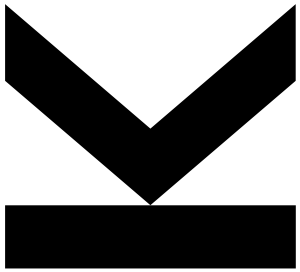
DYNAMOGRAPH: A DISTRIBUTED SYSTEM FOR LARGE-SCALE, TEMPORAL GRAPH PROCESSING, ITS IMPLEMENTATION AND FIRST OBSERVATIONS



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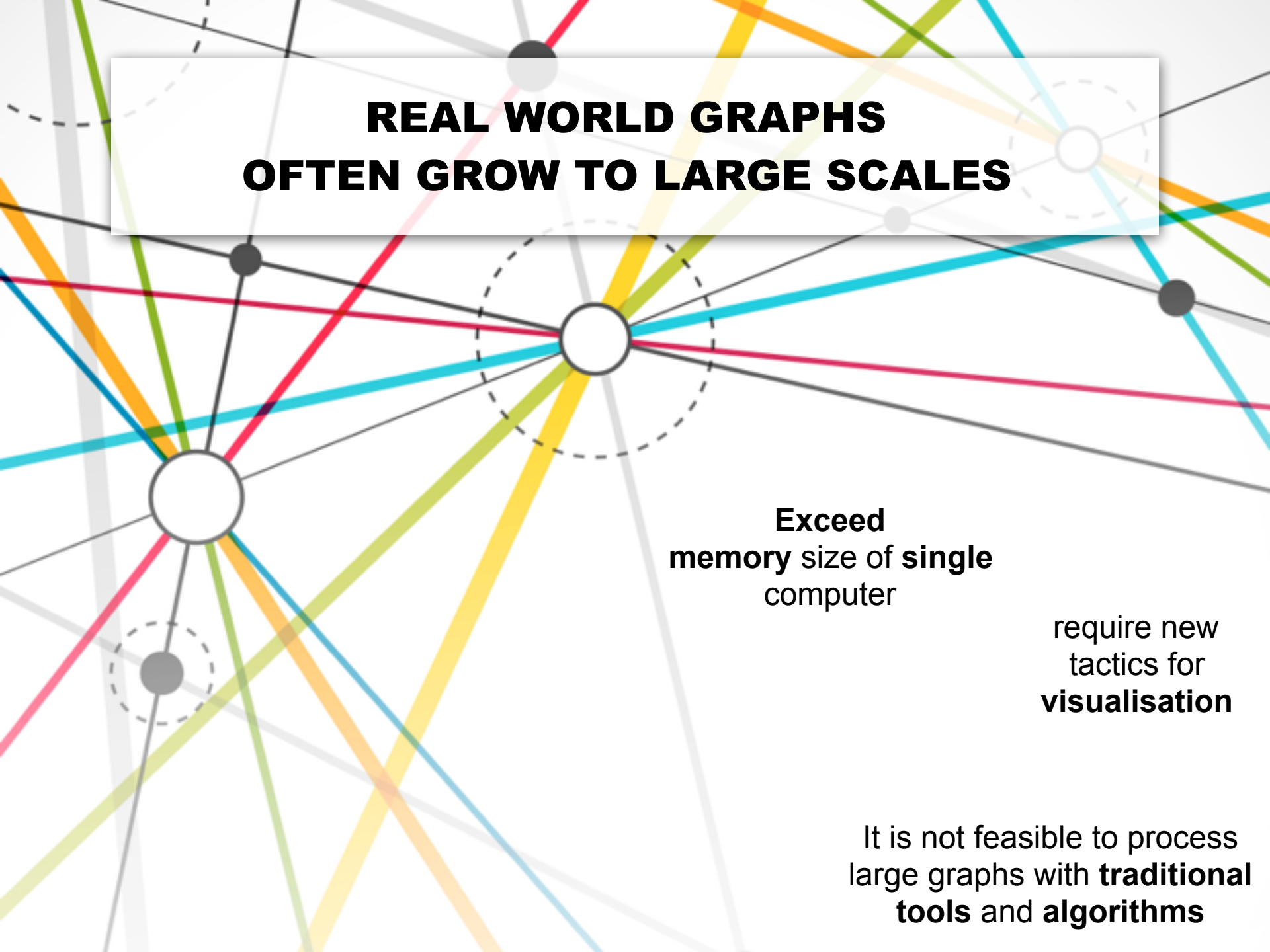
TALK OUTLINE

- Introduction and Motivation
- Temporal Graph Models and Related Work
- DynamoGraph
  - Architecture
  - Pregel and Extensions
- Examples
  - PageRank
  - Community Detection
  - Web-based Workbench
- Conclusions

INTRODUCTION / MOTIVATION

- Graphs serve as models for real world structures in many different disciplines
  - Social sciences > Social networks
  - Biology > Protein-Protein Interactions
  - Cartography > Digital road maps
  - Web > The web graph
- Graph and network models are very well studied in mathematics computer science and related disciplines
- So why is there need for new research in this area?



REAL WORLD GRAPHS OFTEN GROW TO LARGE SCALES

Exceed
memory size of **single** computer

require new tactics for **visualisation**

It is not feasible to process large graphs with **traditional tools** and **algorithms**

THE DIMENSION OF TIME CANNOT BE NEGLECTED

Static views on graphs often show **blurred** or **too dense** data

Biological processes are **time** dependent

Static r**eachability** measures in social networks do not hold for dynamic networks

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 given 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 $G_{tm..tn}$ as a selection of multiple G_x from T is a static snapshot for a **timespan**

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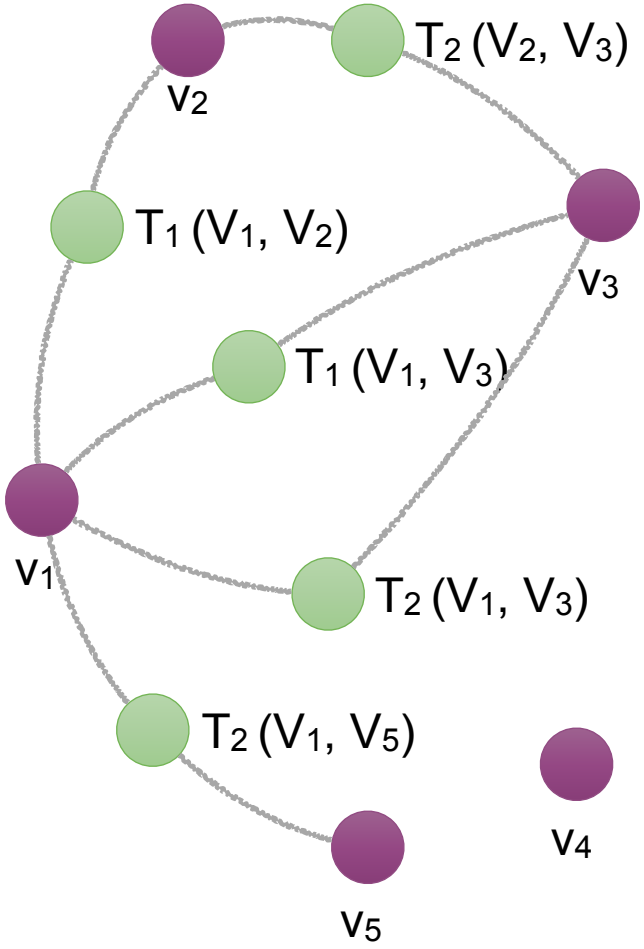
F. Harary and G. Gupta. Dynamic Graph Models. Mathl. Comput. Modelling, 25(7):79–87, 1997.

