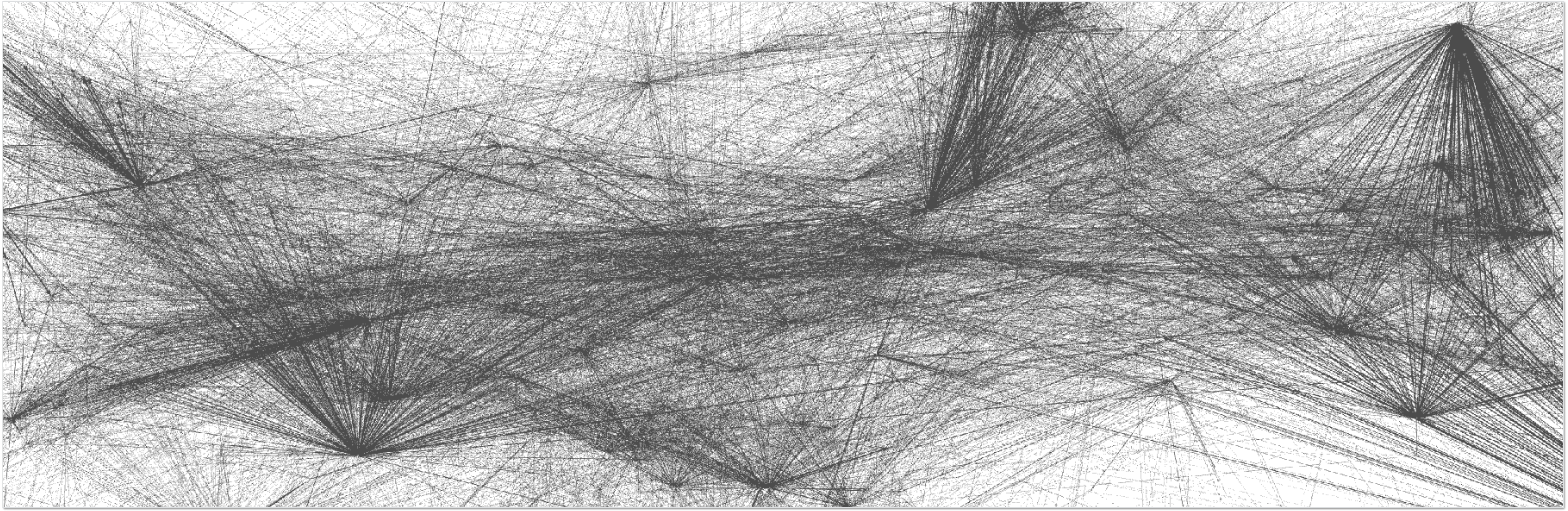
DynamoGraph:
Large-scale Temporal Graph Processing and its Application Scenarios



Matthias Steinbauer

31st of January, 2017

Outline

Introduction

- Motivation
- Addressed Application Areas
- Hypothesis

Related Work Preliminaries

- Temporal Graphs
- Large Graphs
- Distributed Computing

DynamoGraph

- Partitioning Strategies
- Temporal Maps
- Distributed Processing

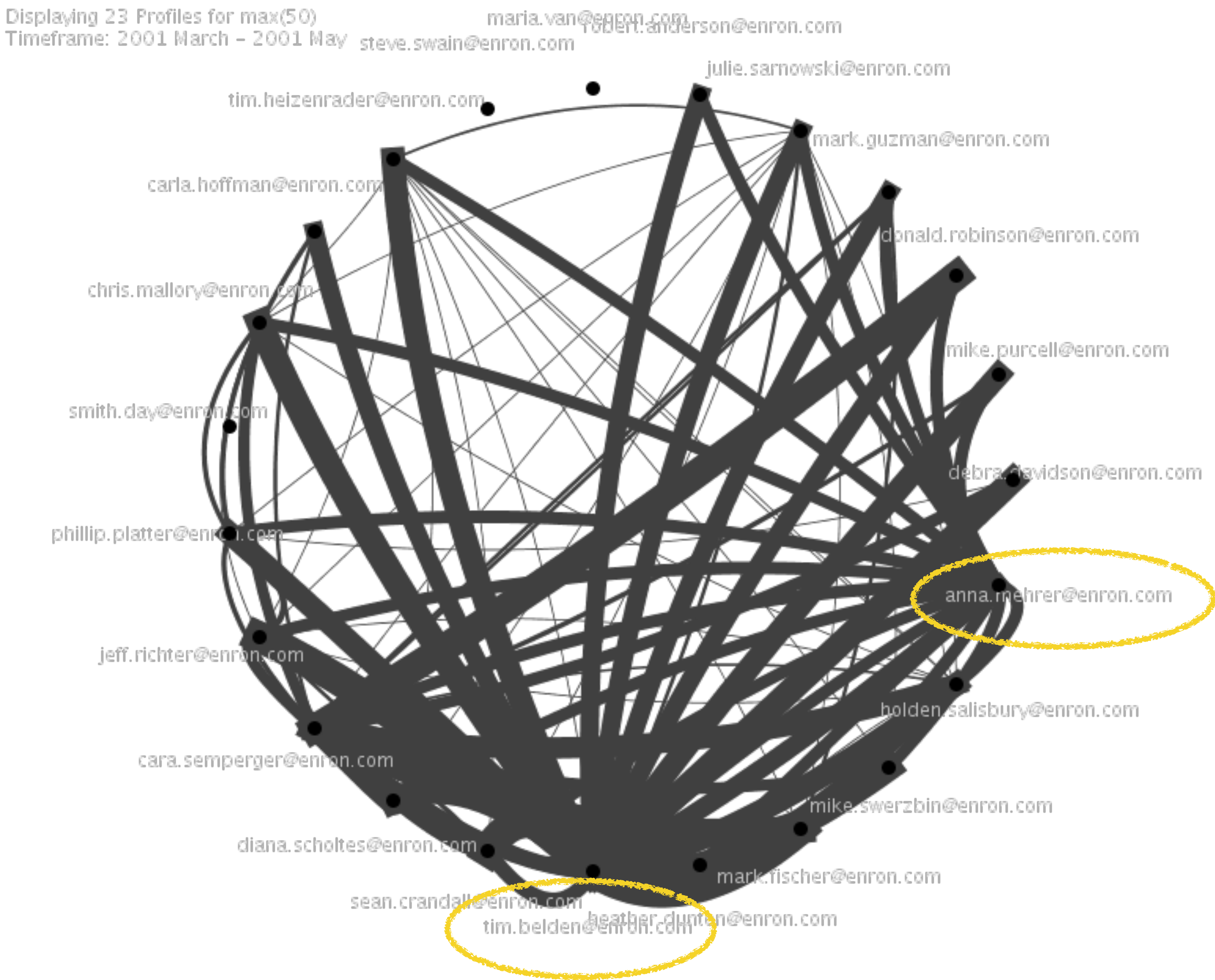
Outline

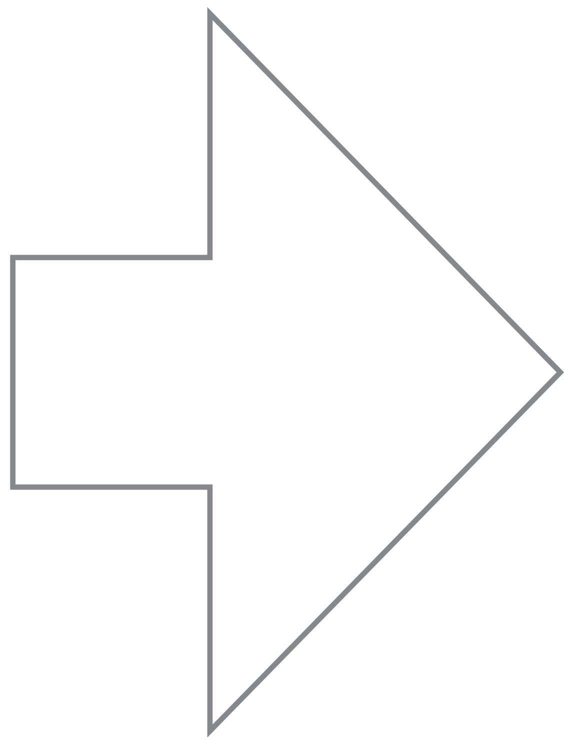
Implementation	Results	Conclusion
• Prototype Overview • Example Algorithm	• Evaluation Setup • Results over Real-World Datasets • Discussion • Selected Case Study	• Future Work • Concluding Remarks

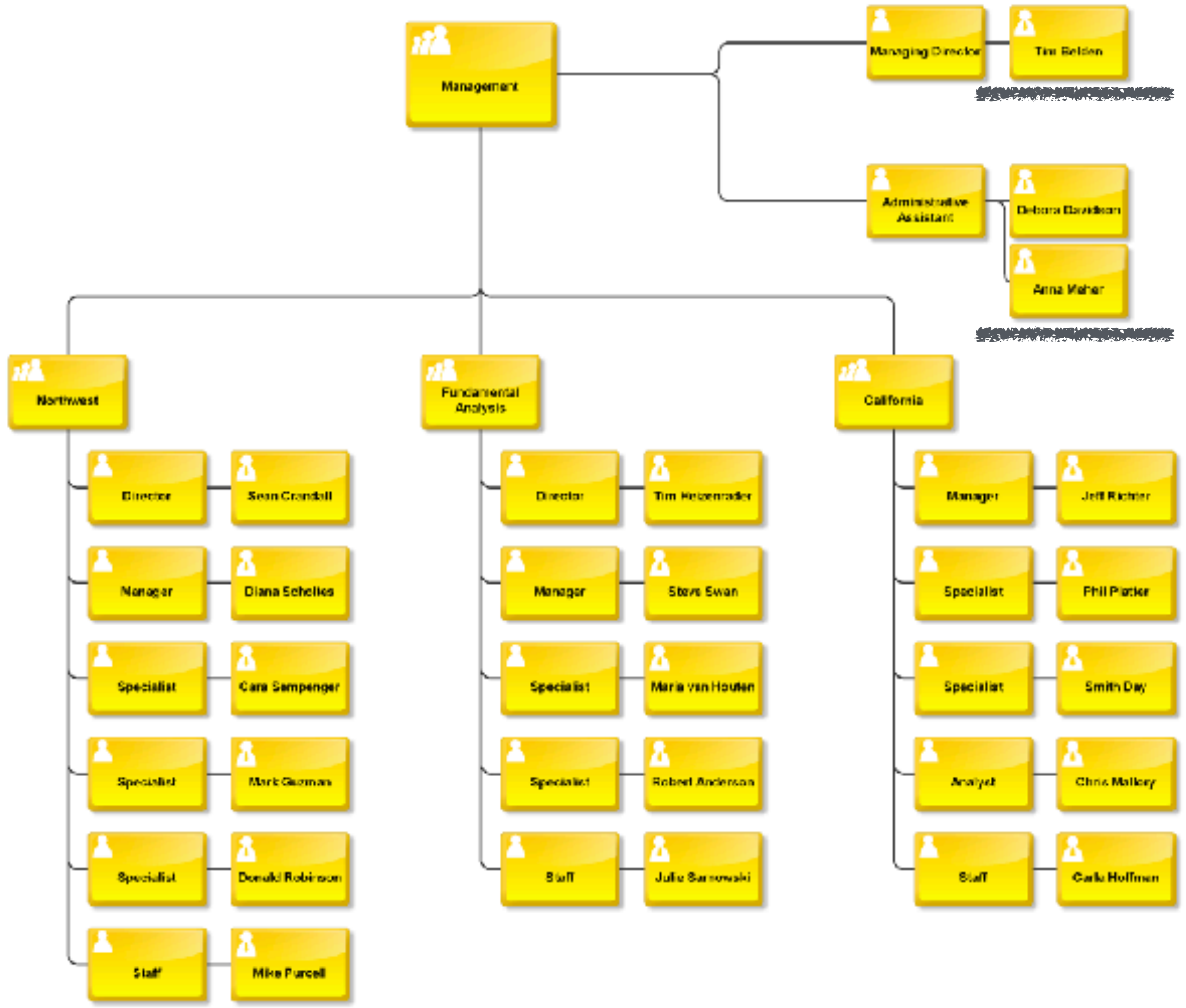
“When people are **networked**, their **power multiplies** geometrically. […] [T]hey can reach out and instantly tap the power of other machines [and] people, essentially **making** the entire **network** their **computer**.”

