### RINGO: A System for Interactive Graph Analytics

#### Jure Leskovec (@jure)

Including joint work with Y. Perez, R. Sosič, A. Banarjee, M. Raison, R. Puttagunta , P. Shah



### **Background & Motivation**

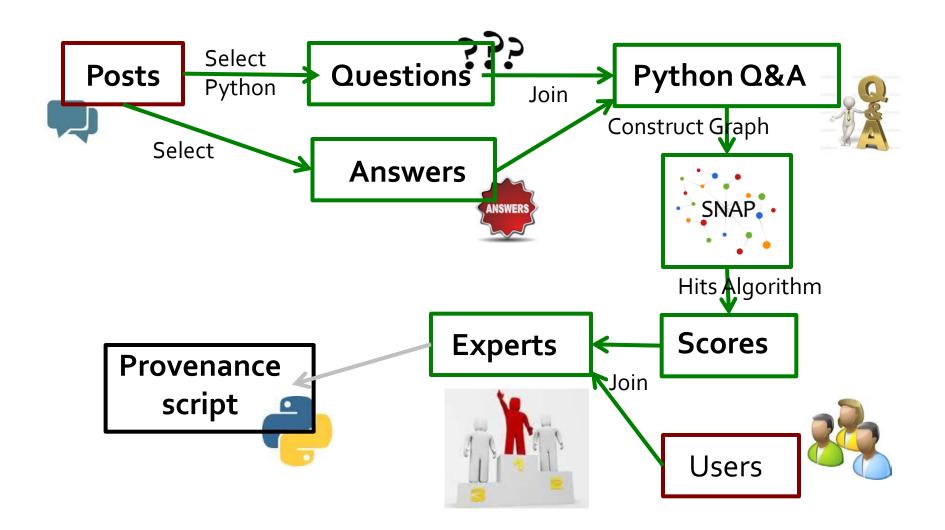
#### My research at Stanford:

- Mining large social and information networks
- We work with data from FaceBook, Yahoo, Twitter, LinkedIn, Wikipedia, StackOverflow

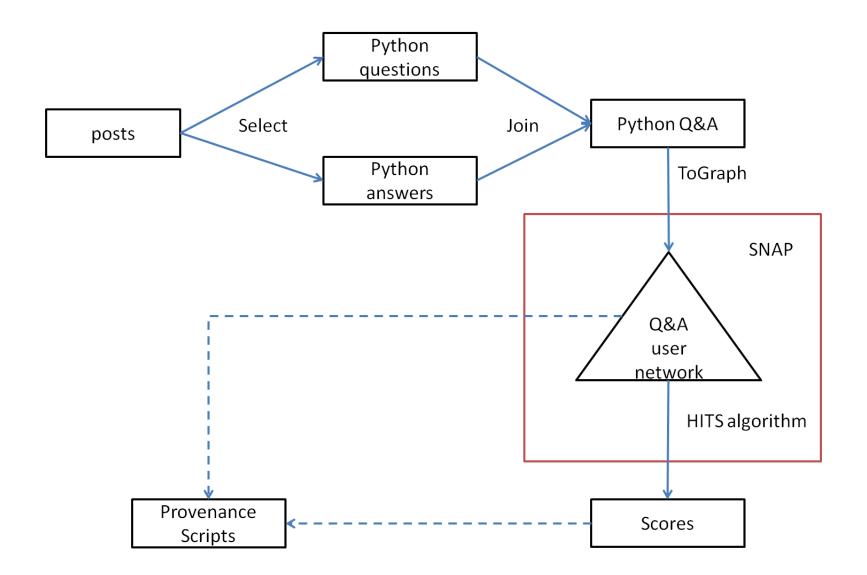
Much research on graph processing systems but we don't find it too useful... Why is that? What tools do we use?

What do we see are some big challenges?

