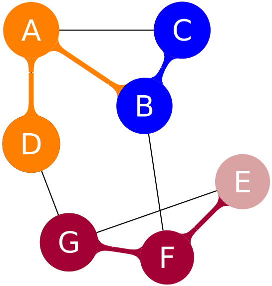


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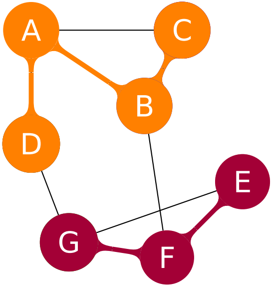


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# Seed Set Expansion

## Problem

- Given a small number of vertices, and
- find a region of interest around them.

- Start with a subset consisting of the selection.
- Evaluate the change in *modularity* around the current subset.
- Absorb all vertices that...
  - may increase modularity by a significant amount, or
  - are within the top 10% of changes, or...
- Repeat until the set is large enough.
- *Step-wise guided expansion doesn't fit current primitives.*

# Observations

- Throughput / latency trade offs:
  - Different levels of parallelism and optimizations
  - Larger batches ⇒ higher throughput, more collisions
  - Small batches ⇒ lower latency, more scattered
  - Impact optimizations similarly to direction-optimized BFS
- Can build proposed building blocks against STINGER
- Many algorithms are not naturally expressed:
  - Matching
  - Guided set expansion by changing criteria
  - Streaming versions of these...
- Targets for version 2?

# STINGER: Where do you get it?


**www.cc.gatech.edu/stinger/**

Gateway to

- code,
- development,
- documentation,
- presentations...
- (working on usage and development screencasts)

Remember: Still academic code, but maturing.

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