



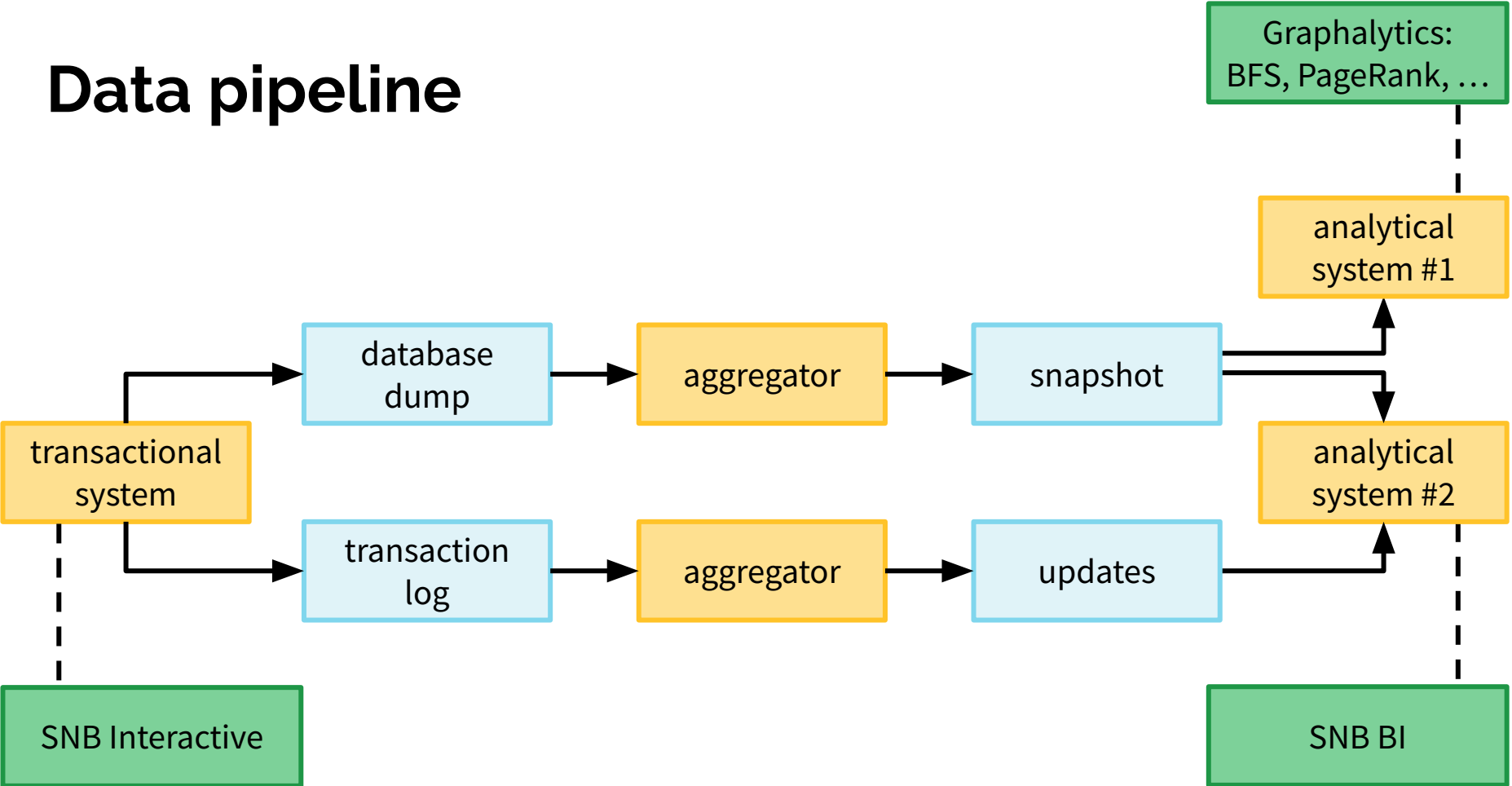
# The LDBC Social Network Benchmark: Business Intelligence workload