### **Experts on StackOverflow**



### **Experts on StackOverflow**



### Observation

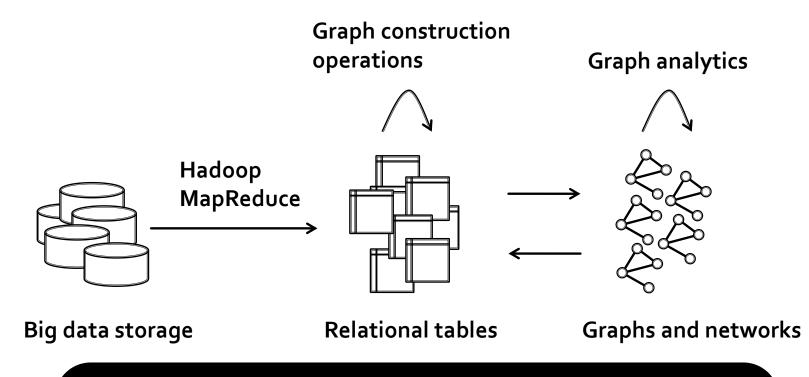
# Graphs are never given. They have to be constructed from input data!

(graph constructions is a part of discovery process)

#### **Examples:**

- Facebook graphs: Friend, Communication, Poke, Co-Tag, Co-location, Co-Event
- Cellphone/Email graphs: How many calls?
- Biology: P2P, Gene interaction networks

### **Graph Analytics Workflow**



#### We need a system that allows for fast <u>creation</u> and <u>processing</u> of big graphs!

### **Desiderata for Graph Analytics**

#### Easy to use front-end

# Common high-level programming language Fast execution times

# Interactive use (as opposed to batch use) Ability to process large graphs

# Tens of billions of edges Support for several data representations

# Transformations between tables and graphs Large number of graph algorithms

# Straightforward to use Workflow management and reproducibility Provenance

### **Machines and Graph Sizes**

#### **Two observations:**

(1) Most graphs are not that large

(2) Big-memory
machines are here!
4x Intel CPU, 64 cores,
1TB RAM, \$30K

Number of Edges	Number of Graphs	
<0.1M	16	
0.1M – 1M	25	
1M – 10M	17	
10M – 100M	7	
100M – 1B	5	
> 1B	1	
SNAP Network Collection		

71 graphs

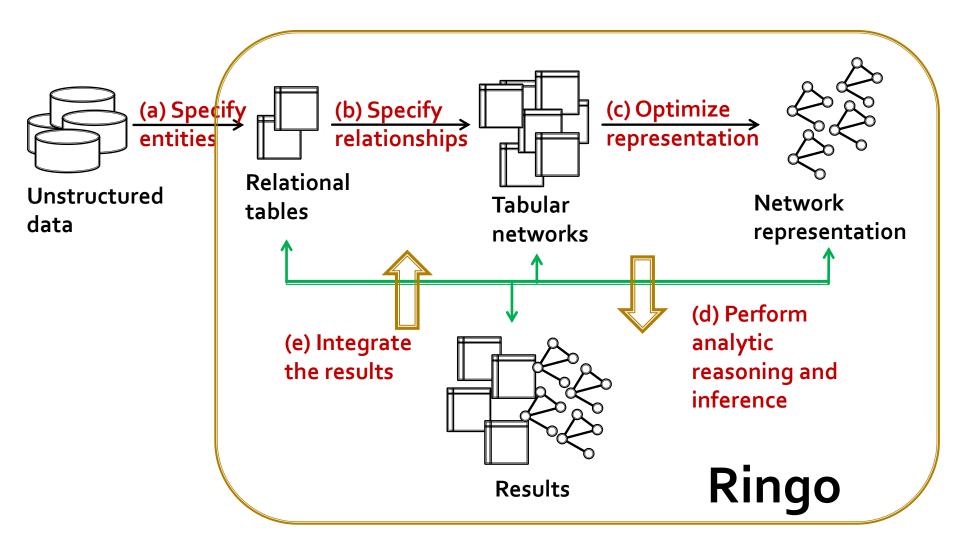
### **Trade-offs**

Option 1	Option 2
Standard SQL database	Custom representations
Separate systems for tables and graphs	Integrated system for tables and graphs
Single representation for tables and graphs	Separate table and graph representations
Distributed system	Single machine system
Disk based structures	In-memory structures