— Scott McNeely (Sun Microsystems)

Motivation







*Matthias Steinbauer, Sensor Based, **Automated Detection of Behavioural Stereotypes in Informally Formed Workgroups**, Masters Thesis, Johannes Kepler University Linz, 2012.*
*Matthias Steinbauer and Gabriele Kotsis, **Building an Information System for Reality Mining Based on Communication Traces**, in Proceedings of the 15th International Conference on Network-Based Information Systems, Melbourne, 2012.*

Graphs have a Temporal Dimension

- **Static snapshots** of a graph give an **incomplete view**
- Many **systems** modelled by graphs are in fact **highly dynamic**
  - Social networks
  - Biological processes
  - Politics / communication
  - WWW / the Internet

Real-World Networks are Large

They …

- … exceed the **memory capacity** of a single computer
- … cannot be **visualised** with traditional graph vis methods
- … are not **feasible to process** with traditional (sequential) tools and algorithms
- … **keep growing**

facebook

1,818,823,208

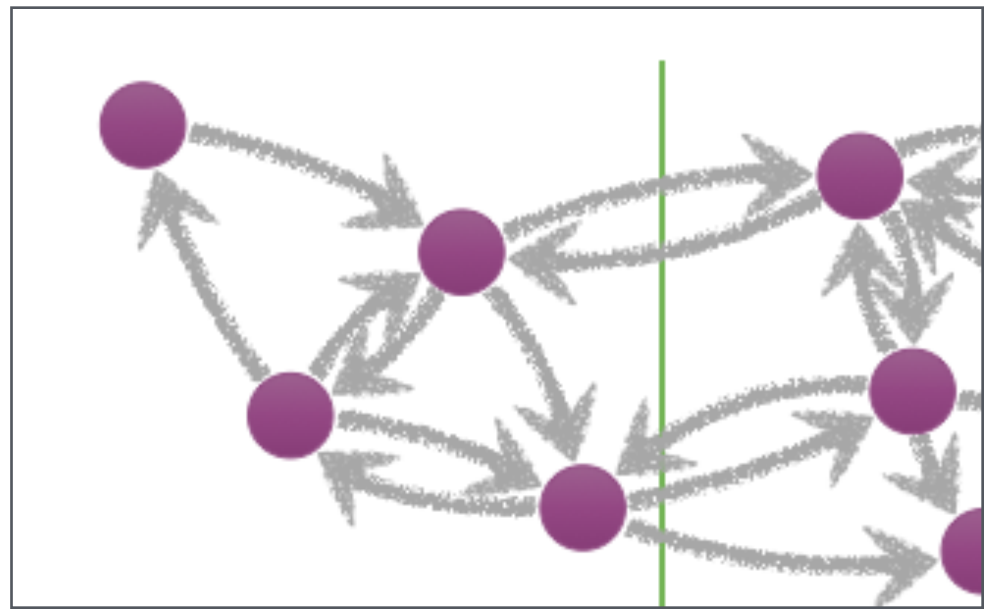
websites

1,141,592,432

examples from internetlivestats.com 28th of January, 2017

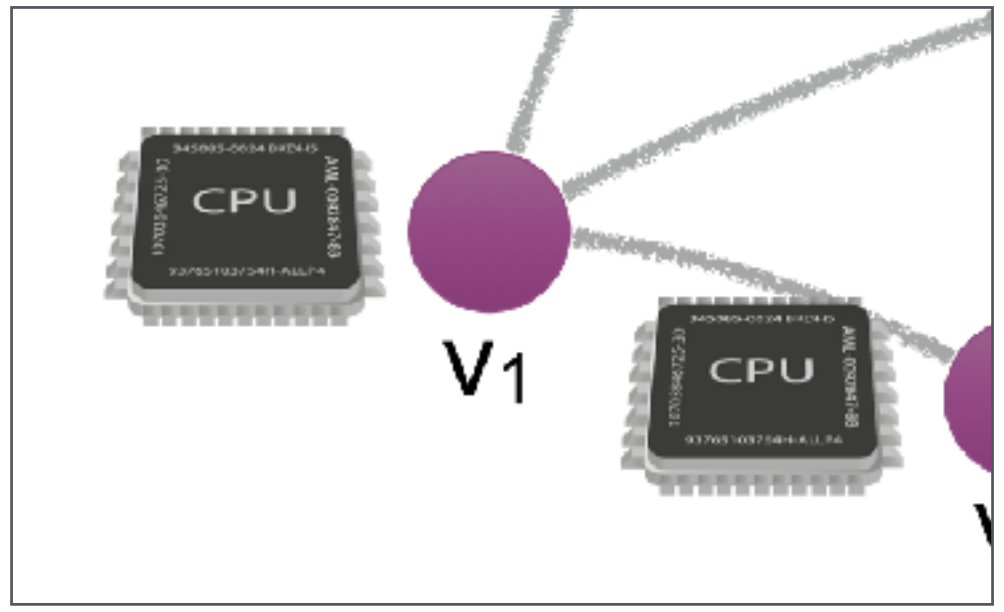
Hypothesis

- **Temporal Graph Partitioning**
  traditional graph partitioning schemes
  can be used



- **Distributed Temporal Graph Storage**
  self contained (temporal) vertex
  representation allows for mobile data storage

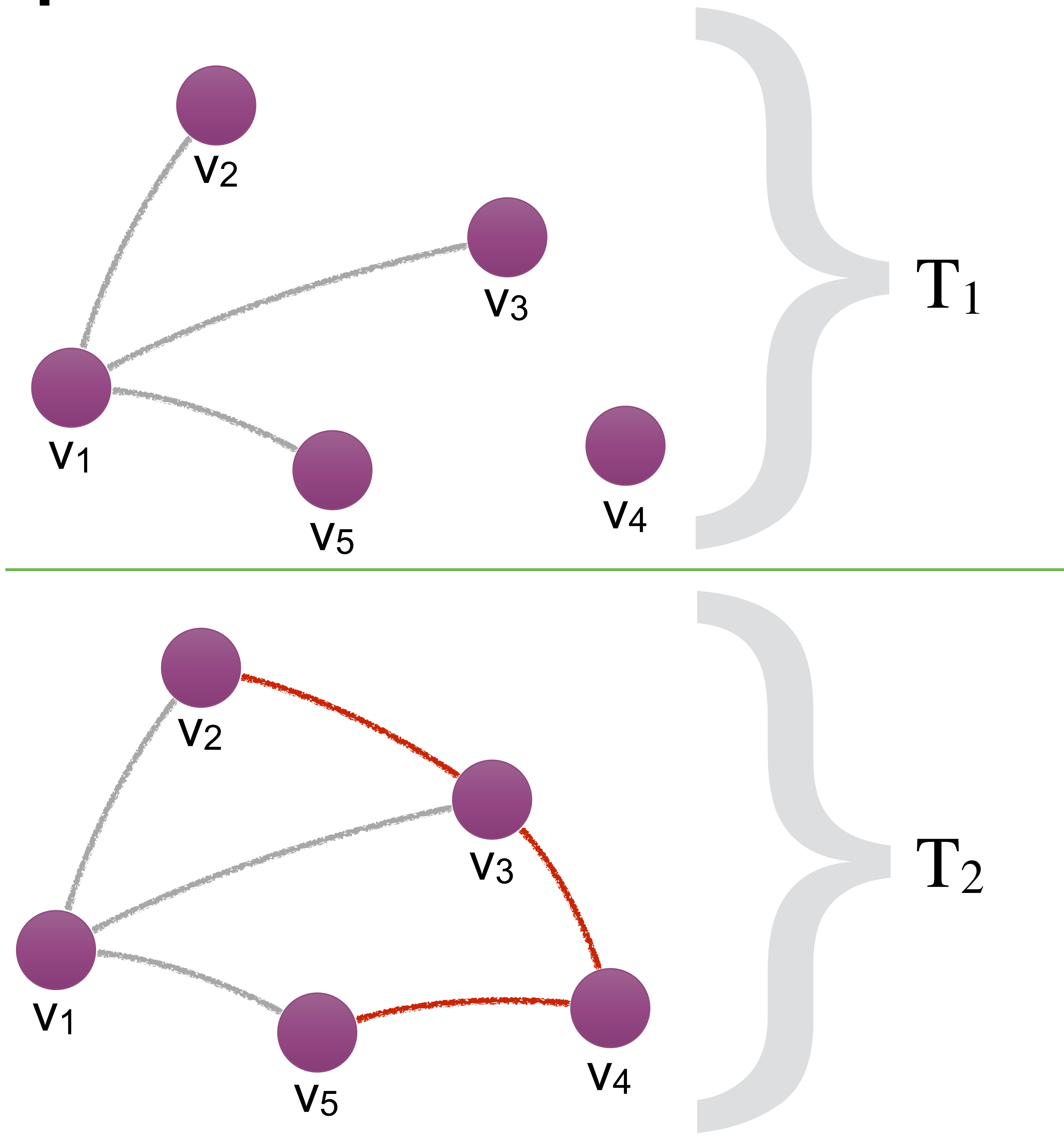
- **Distributed Temporal Graph Processing**
  distributed code, executed locally near
  the data can be used to process over
  very large datasets



Temporal Graphs

Graph G is a pair (V, E)
where V denotes the set of vertices and E
denotes the set of edges between any $v, e \in V$

A **temporal graph** T can be interpreted
as a **set of graphs**
$T = \{G_1, G_2, G_3, \ldots, G_t\}$ where each $G_x = (V_x, E_x)$
G_x is called a **static snapshot** at **time** x
And $G_{tm..tn}$ a selection of multiple G_x from T is
a static snapshot for a **timespan**



F. Harary and G. Gupta. ***Dynamic Graph Models****. Mathl. Comput. Modelling, 25(7):79–87, 1997.*

Graph Databases

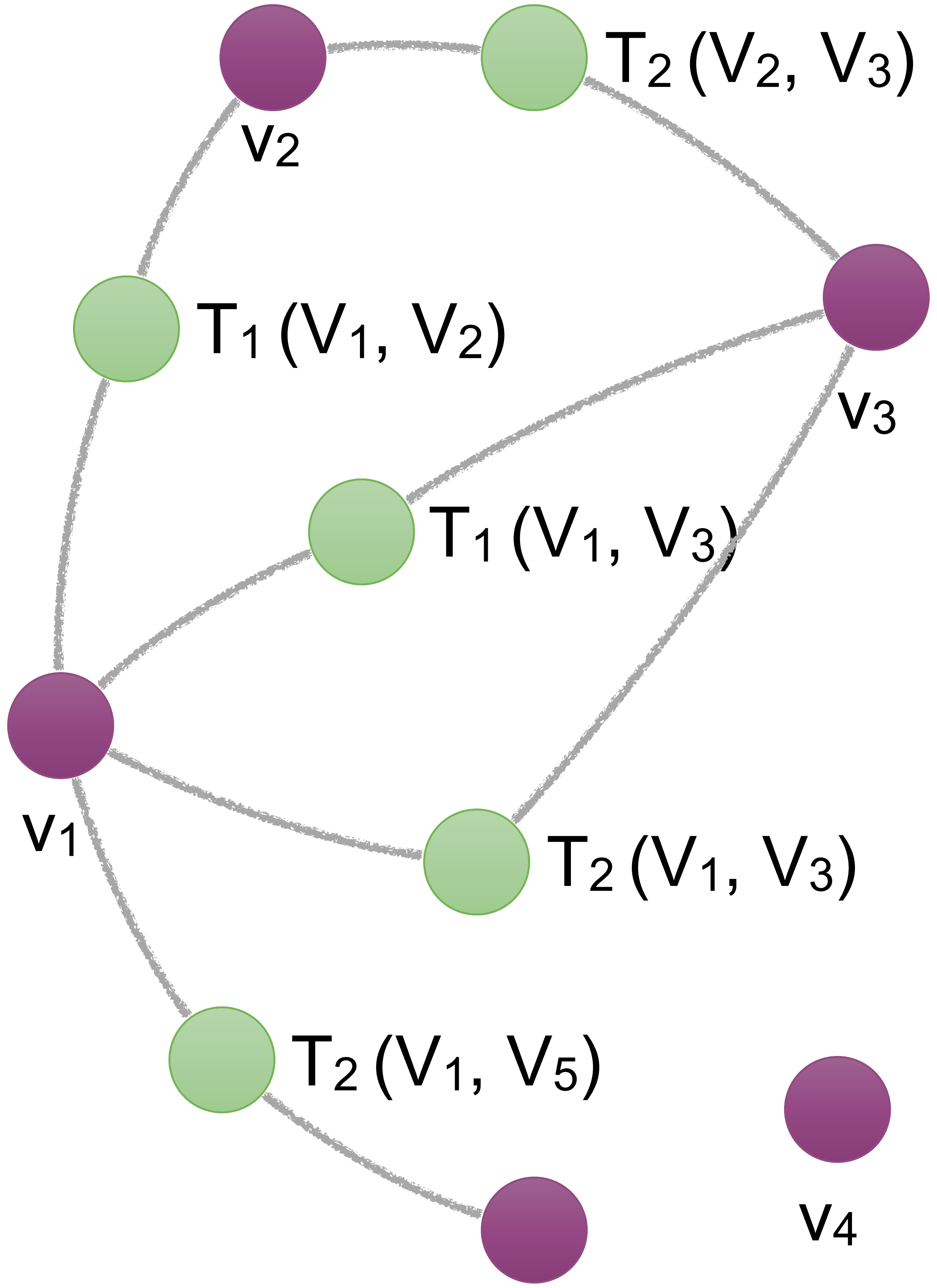
Popular graph databases picked up temporal support only recently

