# Parallel computation of community structures in graphs

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The rising STAR of Texas

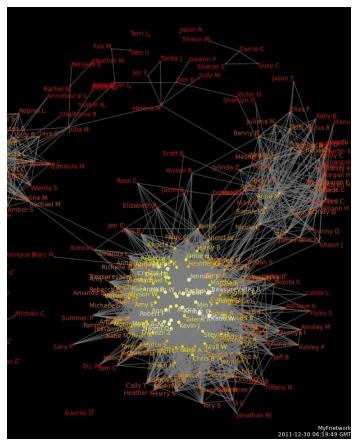
#### **Overview**

- Background of communities in network analysis
- Parallelization project
- Implementation
- Results
- Analysis
- Summary



#### **Network Analysis**

- Information systems and complex networks are represented as graphs
- Nodes/vertices connected by links/edges
- Use in social networks, mobile phone networks, web
- Organization in the randomness

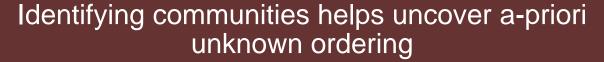


Data visualization of Facebook relationships by the third-party app MyFnetwork <a href="https://commons.wikimedia.org/wiki/User:Kencf0618">https://commons.wikimedia.org/wiki/User:Kencf0618</a>



#### **Communities in Networks**

Communities: subunits in a network



Protein to protein interactions

Communities with shared language dialects

Different group identities discussing a Twitter trend



#### **Community Detection**

- General idea: Optimized network partitioning
  - Communities of densely connected nodes and sparse interconnections between communities
- Precise formulations are known to be computationally intractable
- "Goodness" of partition measured by modularity value Q
- Objective: maximize Q modularity

$$Q = \frac{1}{2m} \sum_{i,j} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

#### where

A<sub>ij</sub>: weight of link between i and j k<sub>i</sub>: sum of link weights attached to node i

c<sub>i</sub>: community of node i

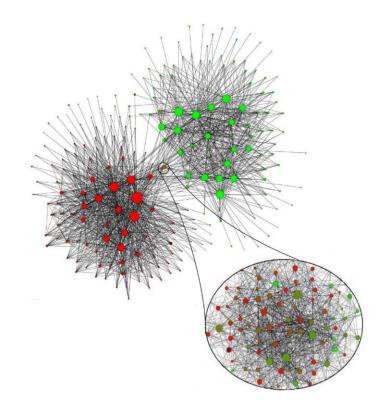
 $\delta(c_i, c_j)$ : 1 if  $c_i == c_j$ , else 0

m = sum of link weights in graph



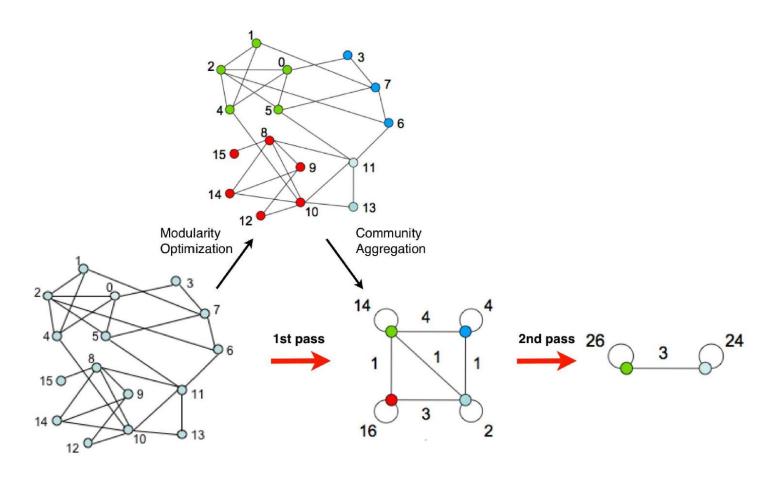
# Louvain Method of Community Detection

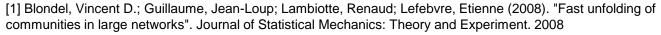
- Rapidly finds high modularity partitions of large networks; Blondel et al.
- Unfolds hierarchical community structure for the network
- Unsupervised clustering