### **Trade-offs**

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### **Graph Analytics: Ringo**

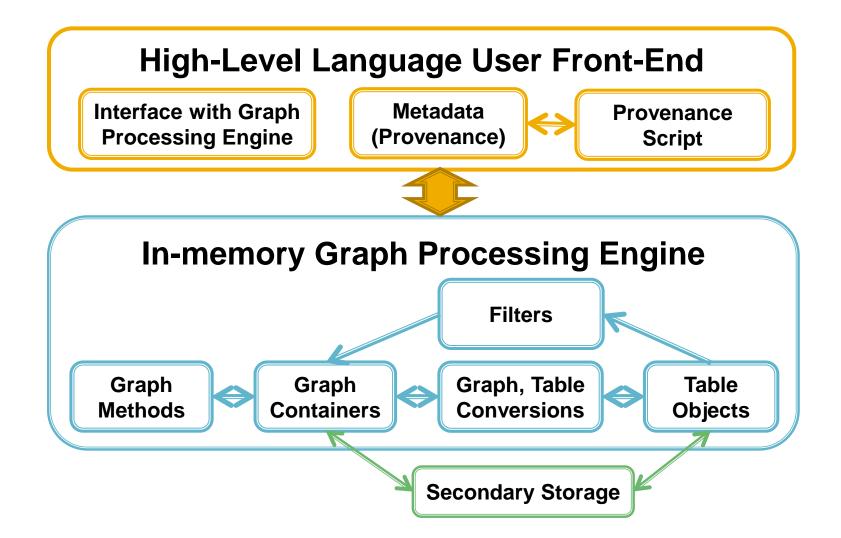


# Ringo!

#### Ringo (Python) code for executing finding the StackOverflow example

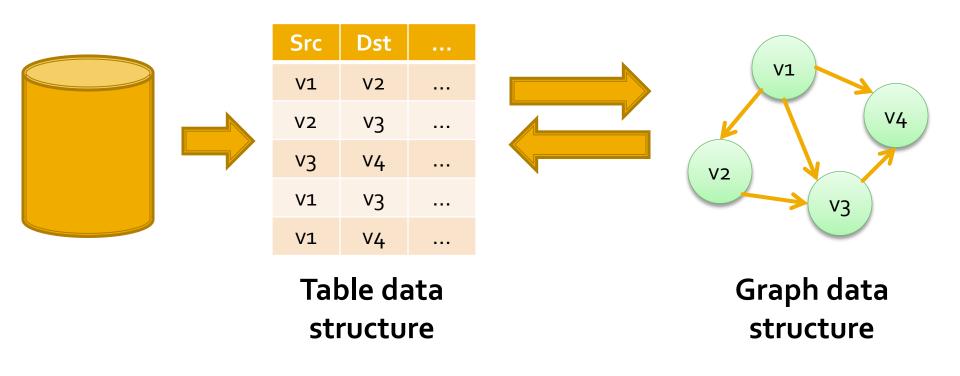
P = ringo.LoadTable(schema,'posts.tsv')
JP = ringo.Select(P,'Tag=Java')
Q = ringo.Select(JP,'Type=question')
A = ringo.Select(JP,'Type=answer')
QA = ringoJoin(Q,A,'AnswerId','PostId')
G = ringo.ToGraph(QA,'UserId.1','UserId.2')
PR = ringo.GetPageRank(G)
S = ringo.ToTable(PR,'UserId','Score')
ringo.Save(S,'scores.bin')