GRAPH DATABASES

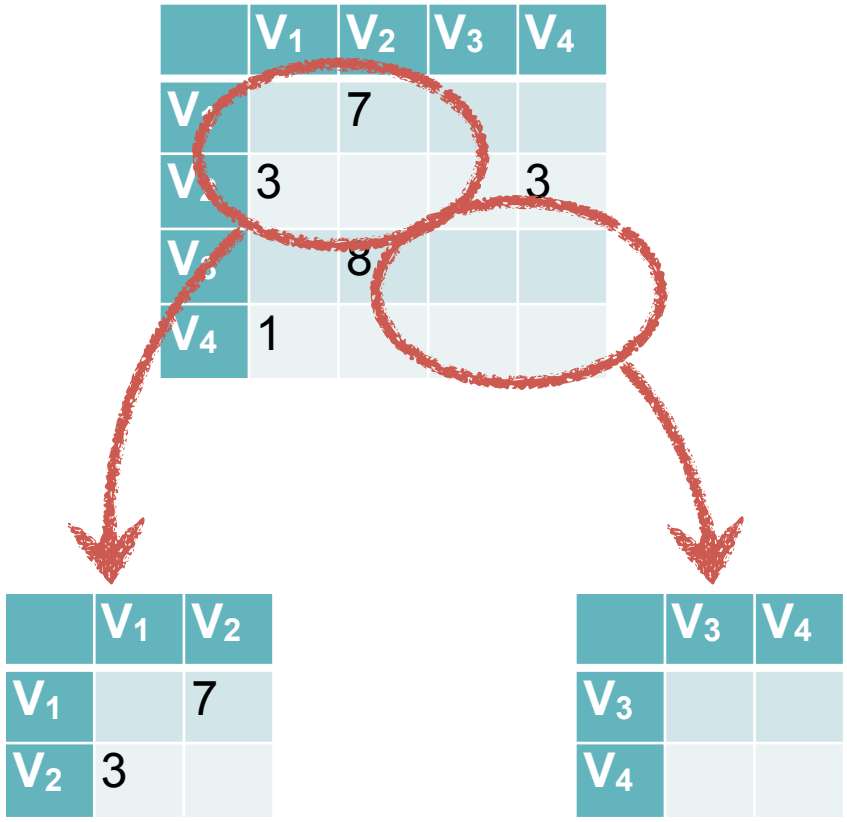
- Due to popular demand traditional graph databases now support temporal data storage
- Trivial solution is to model time-spans as nodes and connect data nodes only via time-span nodes
- Efficient Querying (Important requirement for a database)
  - Get all nodes starting with T_2
- Only distributed / scalable 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

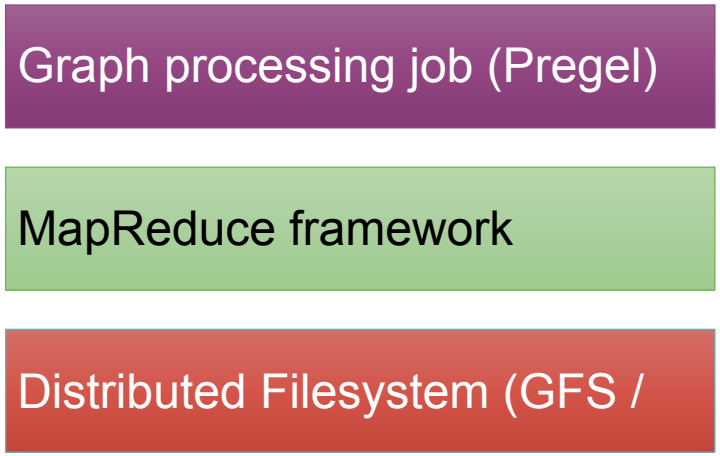
- (Sparse) matrices have long served as model for graphs
- Many popular graph algorithms have efficient implementations for matrices
- Distributed matrix processors (multiplicators) can be used to cope with large scale graphs
- Temporal aspect hard to integrate



U. Kang, C. E. Tsourakakis, and C. Faloutsos, “PEGASUS: A Peta-Scale Graph Mining System - Implementation and Observations,” presented at the 2009 Ninth IEEE International Conference on Data Mining (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
- Famous Google Pregel paper with open source implementations (Giraph, GPS, etc.)
- Temporal aspects not covered



graph.csv

```
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. In ACM SIGMOD International Conference on Management of Data, 2010.

CHRONOS AND IMMORTALGRAPH

- Research line by Microsoft
- Also introduces a concept of time-spans for analysis
- Current iterations designed towards clever **in-memory** layout:
  - **temporal** locality
  - **structural** locality

Y. Miao, W. Han, K. Li, M. Wu, F. Yang, L. Zhou, V. Prabhakaran, E. Chen, and W. Chen, “ImmortalGraph: A System for Storage and Analysis of Temporal Graphs,” ACM Transactions on Storage (TOS), vol. 11, no. 3, pp. 14–34, Jul. 2015.

W. Hant, Y. Miao, K. Li, M. Wu, F. Yang, L. Zhou, V. Prabhakaran, W. Chen, and E. Chen, “Chronos,” presented at the the Ninth European Conference, New York, New York, USA, 2014, pp. 1–14.

VERTEX CENTRIC EMBODIMENT WITH TEMPORAL DOCUMENT