- Extension on the **time-stamped edges** concept *(Kempe, Kleinberg, Kumar 2002)*

- Introduction of **intermediate temporal vertexs** allows **efficient** temporal **queries**

```
get all edges at time T2
```

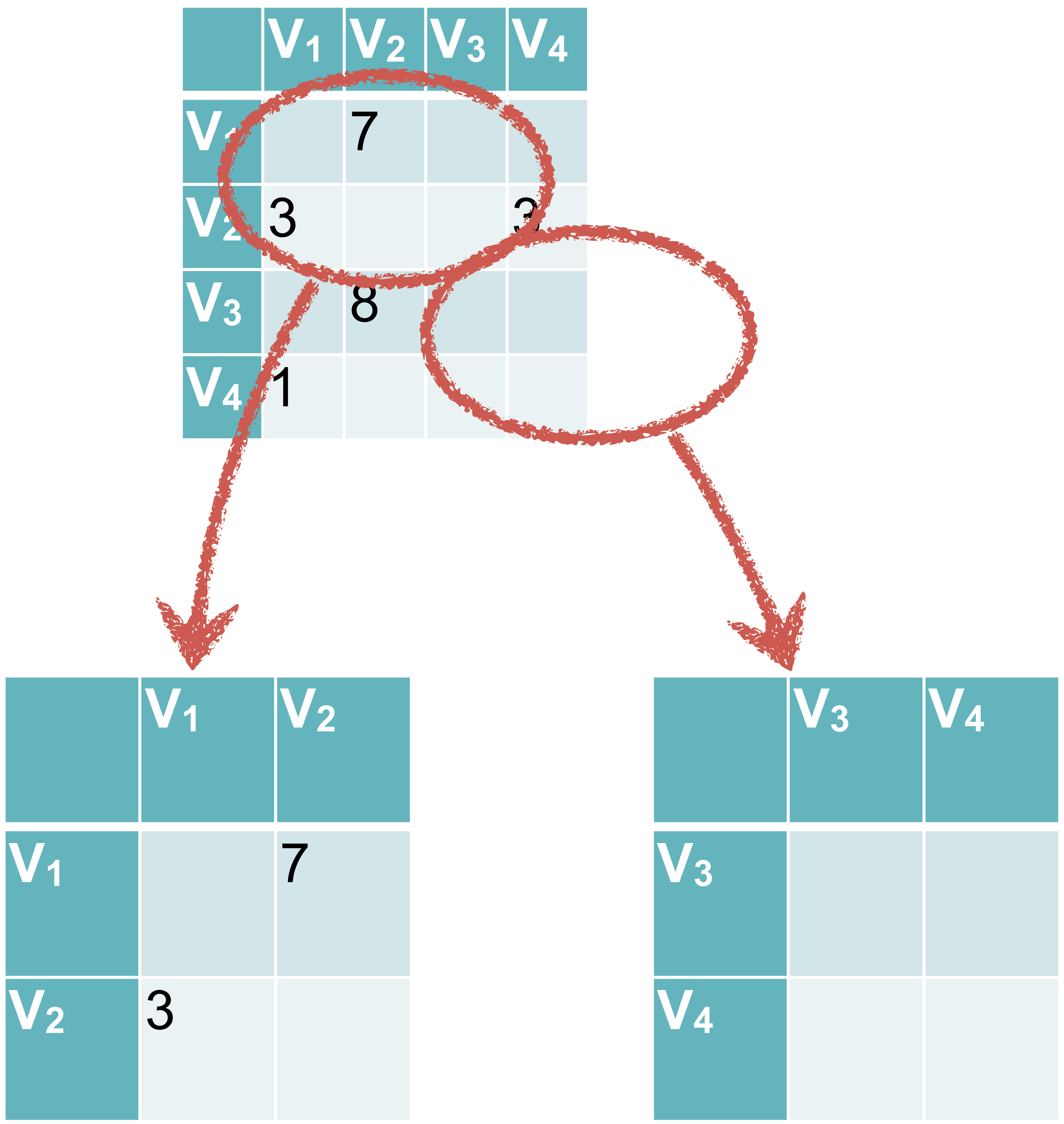
- Focus is on **distributed storage** but not processing



C. Cattuto, M. Quaggiotto, A. Panisson, and A. Averbuch, ***Time-Varying Social Networks in a Graph Database: a Neo4j Use Case****. New York, New York, USA: ACM, 2013, pp. 11–6.*

Distributed Matrix Processing

- (Sparse) **adjacency matrices** are a popular in-memory model for graphs
- Many **popular graph algorithms** have **efficient implementations** for **matrices**
- Distributed matrix processors (multiplicators) can be used to cope with large scale graphs
- Temporal aspect hard to integrate



* two blocks omitted for readability

U. Kang, C. E. Tsourakakis, and C. Faloutsos, ***PEGASUS: A Peta-Scale Graph Mining System - Implementation and Observations****. ICDM, 2009, pp. 229–238.*

Distributed Graph Processing

- Dominantly **implementations** on top of **Big Data** systems
- **Data-set** is living on a **distributed file-system**
- Graph processing jobs are implemented as **MapReduce** jobs
- Most popular: **Pregel**, by Google but with Open Source implementations (Giraph, GPS, etc.)
- Temporal aspects not covered in framework

Graph processing job (Pregel)

MapReduce framework

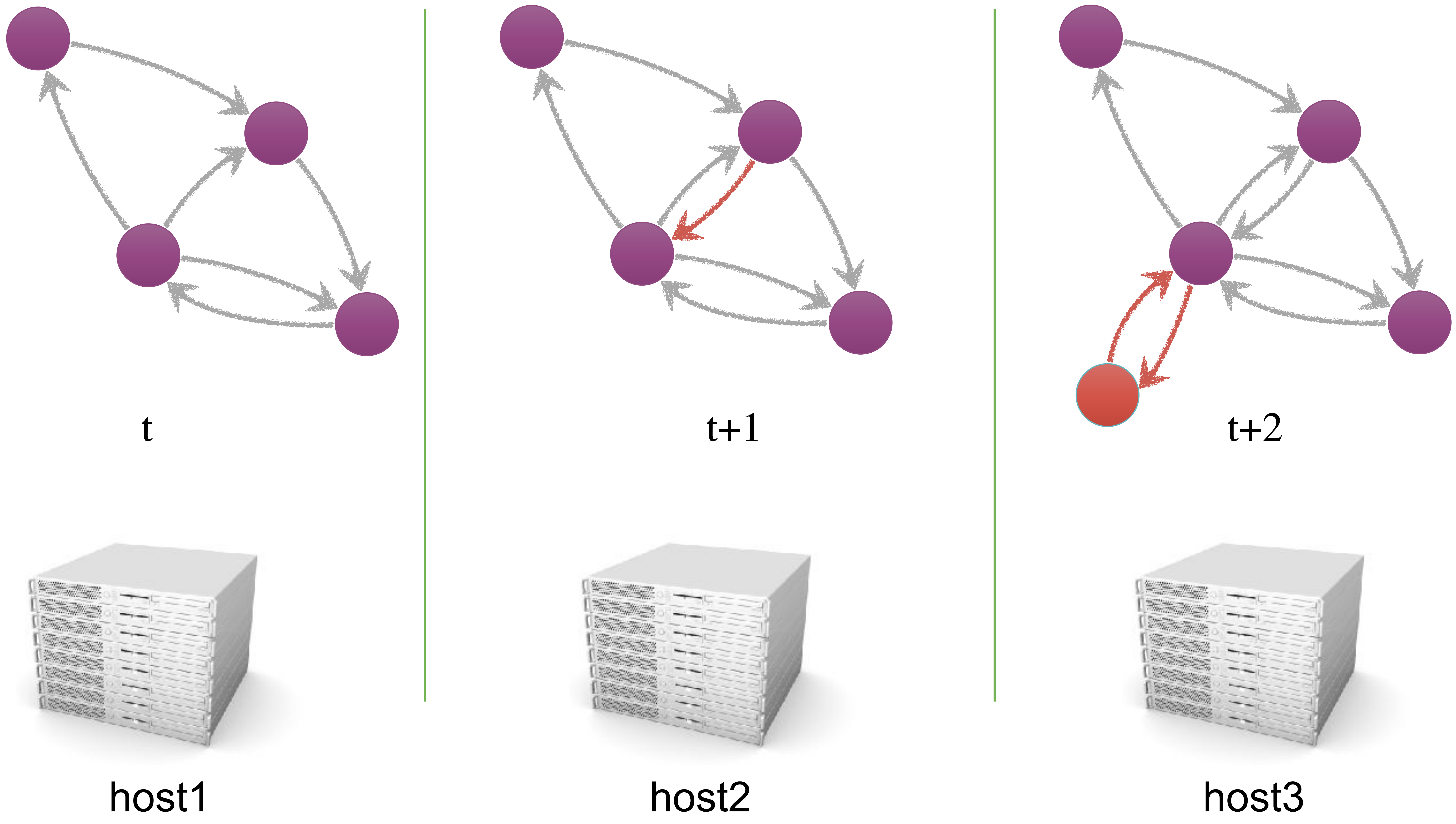
Distributed Filesystem (GFS / HDFS)

graph.csv

S	T	W
7	19	8
7	4	3
8	27	4

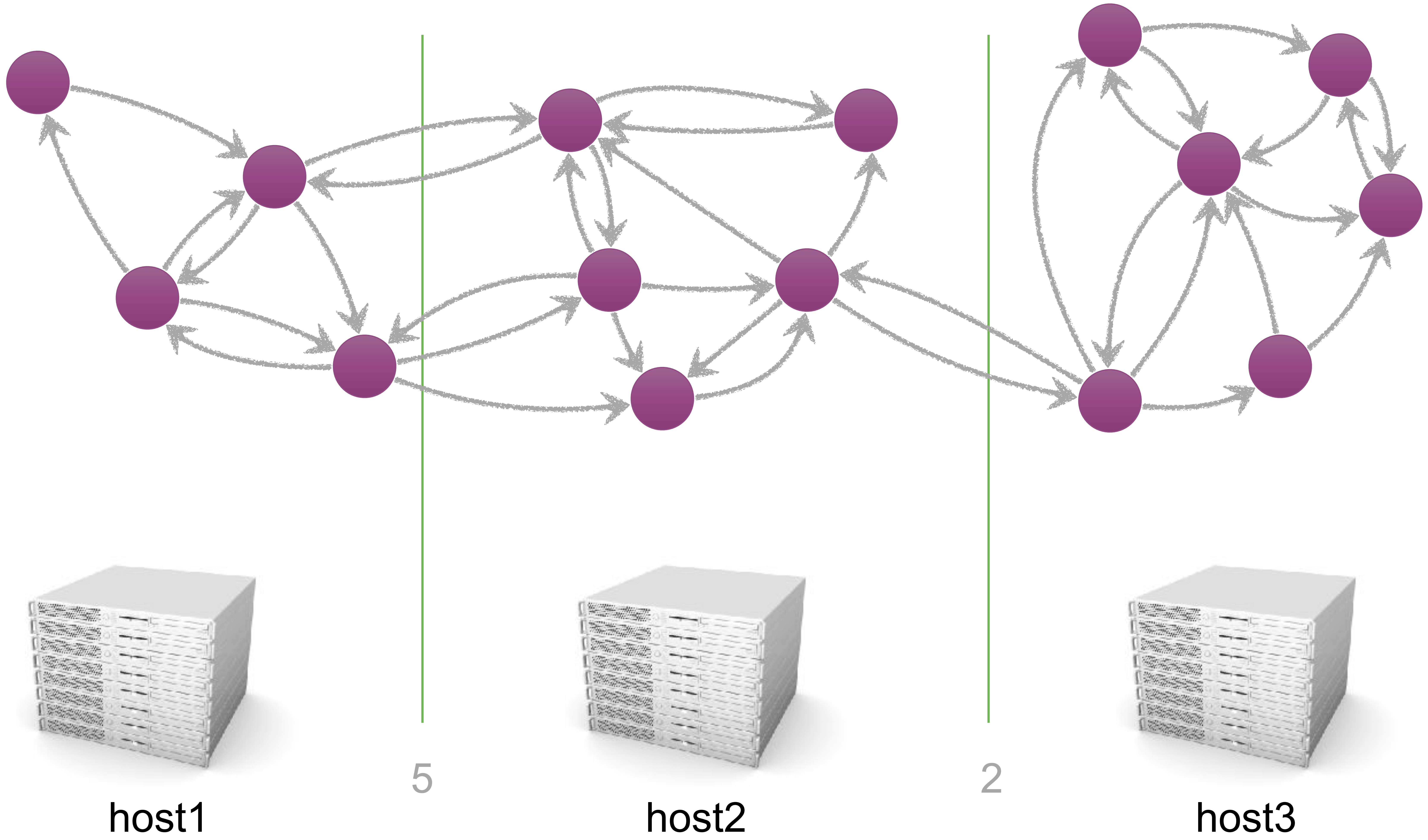
G. Malewicz, M. Austern, A. Bik, J. Dehnert, I. Horn, N. Leiser, and G. Czajkowski. ***Pregel: A System for Large-Scale Graph Processing****. ACM SIGMOD, 2010.*