# **Ringo Overview**



### **Graph Construction**

#### Input data must be manipulated and transformed into graphs



# **Creating a Graph in Ringo**

- Four ways to create a graph:
  - The data already contains edges as source and destination pairs
  - Nodes connected based on:
    - Pairwise node similarity
    - Temporal order of nodes
    - Grouping and aggregation of nodes

# **Creating Graphs in Ringo**

#### Use case: In a forum, connect users that post to similar topics:

- Distance metrics
  - Euclidean, Haversine, Jaccard distance
- Connect similar nodes
  - SimJoin, connect if closer than the threshold
- Quadratic complexity
  - Locality sensitive hashing

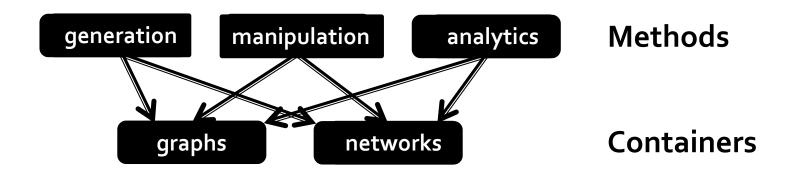
# **Creating Graphs in Ringo**

- Use case: In a Web log, connect pages in a temporal order as clicked by the users
  - Connect a node with its successors
    - Events selected per user, ordered by timestamps
    - NextK, connect K successors

# **Creating Graphs in Ringo**

- Use case: In a Web log, measure the activity level of different user groups
  - Edge creation
    - Partition users to groups
    - Identify interactions within each group
    - Compute a score for each group based on interactions
  - Treat groups as super-nodes in a graph

### **Graphs & Methods**



Several graph types are supported
 Directed, Undirected, Multigraph
 >200 graph algorithms (by SNAP)

### **Graph Representation**

#### **Requirements:**

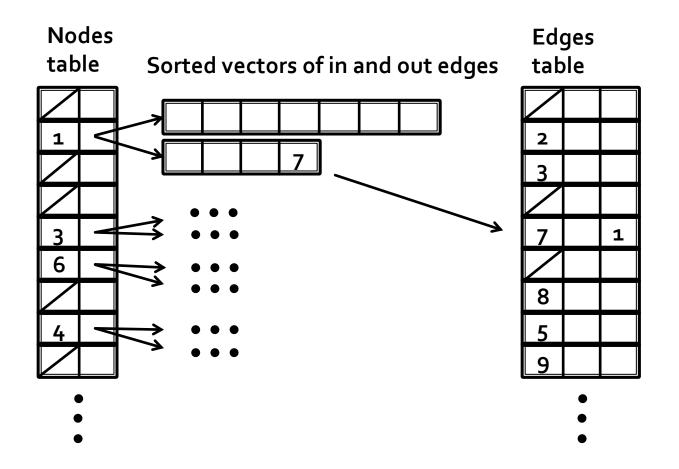
- Fast processing
  - Efficient traversal of nodes and edges

#### Dynamic structure

- Quickly add/remove nodes and edges
  - Create subgraphs, dynamic graphs, …

#### How to achieve good balance?

### **Multigraph in Ringo**



### **Ringo Implementation**

#### High-level front end

- Python module
- Based on Snap.py, uses SWIG for C++ interface

#### High-performance graph engine

- C++ based on SNAP
- Multi-core support
  - OpenMP to parallelize loops
  - Fast, concurrent hash table, vector operations

### **Experiments: Datasets**

Dataset	LiveJournal	Twitter2010
Nodes	4.8M	42M
Edges	69M	1.5B
Text Size (disk)	1.1GB	26.2GB
Graph Size (RAM)	o.7GB	13.2GB
Table Size (RAM)	1.1GB	23.5GB