```
{
    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: [ {
            weight: 4.0,
            edgeType: 'PHONE',
```

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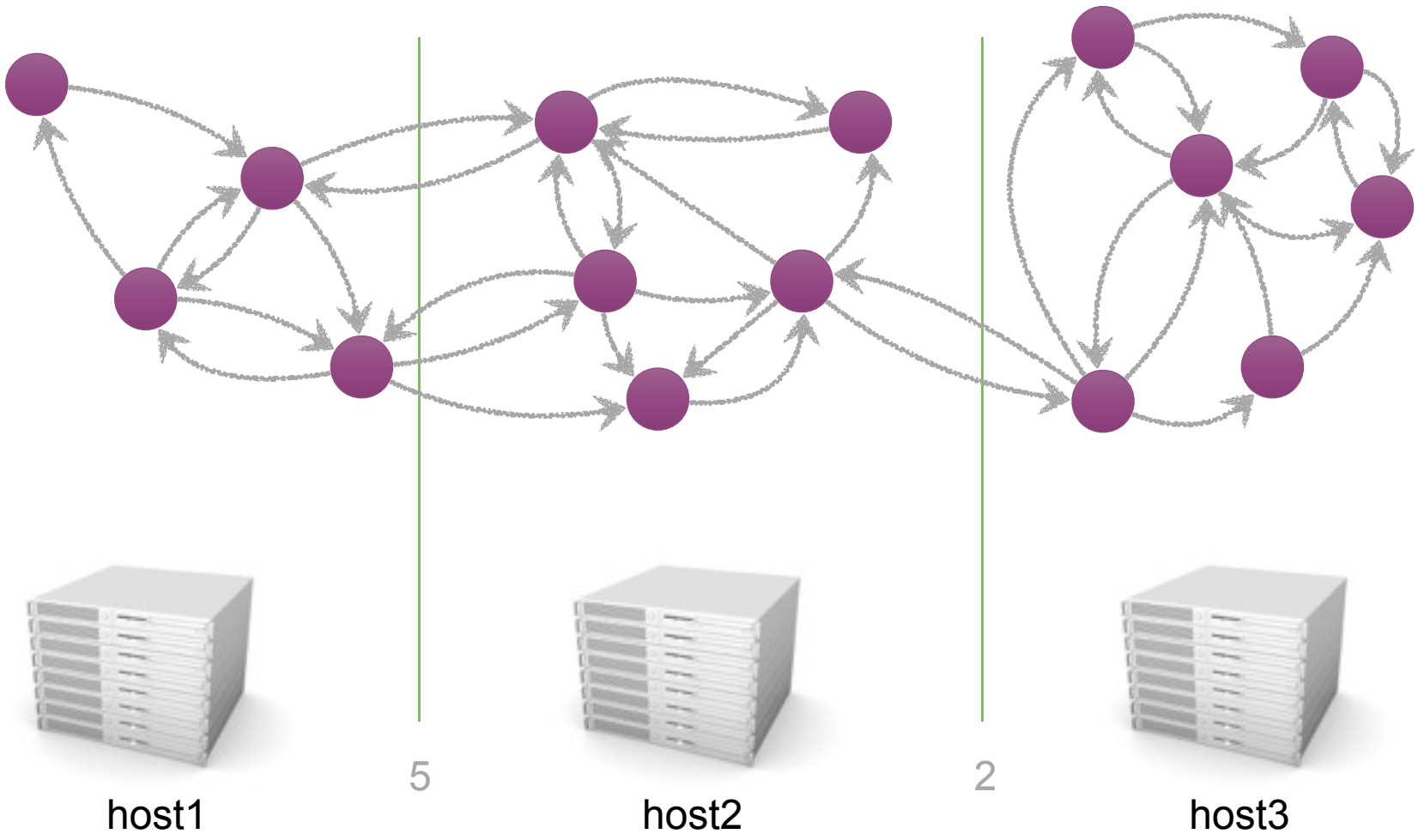
HORIZONTAL SCALABILITY



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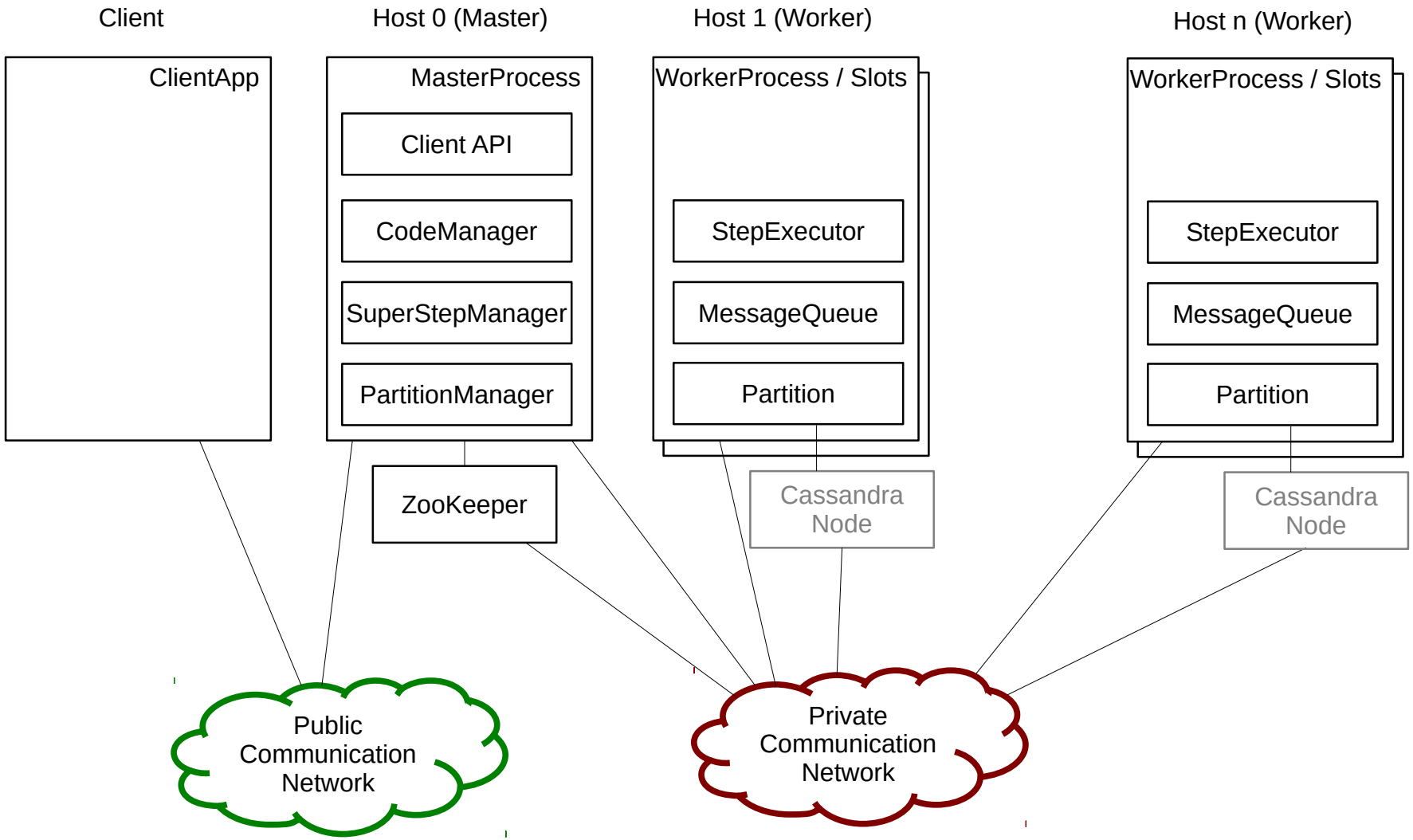
DYNAMOGRAPH ARCHITECTURE



TEMPORAL PREGEL IN A SINGLE SLIDE

- A **compute** function *c* / *execute* is implemented by the **application developer** which is executed in **iterations** / **steps**
  - It runs in the context of a vertex *v*, a timespan t, and receives a list of incoming messages {m_0, m_1, …, m_n}
  - *c* sees *v* as it would have looked in timespan *t*
  - Since *c* relies on **local information** only, it can be executed **in parallel** for all vertices
- Messages can be sent to other vertex threads through a **messaging function** *m(v, x)* sending message *x* to vertex *v*
  - Messages **sent** in step *s* are **received** in step *s+1*
- The code in *c* can **vote to halt** algorithm execution; execution halts if **all vertices** voted to halt; vertices that voted get **disabled**
  - Vertices are **enabled** if they **receive messages**

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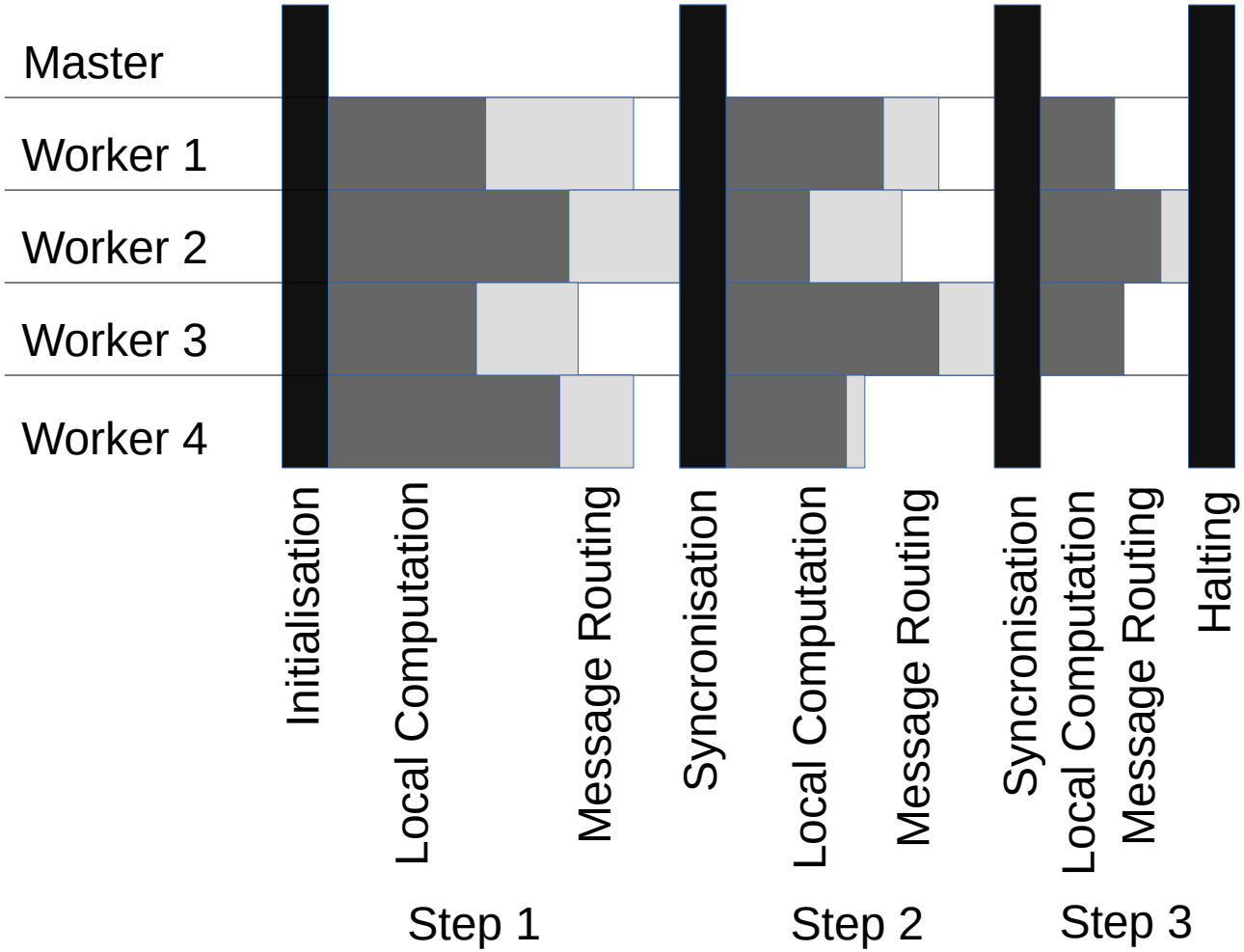
EXTENSIONS OVER THE ORIGINAL PREGEL FRAMEWORK

- **Temporal filtering**: algorithms can be run in the context of a **timespan** such that only data from this timespan is considered by the framework