#### **Louvain Algorithm**



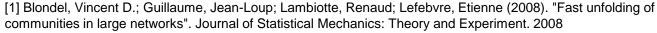




#### **Room for Improvement?**

- While Louvain outperforms other methods, graphs of many millions of nodes/links will take minutes
  - Example: "Web uk-2005" has 39M/783M nodes/links took 738s to achieve 0.979 modularity
- Explore parallel processing using GPUs to further reduce overall computation time in partitioning nodes into communities

Modularity Optimization/Computation Comparison									
Graph name	Karate	Arxiv	Internet	Web nd.edu	Phone	Web uk-2005	Web WebBase 2001		
Nodes/links	34 / 77	9k / 24k	70k / 351k	325k / 1M	2.6M / 6.3M	39M / 783M	118M / 1B		
Clauset, Newman, and Moore method	.38 / 0s	.772 / 3.6s	.692 / 799s	.927 / 5034s	-/-	-/-	-/-		
Pons and Latapy method	.42 / 0s	.757 / 3.3s	.729 / 575s	.895 / 6666s	-/-	-/-	-/-		
Wakita and Tsurumi method	.42 / 0s	.761 / 0.7s	.667 / 62s	.898 / 248s	.56 / 464s	-/-	-/-		
Louvain Method	.42 / 0s	.813 / 0s	.781 / 1s	.935 / 3s	.769 / 134s	.979 / 738s	.984 / 152min		



<sup>\*</sup> modularity value/run time

<sup>\*\* -/-</sup> means the method took over 24hrs to run.



# Parallelizing the Louvain Method



# **Porting Strategy**



Understand general description of algorithm



Top down read of serial code: Start at general operation and drill into specific functions.



Understand flow and data structures



Identify what is calculated, modified, and accounted



Profile serial code and identify functions where time is spent



Identify parallelizable section(s) where most time can be gained back

#### **Serial Timing**

Serial code: Most time spent computing "one level"

```
1741849860 function calls (1740434396 primitive calls) in 2173.463 seconds

Ordered by: cumulative time

ncalls tottime percall cumtime percall filename:lineno(function)

1 0.004 0.004 2173.463 2173.463 {built-in method builtins.exec}

1 0.093 0.093 2173.458 2173.458 <string>:1(<module>)

1 0.175 0.175 2173.365 2173.365 community_louvain.py:161(best_partition)

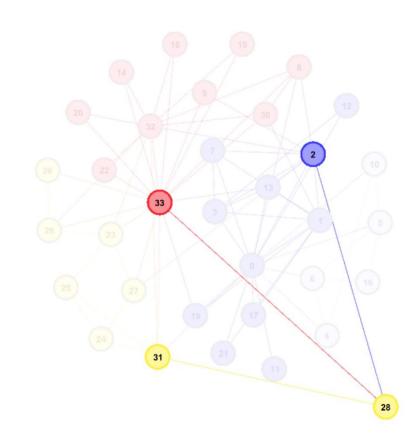
1 2.714 2.714 2171.409 2171.409 community_louvain.py:253(generate_dendrogram)

6 433.219 72.203 2059.197 343.200 community_louvain.py:463(__one_level)
```



# **Computing One Level**

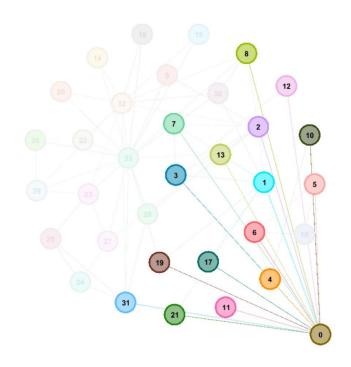
- For each node, consider all neighbors and their communities
- Compute hypothetical modularity if node were reassigned to a neighboring community
- Keep track of change in modularity
- Reassign node to community that gave highest positive change





# **Computing One Level**

- Larger size => more nodes and neighbors to iterate through
- So, assign GPU threads to work on one node and its neighbors
- All nodes simultaneously search for their best community
- Perform a global consensus on which one has the most to gain