Temporal Partitioning Strategies



Growth in V typically faster than along the temporal dimension

Structural Partitioning Strategies



Vertices as Temporal Maps

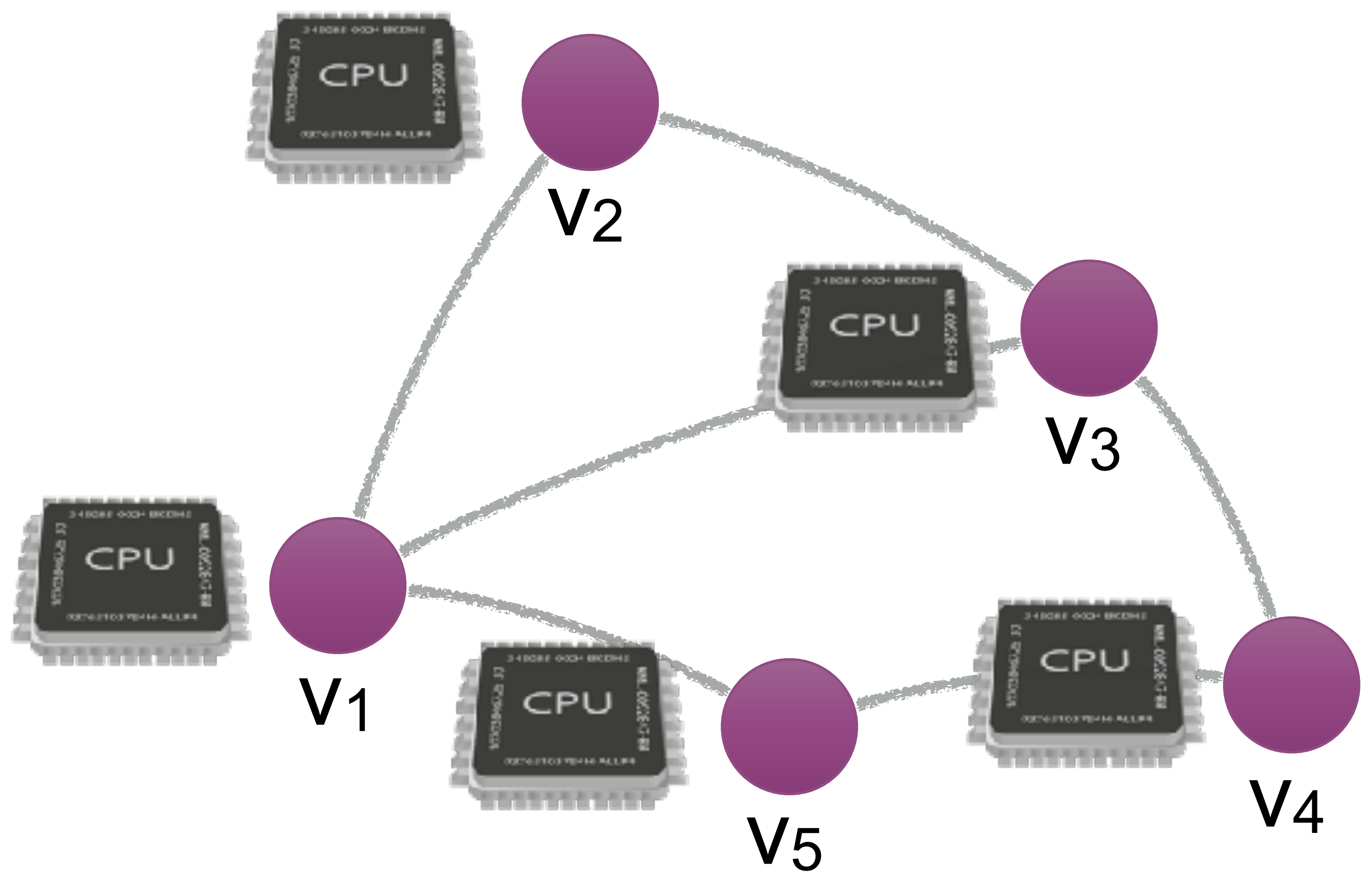
```
{
    id: 39827736,
    resolution: 'MONTHS',
    '1420070400': {
        name: 'Rob Henderson',
        description: '',
        inEdges: [ {
            weight: 3.3,
            edgeType: 'PHONE',
            source: 39761932,
            target: 39827736, } ],
        outEdges: [ {
            weight: 4.0,
            edgeType: 'EMAIL',
            source: 39827736,
            target: 39761932, } ],
    },
    '1422748800': {
        inEdges: [ {
```

- **Multiple versions** of the same vertex are stored in a map
- **Insert** operations require a **insert time** to be specified
- **Read** operations over **timeframes** often requires to **resolve conflicts**
- Vertices **self-contained**, thus mobile

M. Steinbauer and G. Kotsis, ***Platform for General-Purpose Distributed Data-Mining on Large Dynamic Graphs****. WETICE 2013, Hammamet, Tunisia, 2013.*

Pregel w/ Temporal Extensions

- Each **vertex** v_n has its **own processor** and **memory**
- Developers specify a **compute function** c which
  - is **repeatedly executed in parallel** for all vertices in the graph
  - has **access** only to vertex **local memory**
  - can send **messages** to other **vertices**
  - is **restricted** to access data from **timespan t only**
  - in which the vertex can **vote to halt** execution



minVertexId … c

```
mv := min(mv, msgs)
if mv == vn then
  voteToHalt()
else
  neighbours.send(mv)
```

G. Malewicz, M. Austern, A. Bik, J. Dehnert, I. Horn, N. Leiser, and G. Czajkowski. ***Pregel: A System for Large-Scale Graph Processing***. ACM SIGMOD, 2010.

Extensions over Pregel

- **Temporal filtering:** in c only data from a defined timespan t is available

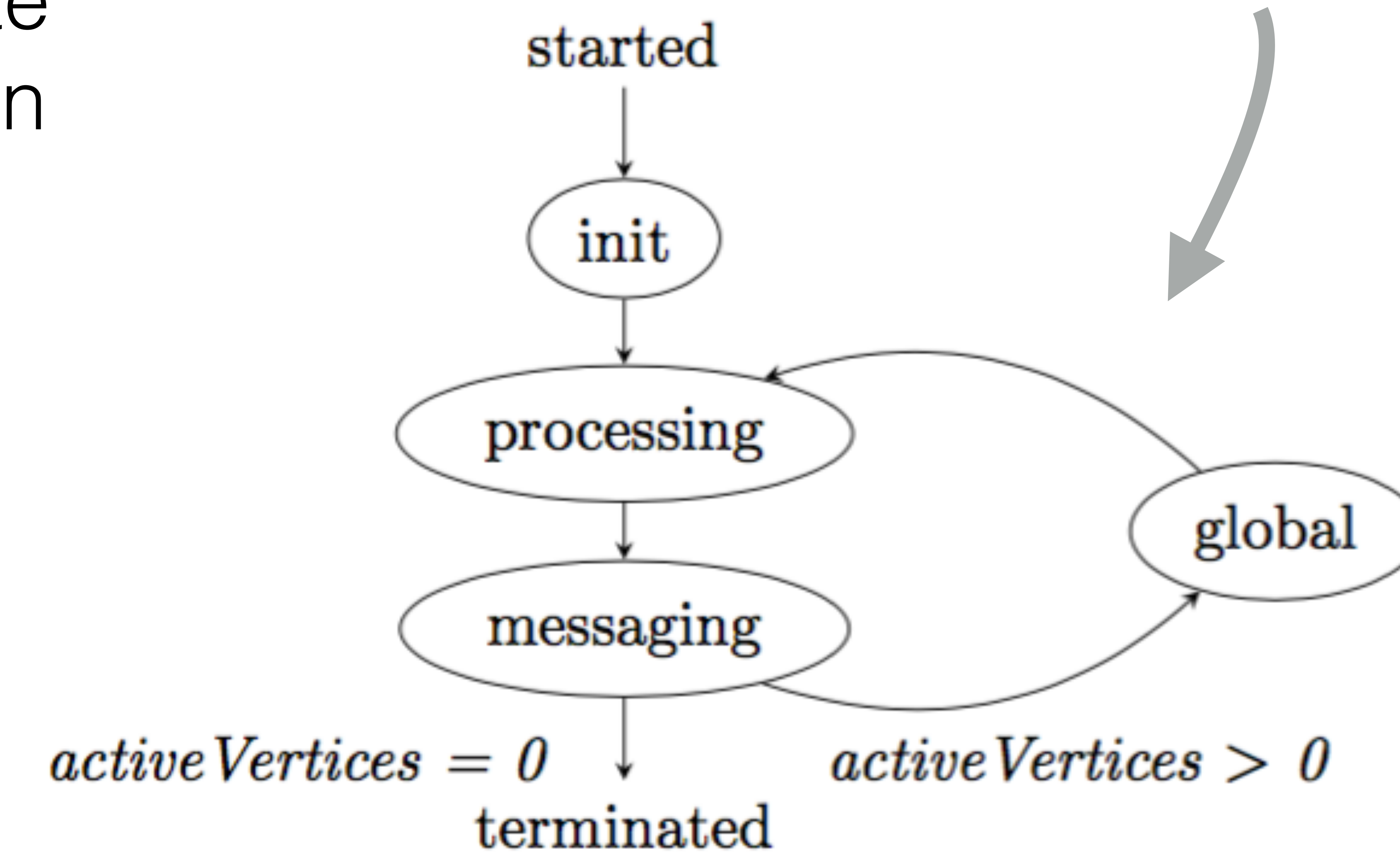
- **Global memory:** all vertices can read and write a **local copy** of global memory; developers can define

  - **conflict resolution** strategies for this global memory and

  - an **initialisation** function

- Write back, job-chaining, triggered execution

each iteration is called **superstep**

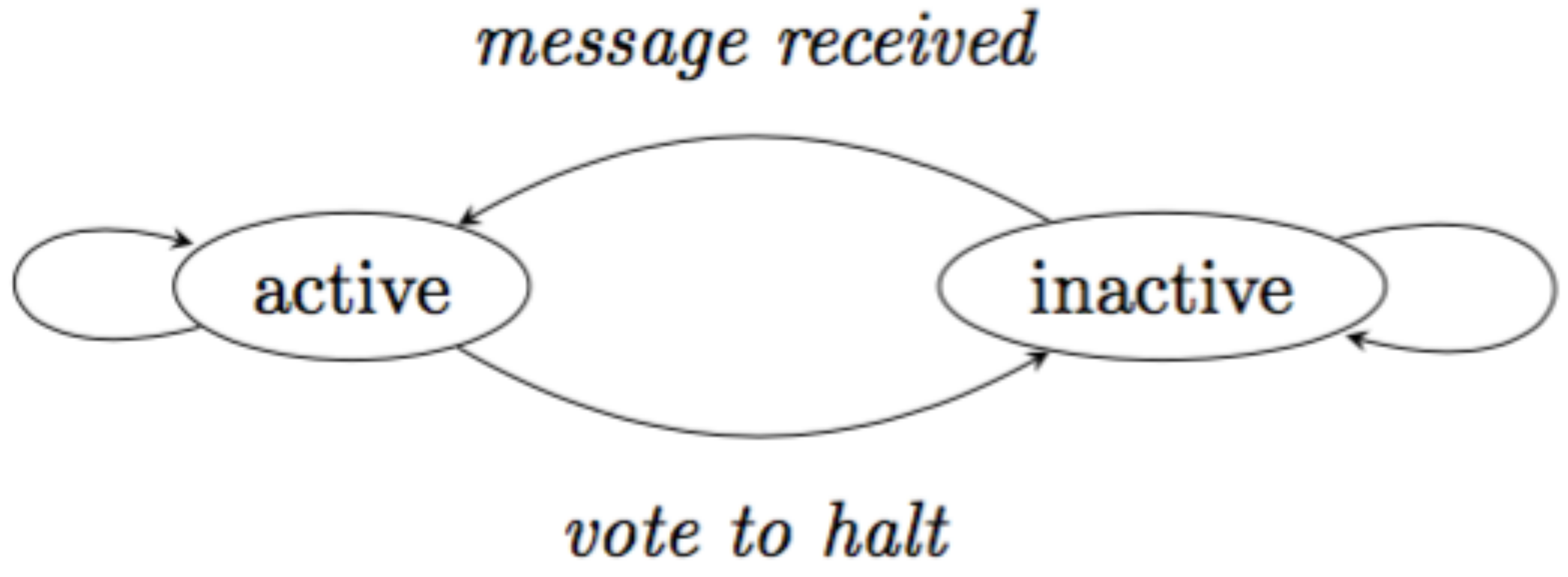


M. Steinbauer and G. Anderst-Kotsis, ***DynamoGraph: Extending the Pregel Paradigm for Large-scale Temporal Graph Processing***. *International Journal on Grid and Utility Computing, Jan. 2015.*