- **Execution Triggers**
- **Global memory**: with related management functionality to allow:
  - *Initialisation*: Prior algorithm scheduling the application developer can initialise (Settings, Parameters, etc.)
  - *Access* and *Update*: Slots see a local copy of the global memory map
  - *Merging*: After each step / iteration conflicts in the global map must be resolved through (user defined) merge strategies

PREGEL / COMPUTE AGGREGATE BROADCAST



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G. Malewicz, M. Austern, A. Bik, J. Dehnert, I. Horn, N. Leiser, and G. Czajkowski. Pregel: A System for Large-Scale Graph Processing. In ACM SIGMOD International Conference on Management of Data, 2010.

PAGE RANK IN DYNAMOGRAPH

- PageRank is a **natural** fit for **Pregel** style computation
- Originally (and perhaps still) used by Google to rate websites for their search index

- Each vertex **starts** out with an **initial PageRank** *INITRANK*
- In a **continuous process** each vertex reads its own PageRank, **divides** it by the **number** of (outgoing) **edges** and sends this number to its **neighbours**
- Vertices **receive** all **messages** from neighbours, and set the **sum** as their **new PageRank**

L. Page, S. Brin, R. Motwani, and T. Winograd, “The PageRank Citation Ranking: Bringing Order to the Web,” Stanford InfoLab, 1999.

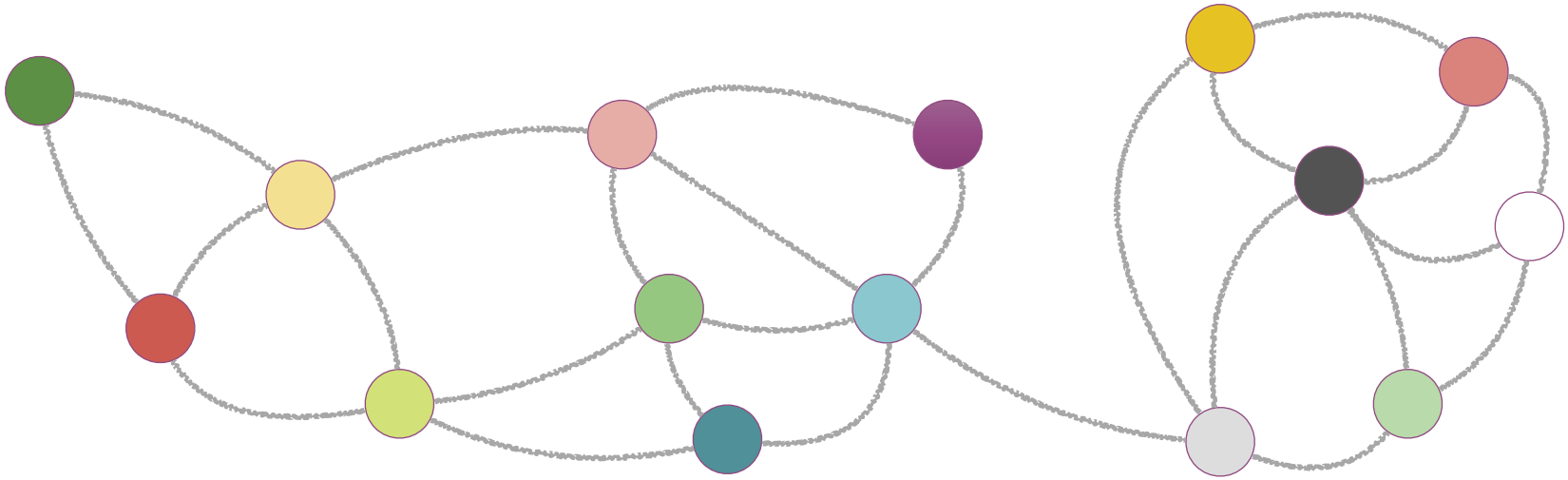
halt

init

processing