Jure Leskovec (@jure), Stanford University

### Benchmarks, One Computer

Algorithm Graph	PageRank LiveJournal	PageRank Twitter2010	Triangles LiveJournal	Triangles Twitter2010
Giraph	45.6s	439.3s	N/A	N/A
GraphX	56.0s	-	67.6s	-
GraphChi	54.0s	595.3s	66.5s	-
PowerGraph	27.5s	251.7s	5.4s	706.8s
Ringo	2.6s	72.0s	13.7s	284.1s

#### Hardware: 4x Intel CPU, 64 cores, 1TB RAM, \$35K

### **Published Benchmarks**

System	Hosts	CPUs host	Host Configuration	Time
GraphChi	1	4	8x core AMD, 64GB RAM	158s
TurboGraph	1	1	6x core Intel, 12GB RAM	30s
Spark	50	2		97s
GraphX	16	1	8X core Intel, 68GB RAM	15s
PowerGraph	64	2	8x hyper Intel, 23GB RAM	3.6s
Ringo	1	4	20x hyper Intel, 1TB RAM	6.0s

#### Twitter2010, one iteration of PageRank

# **Ringo: Sequential Algorithms**

Algorithm	Runtime
3-core	31.0s
Single source shortest path	7.4s
Strongly connected components	18.0s

#### LiveJournal, 1 core

### **Tables and Graphs**

Dataset	LiveJournal	Twitter2010
Table to	<b>8.5s</b>	<b>81.0s</b>
graph	13.0 MEdges/s	18.0 MEdges/s
Graph to	<b>1.5s</b>	29.2s
table	46.0 MEdges/s	50.4 MEdges/s

#### Hardware: 4x Intel CPU, 80 cores, 1TB RAM, \$35K

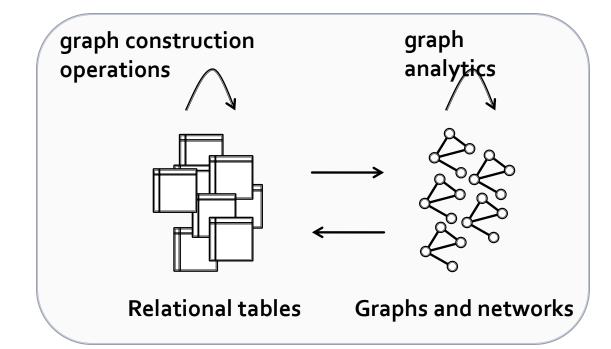
### **Table Operations**

Dataset	LiveJournal	Twitter2010
Select	<0.1s 575.0 MRows/s	<b>1.6s</b> 917.7 MRows/s
Join	<b>0.6s</b> 109.5 MRows/s	<b>4.2s</b> 348.8 MRows/s
Load graph	5.2s	76.6s
Save graph	3.5s	69.0s

### Conclusion

- Big-memory machines are here:
  - ITB RAM, 100 Cores ≈ a small cluster
  - No overheads of distributed systems
  - Easy to program
- Most "useful" datasets fit in memory
- Big-memory machines present a viable solution for analysis of all-but-thelargest networks

### **Conclusion: Ringo**



#### **Ringo: Network science & exploration**

- In-memory graph analytics
- Processing of tables and graphs

#### Fast and scalable

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Jure Leskovec (@jure), Stanford University

# **Bottom line...**

# Get your own 1TB RAM server!

And download RINGO/SNAP http://snap.stanford.edu/snap



Jure Leskovec (@jure), Stanford University

### References

#### Papers:

<u>Ringo: Interactive Graph Analytics on Big-Memory Machines</u> by Y. Perez, R Sosic, A. Banerjee, R. Puttagunta, M. Raison, P. Shah, J. Leskovec. *SIGMOD* 2015.

#### Software:

- <u>http://snap.stanford.edu/ringo/</u>
- <u>http://snap.stanford.edu/snappy</u>
- <u>https://github.com/snap-stanford/snap</u>

#### THANKS! @jure http://snap.stanford.edu

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