# **Computing Modularity Change**

$$\Delta Q = \left[ \frac{\sum_{in} + k_{i,in}}{2m} - \left( \frac{\sum_{tot} + k_i}{2m} \right)^2 \right] - \left[ \frac{\sum_{in} - \left( \frac{\sum_{tot}}{2m} \right)^2 - \left( \frac{k_i}{2m} \right)^2 \right]$$

Given node i and neighboring community C,

 $\Sigma_{in}$  sum of links strictly inside community

k<sub>i,in</sub> sum of links from i to nodes in C

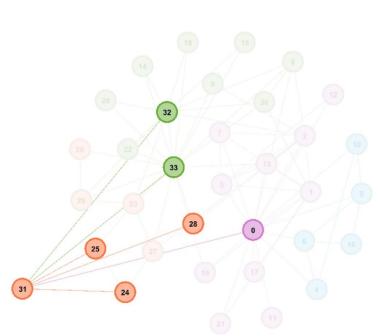
 $\Sigma_{tot}$  sum of links strictly inside community

k<sub>i</sub> sum of links to node i

m sum of all links in entire graph



# **Computing One Level**



Problem: Data dependency of shared community arrays; Q is calculated from these

Solution: Keep arrays as read only; do some personal accounting if community under consideration is current community



# **Implementation**



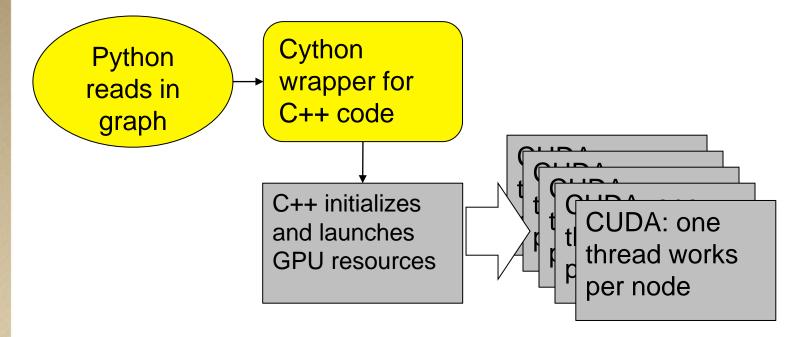
# Python, Cython, CUDA

- Python: High-level, general-purpose, "batteries included"
  - very useful for data analysis when we aren't too concerned with writing new functions from scratch
- Cython: Lets us go "under the hood" to optimize performance
- CUDA C/C++ API: Interface with host (CPU) to GPU device and call operations to take advantage of parallelism
- During analysis, import the Cython wrapper module to run and get results



#### **Data Passing**

- Read in graph and allocate arrays in CPU and GPU memory
- CPU initiates the GPU compute kernel
- GPUs cores run computation for each node in parallel





#### **Hardware**

- ❖ CPU: Two Intel Xeon X5690 @ 3.47 GHz
  - Number of Cores: 12 (2x 6-core UMA)
  - Number of Threads: 12
  - Main Memory: 24 GB
- GPU: NVIDIA Tesla K20 GPU
  - 13 multiprocessors
  - 3.52 TFLOPS single, 1.17 TFLOPS double
  - Threads per multiprocessor: 2048



#### **Data**

Karate social network

Nodes: 34

Links: 78

Average degree: 5

Max degree: 16



#### Results

Graph			Louvain modularity	GPU modularity
karate	0.0044	0.0033	0.417	0.394

Average times are in seconds Serial runs repeated 5 times, randomized nodes



#### **Observations**

- GPU produces a result that original Louvain method can obtain
- Max of max can easily result in lower modularity at the end
- GPU initialization overhead



#### **More Parallelism?**

- Even with shared arrays, some information can be read/written without interfering other thread's calculations.
- Two active nodes are independent if neither writes to same community
  - Process independent nodes in parallel
- Cautious operations
  - Node A and node B are joining/leaving same community
  - Node A leaving a community that node B is joining, or vice versa



#### **Summary**

- Improve Louvain implementation through speedup
  - Parallelization of one level
- Simple global greedy search for highest increase in modularity does not ensure maximum modularity
- Simultaneously assigning non-adjacent communities
  - Requires thread safety mechanisms



# Thank you!