**Gábor Szárnyas**

CWI

15th TUC meeting

# Data pipeline



# LDBC SNB BI workload

A modern OLAP benchmark suite

- Correlated, temporal graph data set
- Analytical queries, including graph operations
- Inserts & deep deletes
- Parameter curation

# Social network data set

- Correlated
- Temporal

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# Example graph

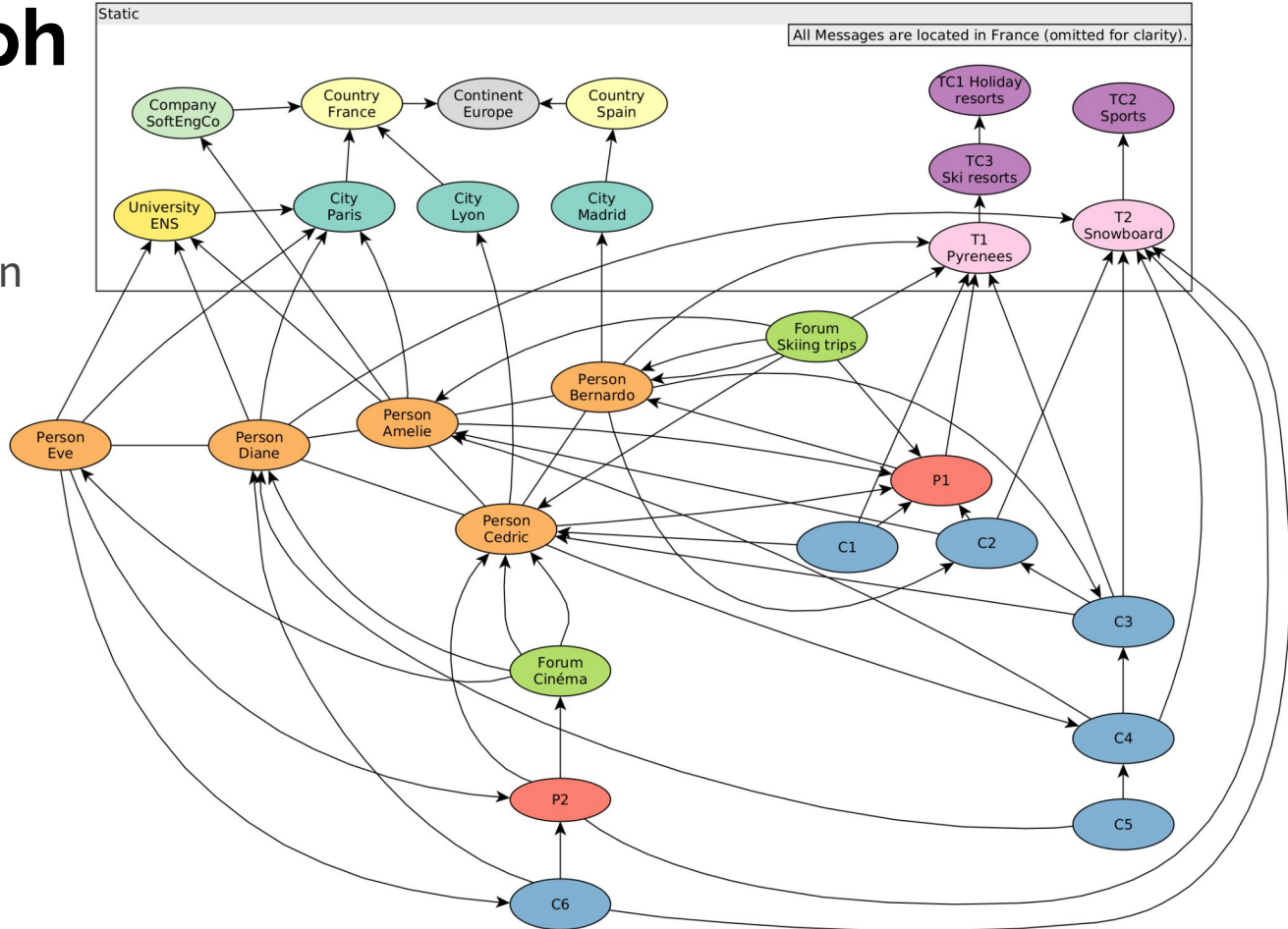
Main entities:

- Person-knows-Person network
- Forums
- Message threads

Correlations:

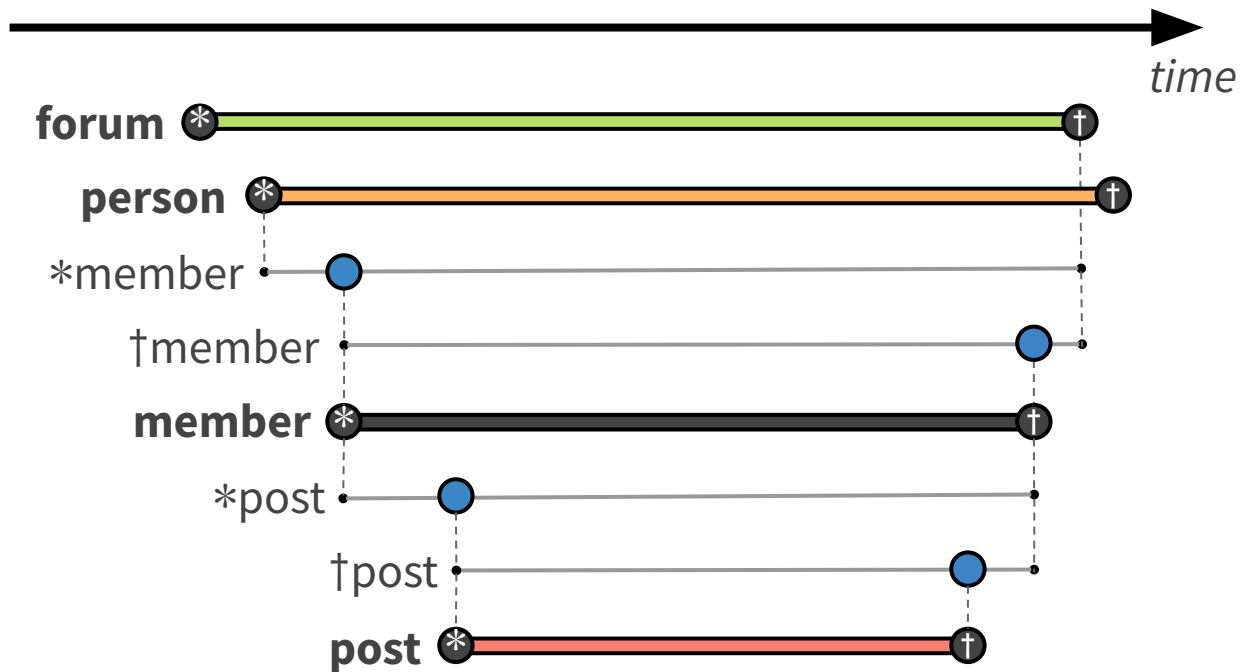
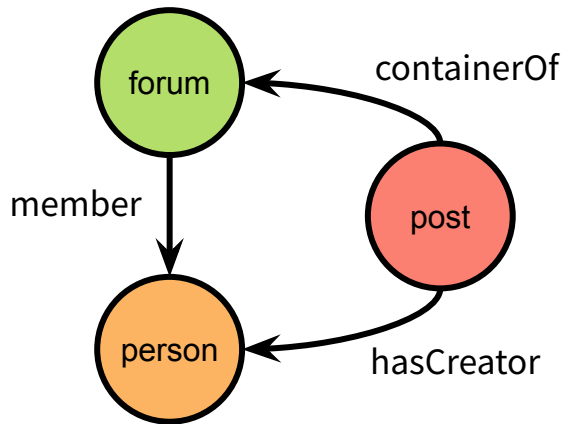
- Structure-level
- Attribute-level