Pregel Computation Cycles

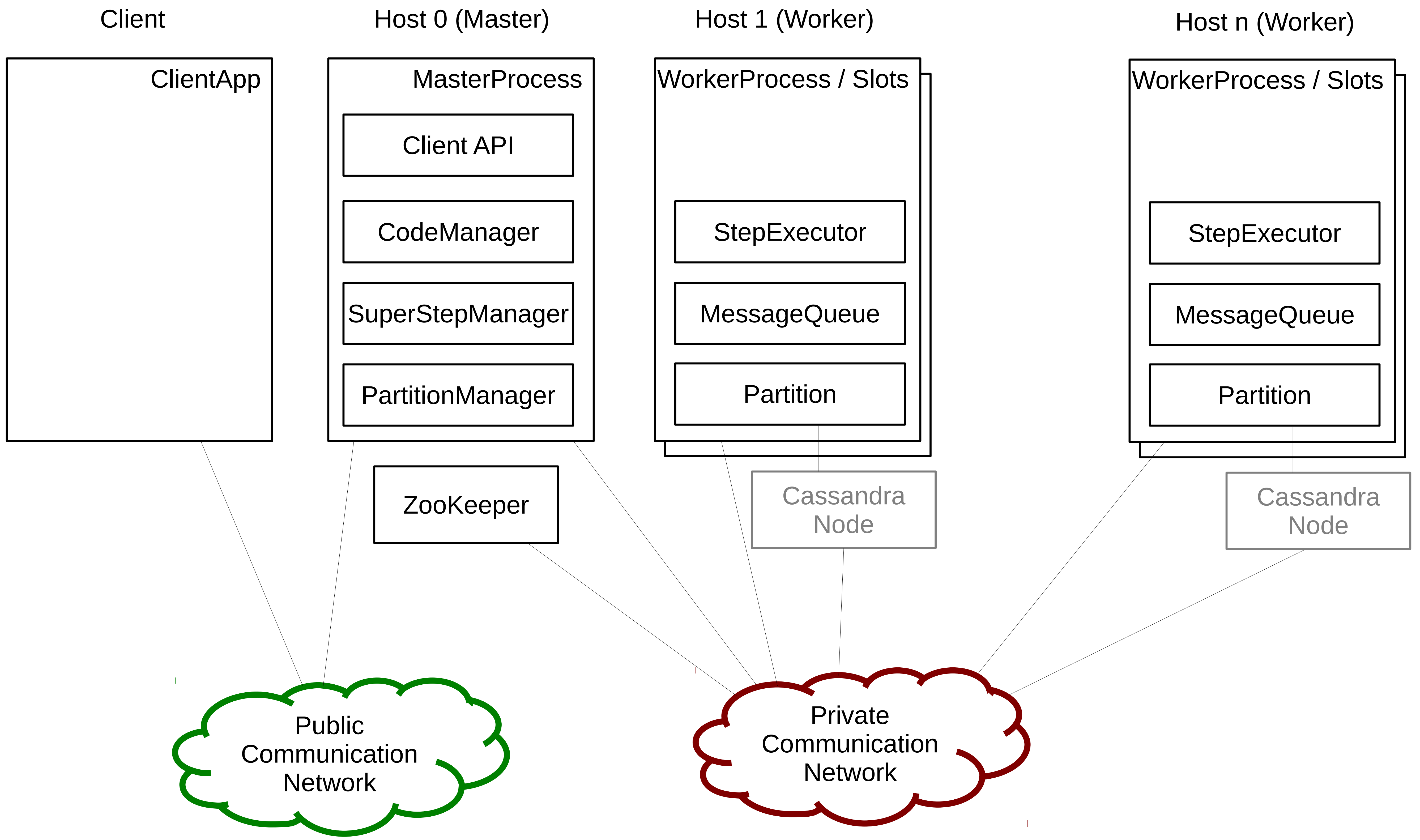
- **Execution** of a Pregel job is **controlled** by a **central instance**
- The central instance repeatedly instructs **all active vertices** to **execute** c; each of these cycles is called a **superstep**
- A **counter** of **active vertices** is kept
- If a **vertex votes to halt** in c it is marked **inactive** and omitted from computation in consecutive supersteps
- Unless the **vertex receives** a **message** in which case it is again marked as **active**

processing stops if **all vertices** are **inactive**



M. Steinbauer and G. Anderst-Kotsis, ***DynamoGraph: Extending the Pregel Paradigm for Large-scale Temporal Graph Processing***. *International Journal on Grid and Utility Computing, Jan. 2015.*

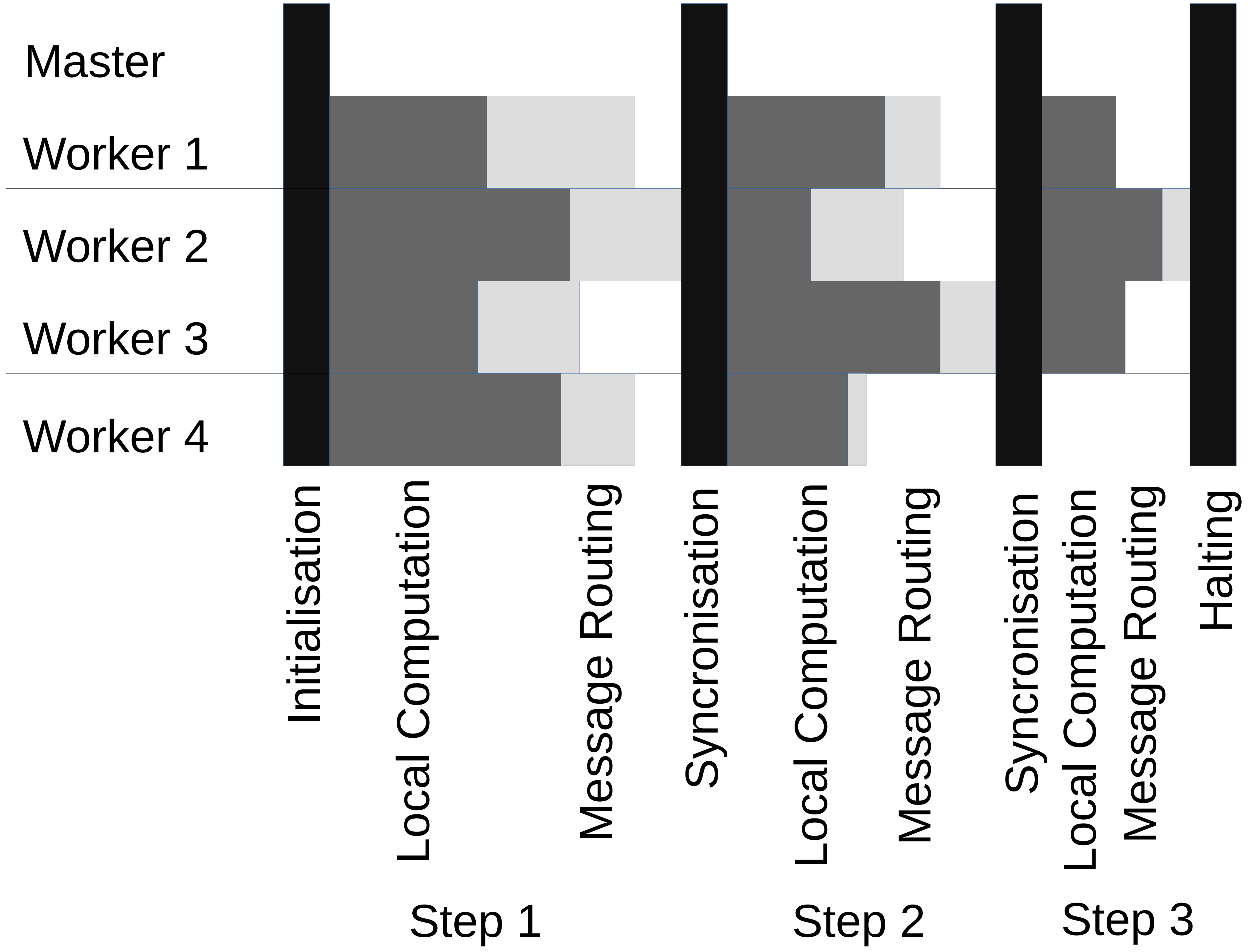
Prototype Architecture



- Provides an **execution environment** for temporal Pregel **jobs**
- Individual **worker nodes** manage **storage** and **processing** for multiple graph partitions (slots)
- Client application can use API to **manipulate** and **import data** and to **upload** and **execute code**

*M. Steinbauer and G. Anderst-Kotsis, **DynamoGraph: Extending the Pregel Paradigm for Large-scale Temporal Graph Processing**. International Journal on Grid and Utility Computing, Jan. 2015.*

Bulk Synchronous Parallel Execution

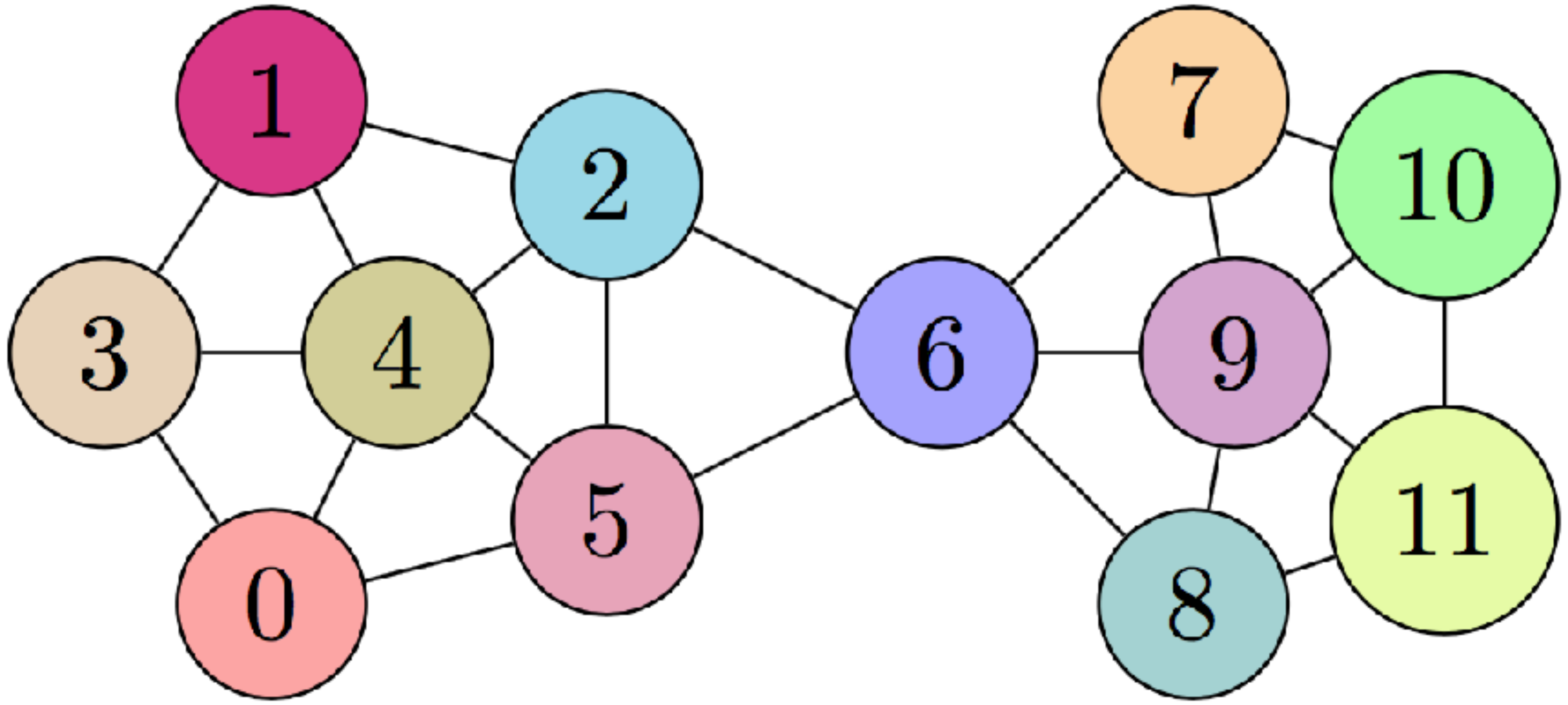


- Executing **jobs** in *DynamoGraph* **produce** the shown **processing patterns**