```
public void execute(
     List<VertexMsg> messages, VertexContext vertexContext,
     SuperStepContext superstepContext,
     Timeframe timeframe, Vertex vertex) {
     if(this.getStep() >= PageRank.MAX_ITER) {
          voteToHalt(vertexContext); return;
     }
     if(this.getStep() == 0L) {
          setPageRank(vertexContext, PageRank.INITRANK);
          Collection<Edge> outEdges = vertex.getWeightedOutEdgesReading();
          float outRank = (pageRank * PageRank.DAMP) / outEdges.size();
          for(Edge out : outEdges) {
               sendMessage(out.getTarget(), outRank);
          }
     }else{
          if(messages.size() > 0) {
               float changedby = 0.0f; float sumIncoming = 0.0f;
               for(VertexMessage m : messages) {
                    sumIncoming += m.getFloatValue();
               }
               changedby = setPageRank(vertexContext, sumIncoming);
               if(changedby >= PageRank.SWING_THRESHOLD) {
                    Collection<Edge> outEdges = vertex.getWeightedOutEdgesReading();
                    float pageRank = getPageRank(vertexContext);
                    float outRank = (pageRank * PageRank.DAMP) / outEdges.size();
                    for(Edge out : outEdges) {
                         sendMessage(out.getTarget(), outRank);
                    }
               }
          }
          voteToHalt(vertexContext);
     }
}
```

LABEL PROPAGATION COMMUNITY DETECTION IN DYNAMOGRAPH



Observe neighbouring community labels
Apply the label most often found or
if none such can be found the smallest one

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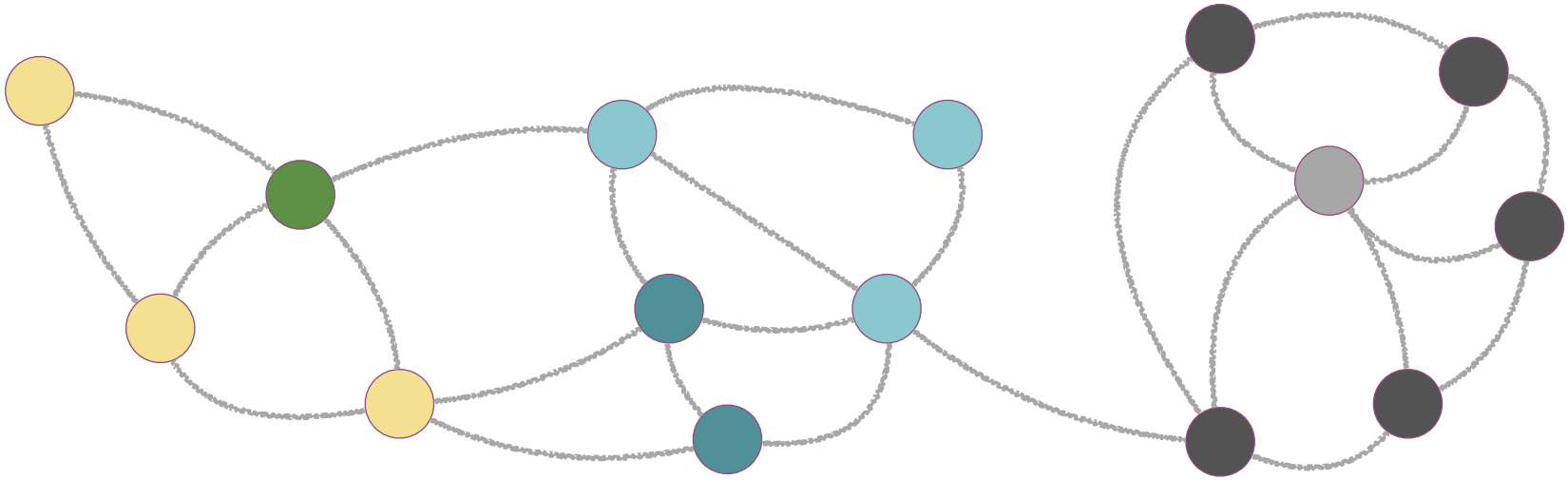
U. N. Raghavan, R. Albert, and S. Kumara, “Near linear time algorithm to detect community structures in large-scale networks,” Phys. Rev. E, vol. 76, no. 3, p. 036106, Sep. 2007.

LABEL PROPAGATION COMMUNITY DETECTION IN DYNAMOGRAPH



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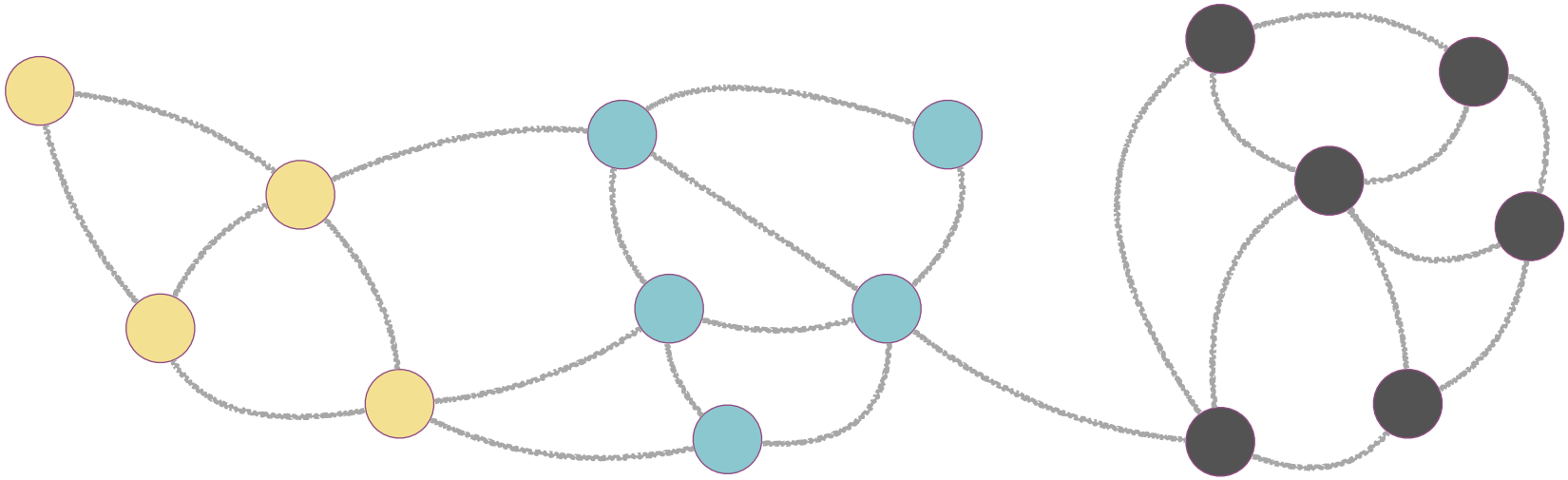
LABEL PROPAGATION COMMUNITY DETECTION IN DYNAMOGRAPH



Observe neighbouring community labels
Apply the label most often found or
if none such can be found the smallest one

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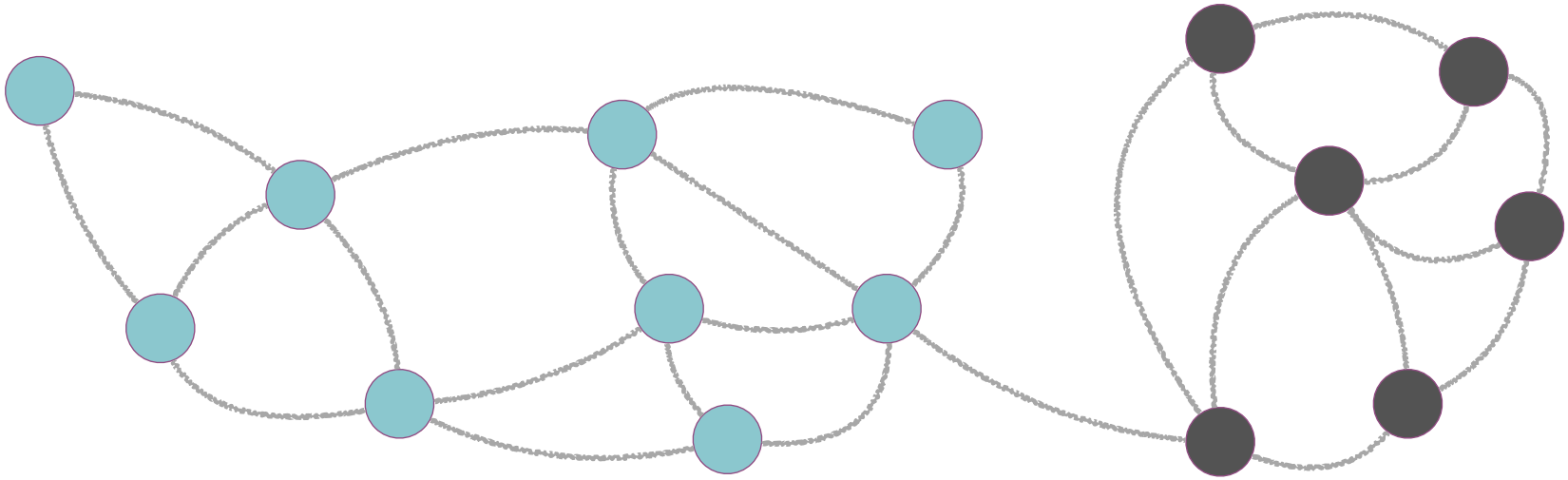
LABEL PROPAGATION COMMUNITY DETECTION IN DYNAMOGRAPH

after some more iterations



Observe neighbouring community labels
Apply the label most often found or
if none such can be found the smallest one

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init

halt

processing