- Typically as **more and more vertices become inactive**, local computation and messaging **phases become shorter**

Label Propagation Community Detection

- Originally published by *(Raghavan et al. 2007)* as an option for **near linear time** community detection $O(m)$
- In an **iterative process** each vertex v in the graph **observes** its **neighbours' community labels**
- The vertex v gets assigned the community label **most often** found among its neighbours
- Algorithm allows for **efficient distributed implementation** in Pregel



Label Propagation Community Detection

```
while s < MAX_IT and g[lc] > 0
  execute compute for each vertex
```

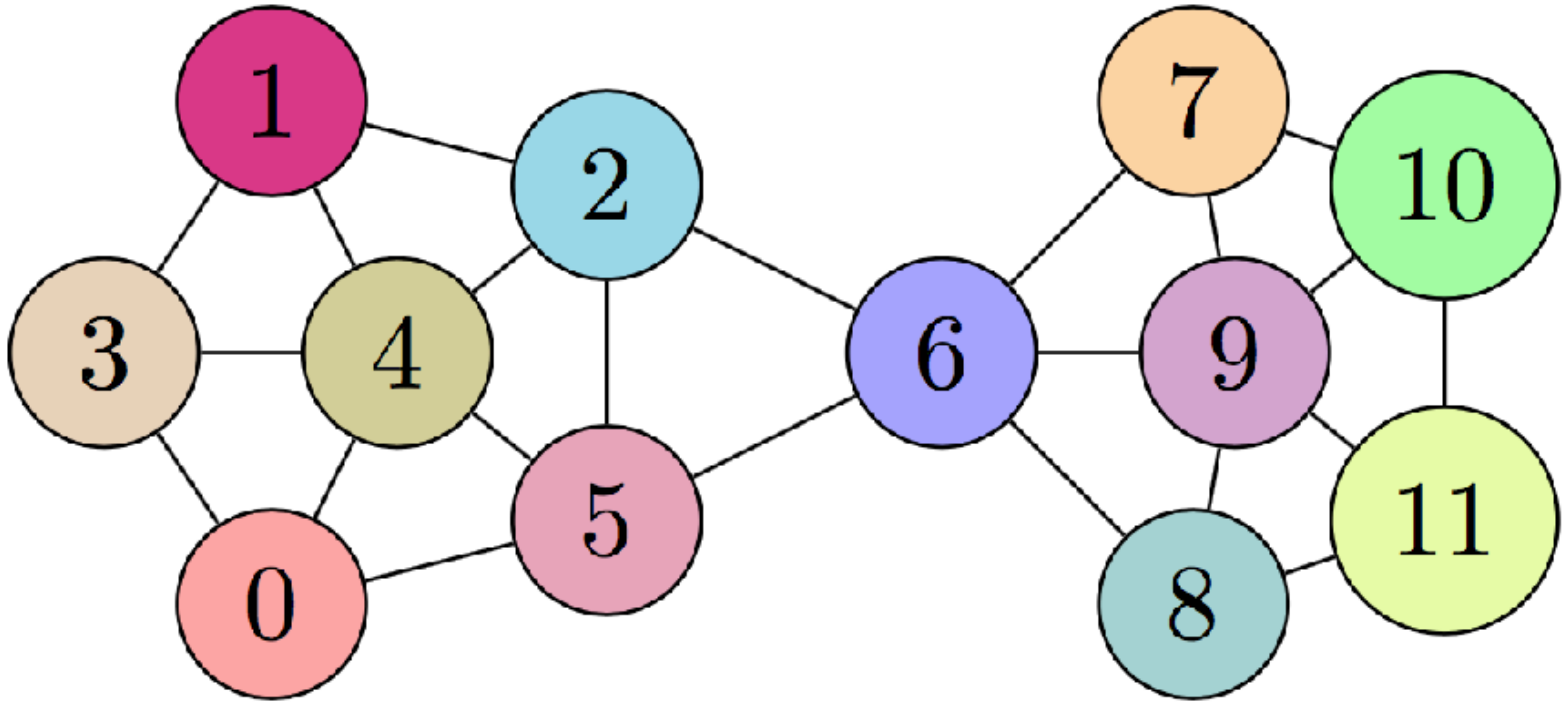
compute(v, msgs, g, t, s)

```
cl := count_max(msgs)
if cl not set then
  let cl be the vertices name
else
  g[lc] := g[lc] + 1
for each neighbour n of v do
    m(n, cl)
```

```
cl ... community label
g  ... global memory
lc ... labels changed
```

provided by framework

implemented by user



Label Propagation Community Detection

(a) Initialized $t = 0$

(b) $t = 1$

(c) $t = 2$

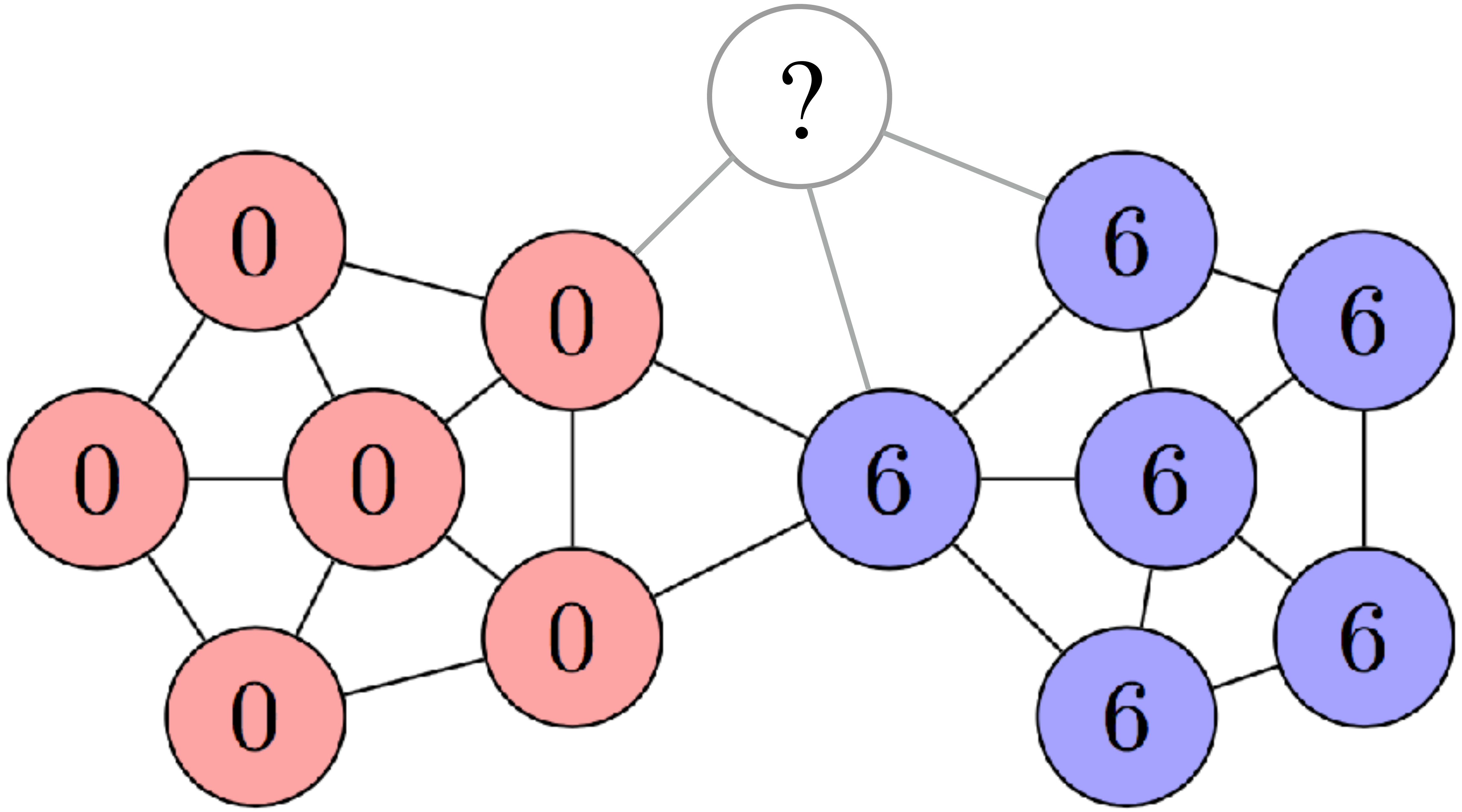
(d) $t = 3$

Outlook: Dynamic Algorithms

- **Dynamic** graph **algorithms** allow to **update** computed **metrics** as the graph changes

- With a temporal graph data structure dynamic graph algorithms can be mimicked by **using results** from an **earlier timeframe** t_n to compute the results for t_{n+1}

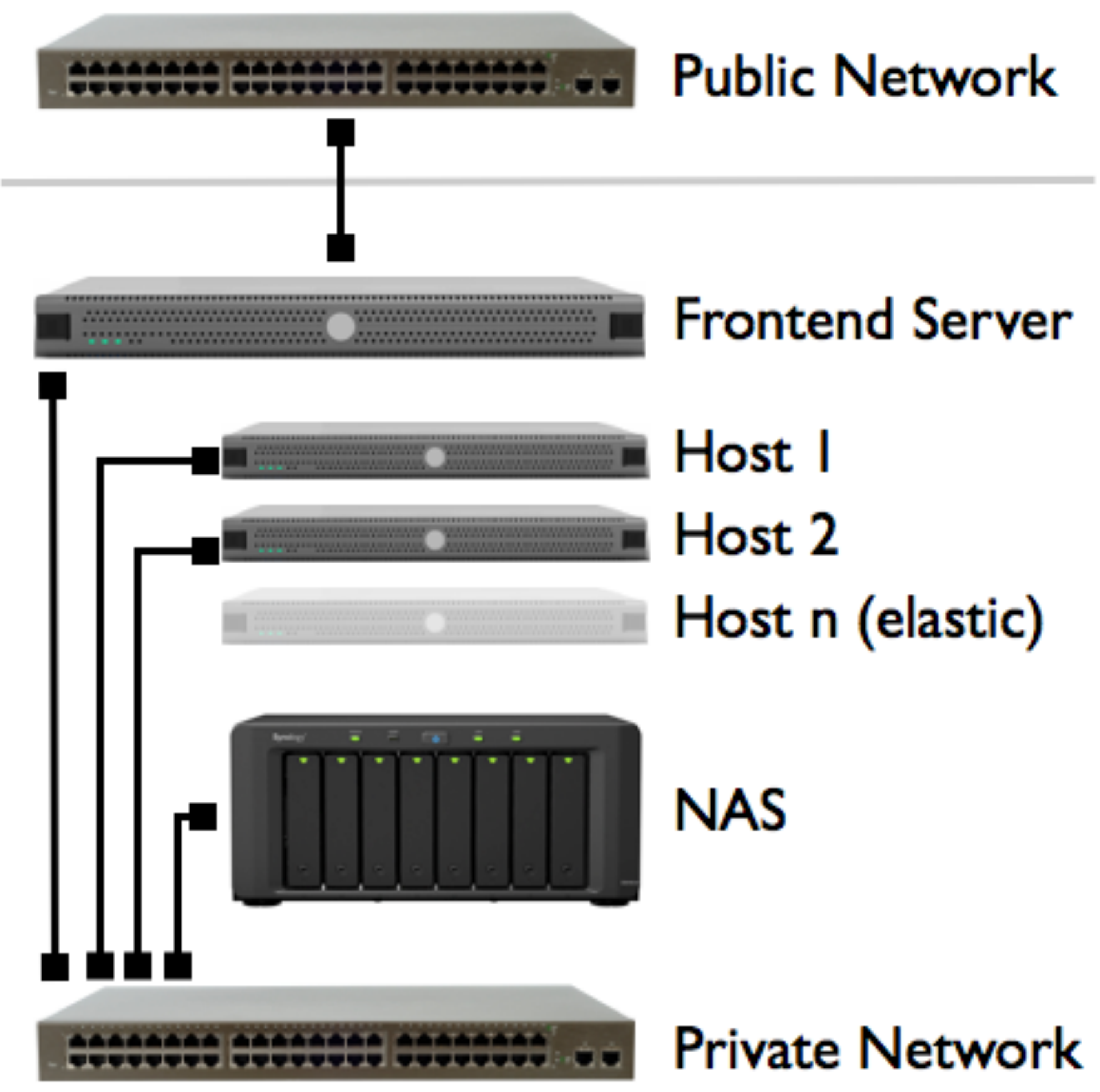
- See the inserted *?* vertex and the behaviour of the presented community detection