```
public void execute(
     List<VertexMsg> messages, VertexContext vertexContext,
     SuperStepContext superstepContext,
     Timeframe timeframe, Vertex vertex) {
          if(this.getStep() == 0L) {
               this.setVertexLabel(vertexContext, vertex.getId());
               propagateVertexLabel(vertex, vertexContext);
          }else if(this.getStep() >= 8){ // 8 iterations
               voteToHalt(vertexContext);
          }else{
               Map<Long, Integer> count = new HashMap<Long, Integer>();
               for(VertexMessage m : messages) {
                    Long clusterId = (Long) m.getBody();
                    if(!count.containsKey(clusterId)) {
                         count.put(clusterId, 1);
                    }else{
                         Integer currentCount = count.get(clusterId);
                         currentCount ++;
                         count.put(clusterId, currentCount);
                    }
               }
               long clusterId = findMaxClusterId(count);
               setVertexLabel(vertexContext, maxClusterId);
               propagateVertexLabel(node, vertexContext);
          }
     }
}
```

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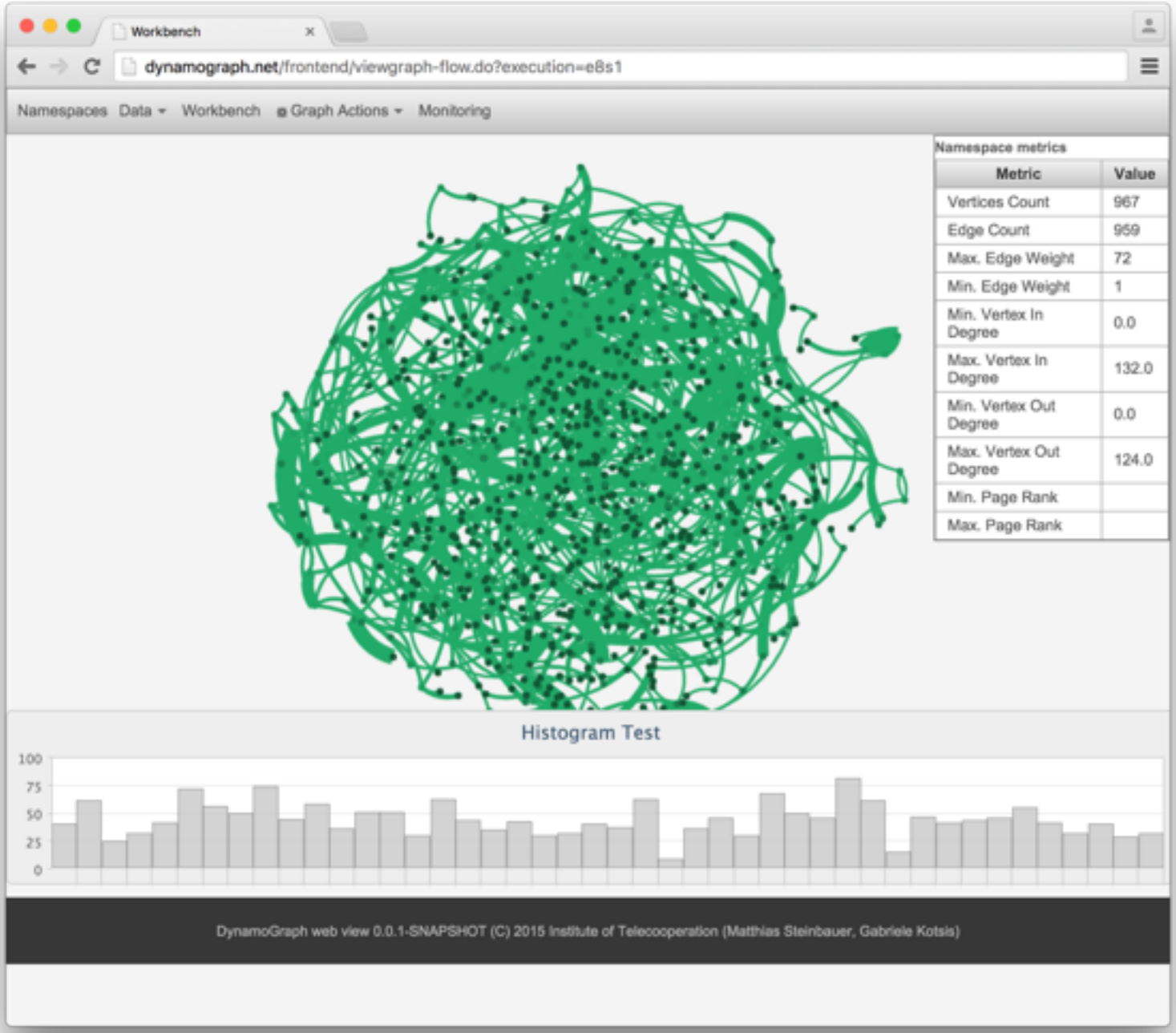
967
members
IRC channel

full time-span



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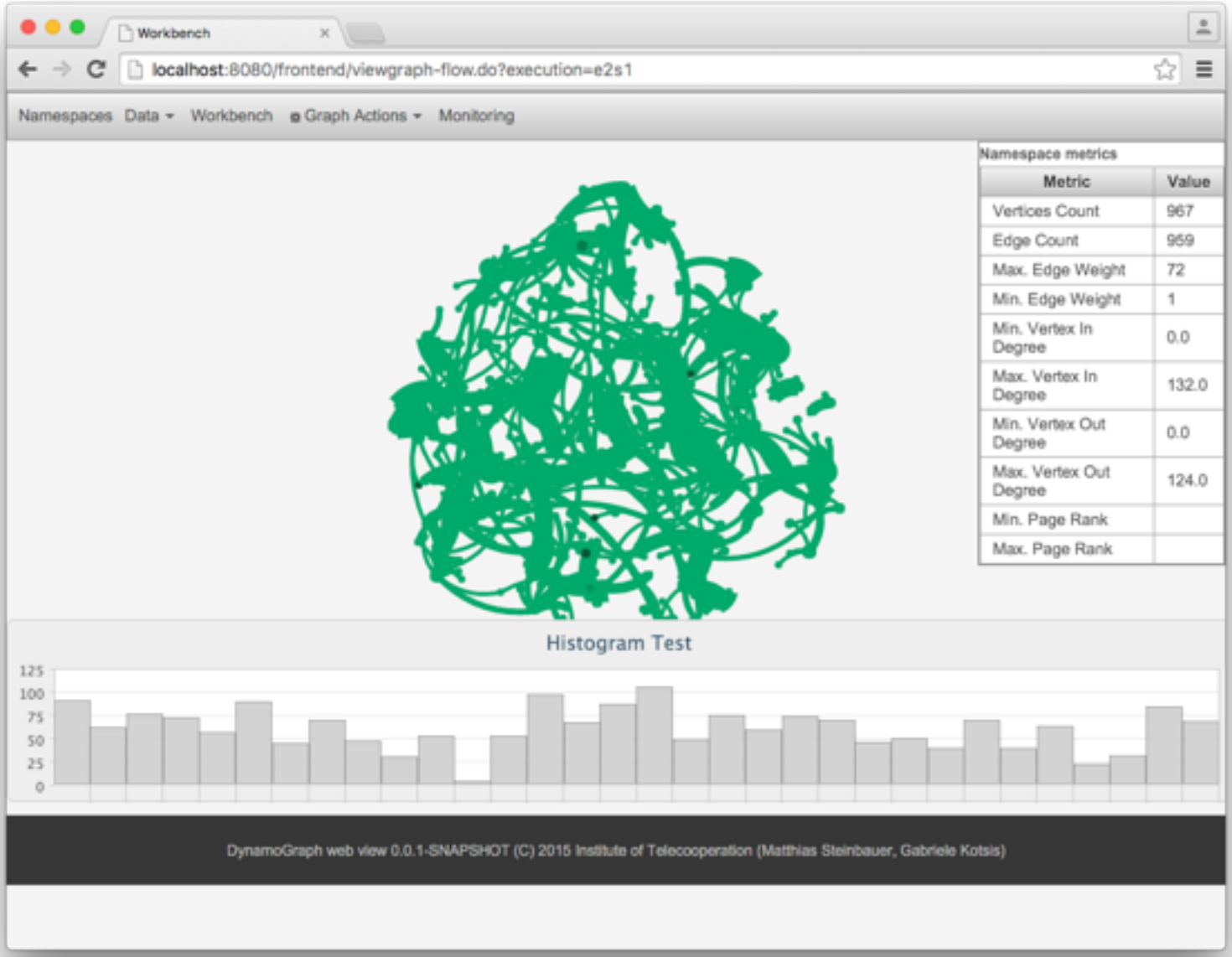
Data from Ecker 2015

967
members
IRC channel

selected
time-span

1st June 2008
15th June 2008



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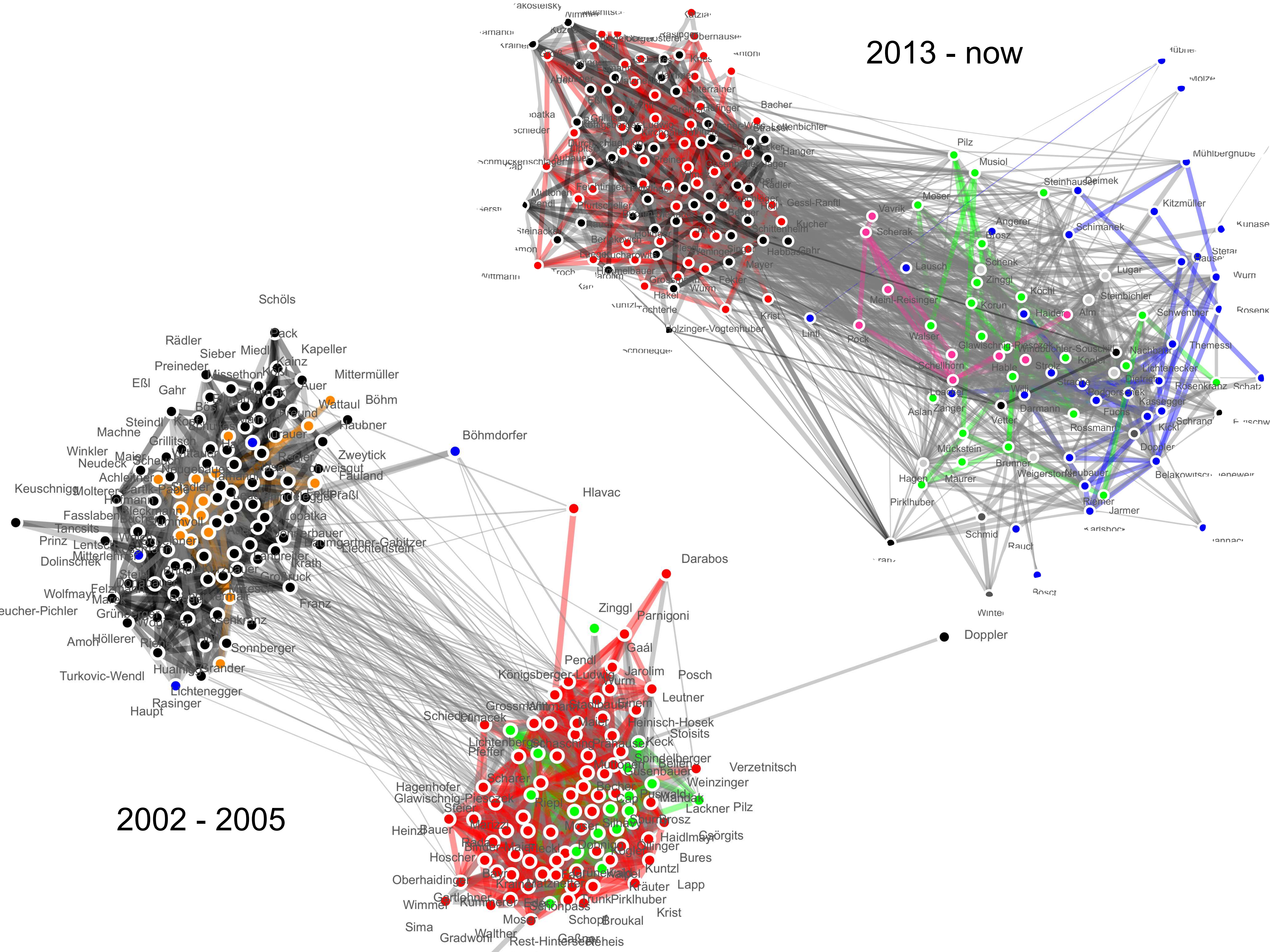

2013 - now
2002 - 2005
Schöls
Rädler
Sieber
Miedl
Kapeller
Preineder
Mittermüller
Eßl
Gahr
Wattaul
Böhm
Steindl
Machne
Haubner
Böhmdorfer
Winkler
Neudeck
Zweytick
Fauland
Achleitner
Keuschnigg
Molterer
Fasslabend
Tancsits
Prinz
Dolinschek
Wolfmayr
Amon
Höllerer
Sonnberger
Turkovic-Wendl
Lichtenegger
Rasinger
Haupt
Hlavac
Darabos
Zinggl
Parnigoni
Gaál
Pendl
Jarolim
Posch
Leutner
Heinisch-Hosek
Stoisits
Keck
Spindelberger
Verzetnitsch
Weinzinger
Lackner
Pilz
Grosz
Csörgits
Bures