Evaluation Setup

openstack™

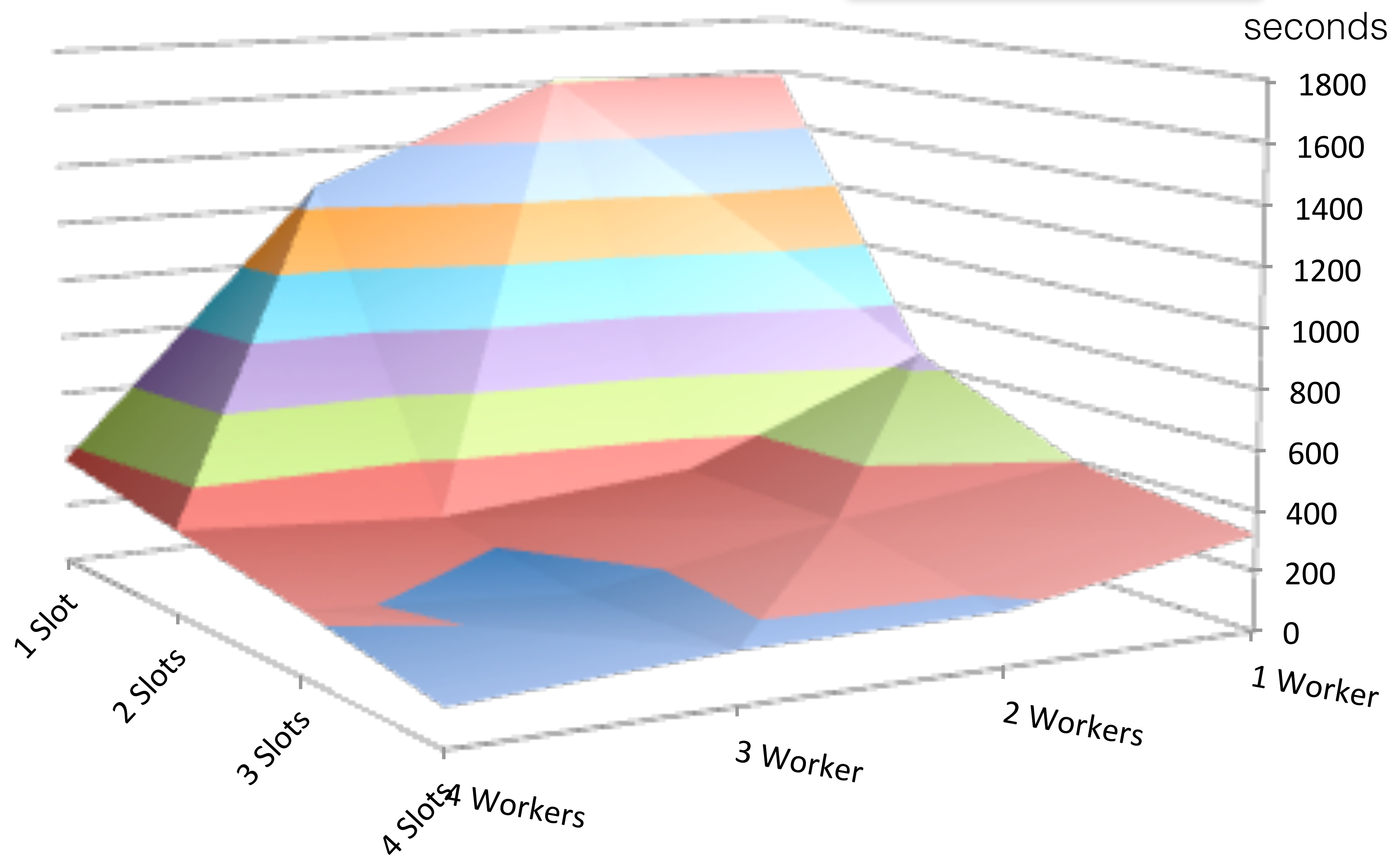
- **Private Cloud** installation @TK based on **openstack**
- During experiments the stack was reserved exclusively
- 2 compute vertexs with a total of:
  48 Intel Xeon 3.47 Ghz CPUs,
  288 GB RAM, and
  2 TB local storage
- Linux, KVM hypervisor, memory ballooning, enterprise grade GBit switch



PageRank over Enron Dataset

Number of edges nosh suchen!?

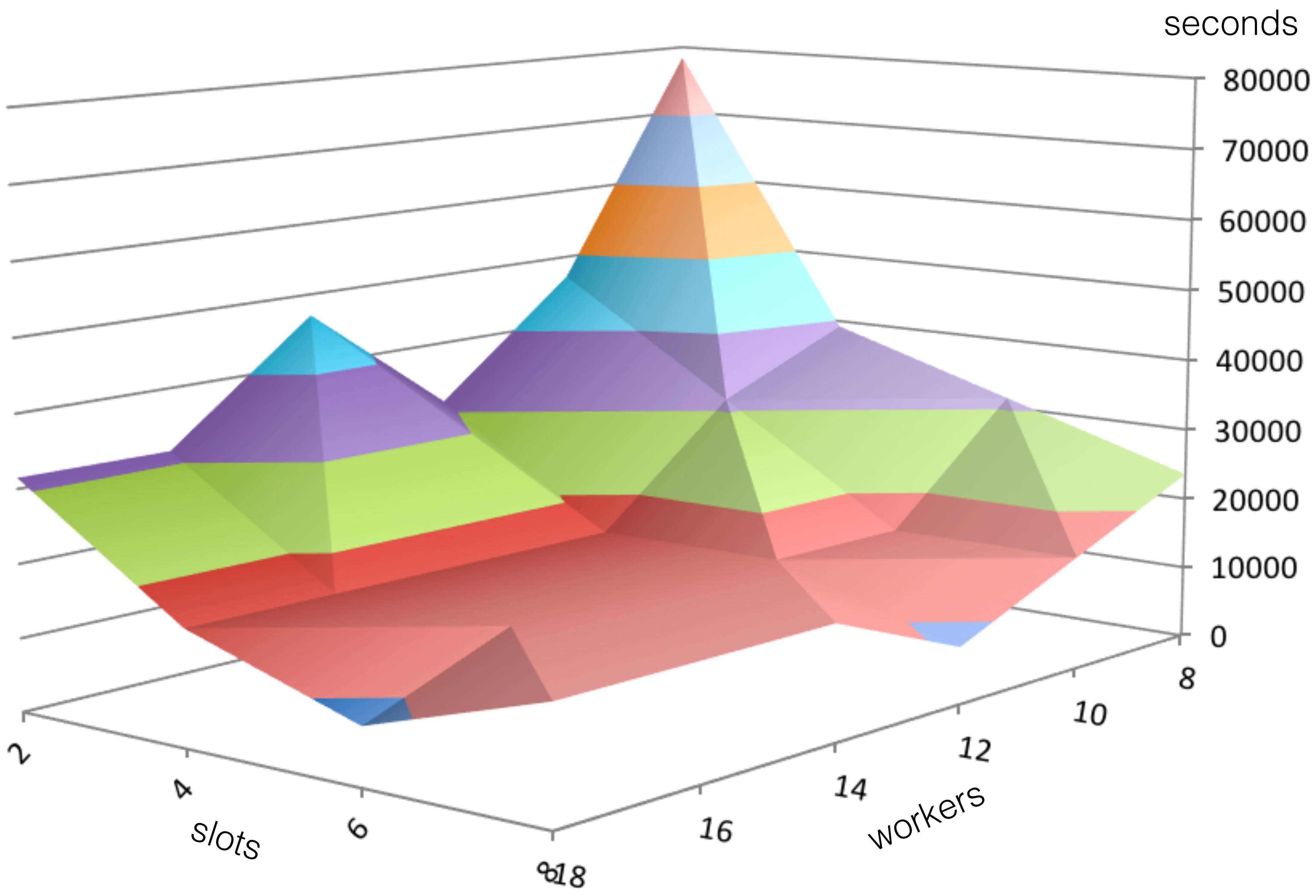
- Email database from Enron scandal
- Available to researches as `maildir` database
- Executing PageRank in a timeframe from Jan 2002 - Dec 2003 results in **expected behaviour**:
  - More **processors** result in **faster execution**
  - Adding **workers** also adds **networking overhead** thus provides comparably inferior speedup



*M. Steinbauer and G. Anderst-Kotsis, **DynamoGraph: Extending the Pregel Paradigm for Large-scale Temporal Graph Processing**. International Journal on Grid and Utility Computing, Jan. 2015.*

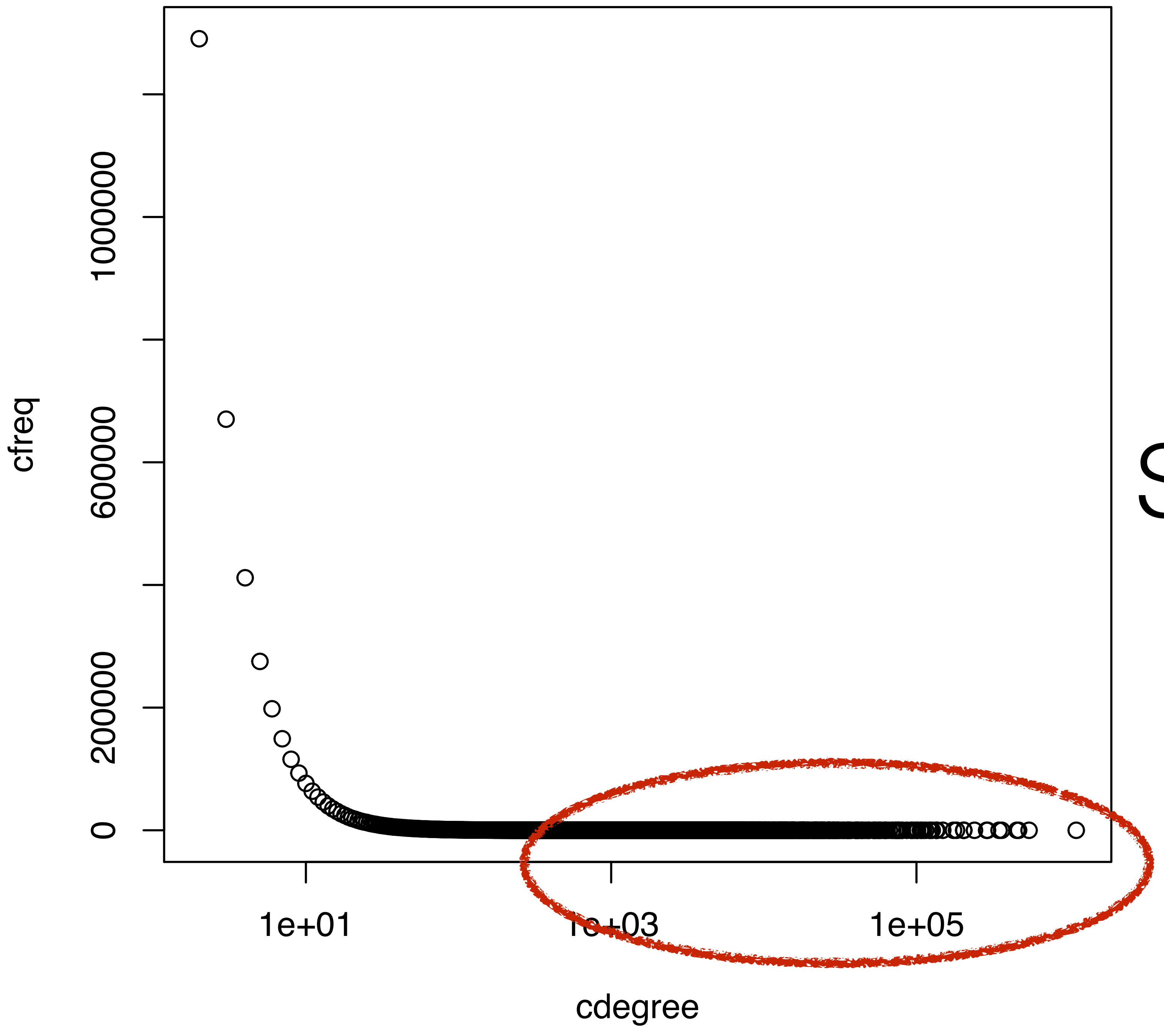
PageRank over Click Dataset

- **HTTP headers (clicks)** recorded by an edge-router Sept 2006 - May 2010
- Custom, anonymised, binary file format, ~3 TB `gzip`, ~13 TB uncompressed
- Preprocessed to a ~93 million edges graph that contains only top domains as vertices at monthly resolution
- **PageRank** computed **in sliding window** of six month
- **Processing reaches** a **plateau**, stalls observed