Kuntzl
Kräuter
Lapp
Pirklhuber
Krist
Broukal
Hagenhofer
Glawischnig-Piesczek
Heinzl
Bauer
Hoscher
Oberhaidinger
Wimmer
Sima
Gradwohl
Walther
Rest-Hinterseer
Doppler
Bacher
Lettenbichler
Hanger
Gessl-Ranftl
Kucher
Musiol
Moser
Vavrik
Scherak
Lausch
Meinl-Reisinger
Walser
Pock
Lintl
Steinhauser
Kitzmüller
Schimanek
Angerer
Lugar
Steinbichler
Schwentner
Themessl
Nachbaur
Rosenkranz
Schenk
Zinggl
Köchl
Korun
Strolz
Rossmann
Kickl
Belakowitsch
Hagen
Maurer
Pirklhuber
Schmid
Rauch
Jarmer
Riemer
Mühlberghuber
Mückstein
Brunner
Aslan
Zanger
Vetter
Darmann
Fuchs
Schellhorn
Hable
Holzinger-Vogtenhuber

REAL WORLD SOCIAL NETWORKS

- Data is available as online resource
- Users can filter and load data into DynamoGraph
- Algorithms for automatic layout of the visualisation are available (ForceAtlas2)

- In visualisation it is already clear that reachability measures computed on the full time-span will often not hold on shorter time-spans
  - How is information dissemination influenced by that fact?
  - Can we perform cluster analysis on users and identify topics of interest?

FUTURE WORK

- **More** temporal graph **algorithms** are to be implemented (reachability, clustering, …) to provide more interesting metrics to our users
- Proper Evaluation targeted Dataset: Click from Indiana University
  - Private Cloud test with 24 CPUs ~288 GB of memory
  - MACH super computing infrastructure single system image machine (2048x4 cores, 16 TB memory)

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CONCLUSIONS AND FUTURE WORK

- **DynamoGraph** as a platform for large-scale temporal graph processing has matured enough to be evaluated in scientific scenarios
- Two example algorithms were shown that demonstrate how potential application developers can create processing pipelines in this paradigm
- A web-based graph work-bench as a first prototype was briefly shown to demonstrate the necessity of temporal analysis

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slides available at
http://steinbauer.org/

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