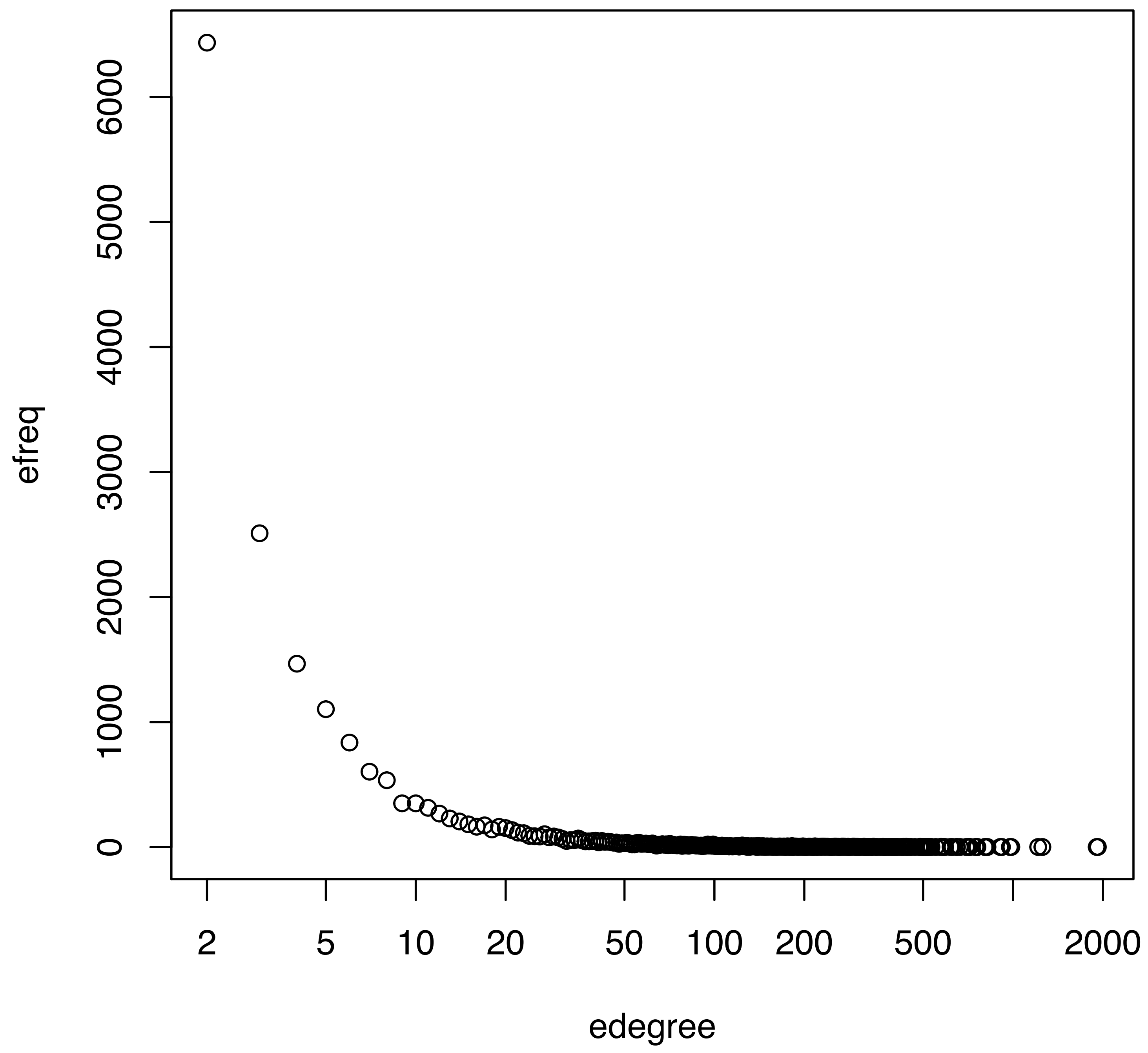


Discussion

- **Distributed processing** shows clear **advantage** in the described usage scenarios but significant **difference** in scalability between **social** and **technical network** becomes visible



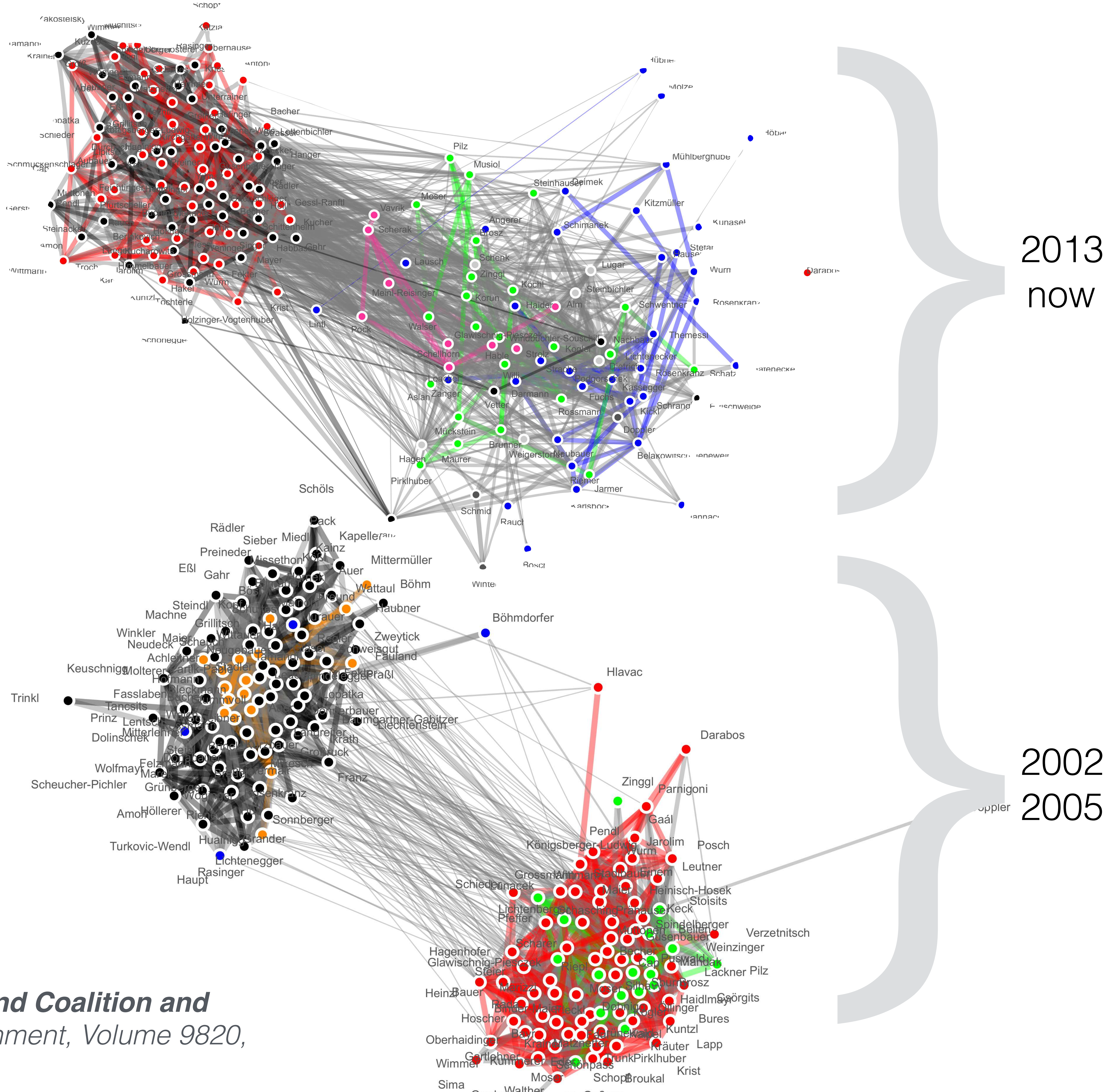
technical net.
Several vertices edge degree 1000 - 100,000



email
max degree ~2000

Selected Case / Political Network

- Temporal graphs can be used to **observe political networks**
- **Label propagation community detection** used to determine whether a person belongs to **coalition** or to **opposition**
- Visualisation shows **discussion** in **Austrian parliament** automatically **extracted** from **transcripts**



*Matthias Steinbauer, Markus Hiesmair and Gabriele Anderst-Kotsis, **Making Computers Understand Coalition and Opposition in Parliamentary Democracy**, Lecture Notes on Computer Science, Electronic Government, Volume 9820, Springer, 2016 (received outstanding paper award).*

Future Work

- **Visualisation** and **tooling** are in **prototypical state** and far from be used in production environments

- Many spots for **performance improvements** identified: **vertex-cuts** over edge-cuts *(Gonzales et al. 2012)*, **decoupling profile data** from network data

- **Dynamic notion of time** vs. fixed size time resolution in *DynamoGraph*

- Support **incremental processing** for **dynamic** graph **algorithms**

Conclusion / Contribution

- **Closes a gap** between the **theoretical work** found for **temporal graphs** and **applied computer science** concepts for **large-scale graph processing**.

- Resulted in an **Open Source prototype implementation** called ***DynamoGraph*** which has been shown to be generally technically **feasible** and **scalable**.

- **Provides a platform** for continued **application oriented research** in this area (see case studies).

- 7 peer reviewed and 2 invited publications.

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31st of January, 2017

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slides available at
https://steinbauer.org/

List of Relevant Publications

thesis — *Matthias Steinbauer, Sensor Based,* ***Automated Detection of Behavioural Stereotypes in Informally Formed Workgroups****, Masters Thesis, Johannes Kepler University Linz, 2012.*

conf. — *Matthias Steinbauer and Gabriele Kotsis,* ***Building an Information System for Reality Mining Based on Communication Traces****, in Proceedings of the 15th International Conference on Network-Based Information Systems, Melbourne, 2012.*

magazine — *Matthias Steinbauer, Ismail Khalil, and Gabriele Kotsis,* ***Reality Mining at the Convergence of Cloud Computing and Mobile Computing****, ERCIM News, 04-Mar-2013 (invited/not refereed).*

conf. — *Matthias Steinbauer and Gabriele Kotsis,* ***Platform for General-Purpose Distributed Data-Mining on Large Dynamic Graphs*** *presented at the 22nd Workshops on Enabling Technologies Infrastructure for Collaborating Enterprises, Hammamet, Tunisia, 2013.*

conf. — *Matthias Steinbauer and Gabriele Kotsis,* ***Towards Cloud-based Distributed Scaleable Processing over Large-scale Temporal Graphs****, presented at the 23rd Workshops on Enabling Technologies Infrastructure for Collaborating Enterprises, Parma, Italy, 2014.*

conf. — *Matthias Steinbauer and Gabriele Anderst-Kotsis,* ***Using DynamoGraph: Application Scenarios for Large-scale Temporal Graph Processing****, presented at the 17th International Conference on Information Integration and Web-based Applications & Services, Brussels, Belgium, 2015.*

workshop — *Matthias Steinbauer and Gabriele Anderst-Kotsis,* ***DynamoGraph: A Distributed System for Large-scale, Temporal Graph Processing, its Implementation and First Observations****, Temporal Web Analytics Workshop at WWW2016, Montréal, Canada, 2016.*

journal — *Matthias Steinbauer and Gabriele Anderst-Kotsis,* ***DynamoGraph: Extending the Pregel Paradigm for Large-scale Temporal Graph Processing****, International Journal on Grid and Utility Computing, Volume 7, No. 2, 2016.*

conf. — *Matthias Steinbauer, Markus Hiesmair and Gabriele Anderst-Kotsis,* ***Making Computers Understand Coalition and Opposition in Parliamentary Democracy****, Lecture Notes on Computer Science, Electronic Government, Volume 9820, Springer, 2016 (received outstanding paper award).*