Dynamic graph



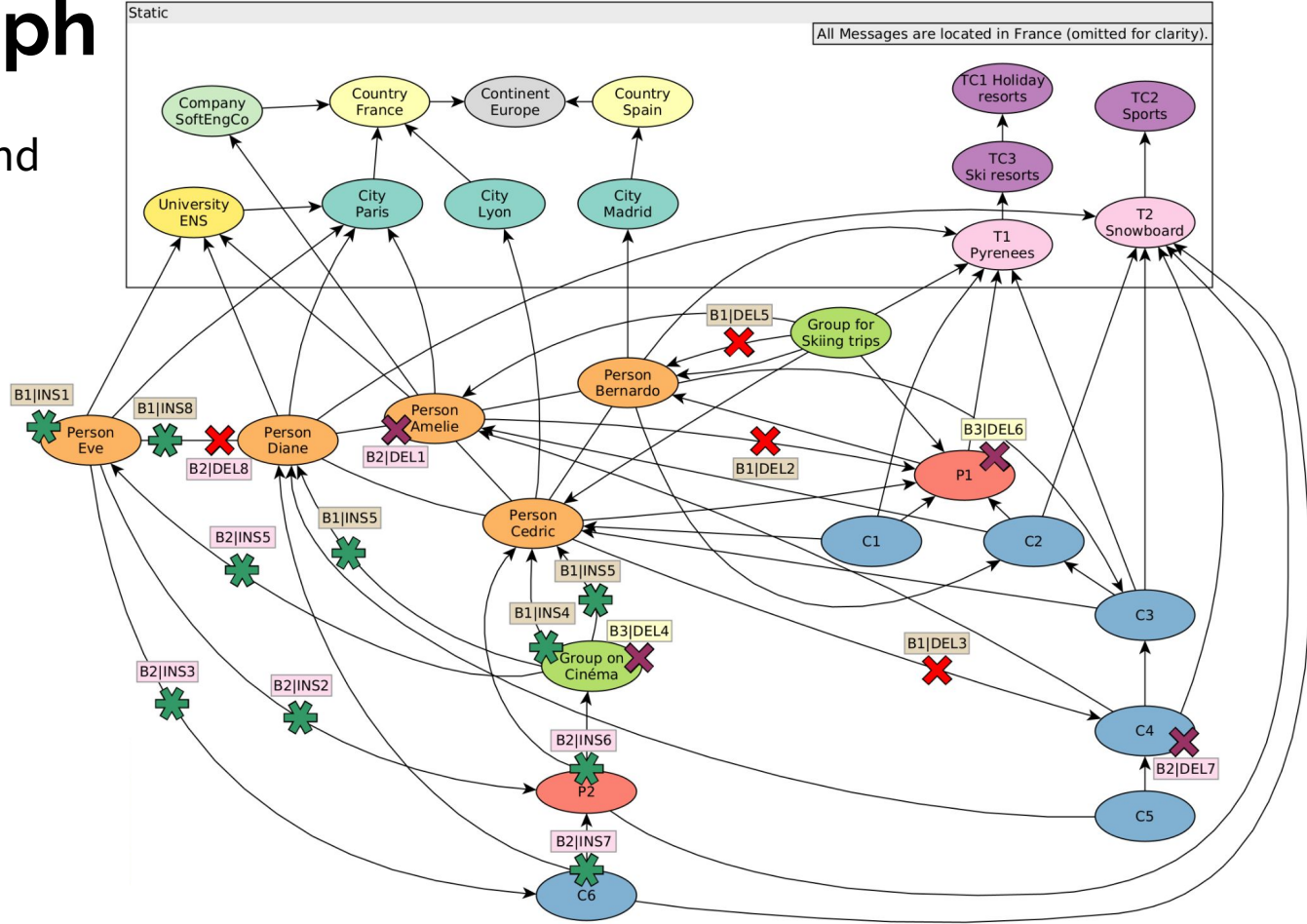
# Lifespans

The generator generates the entire temporal with creation dates \* and deletion dates †



# Dynamic graph

Initial snapshot (97%) and  
insert/delete batches

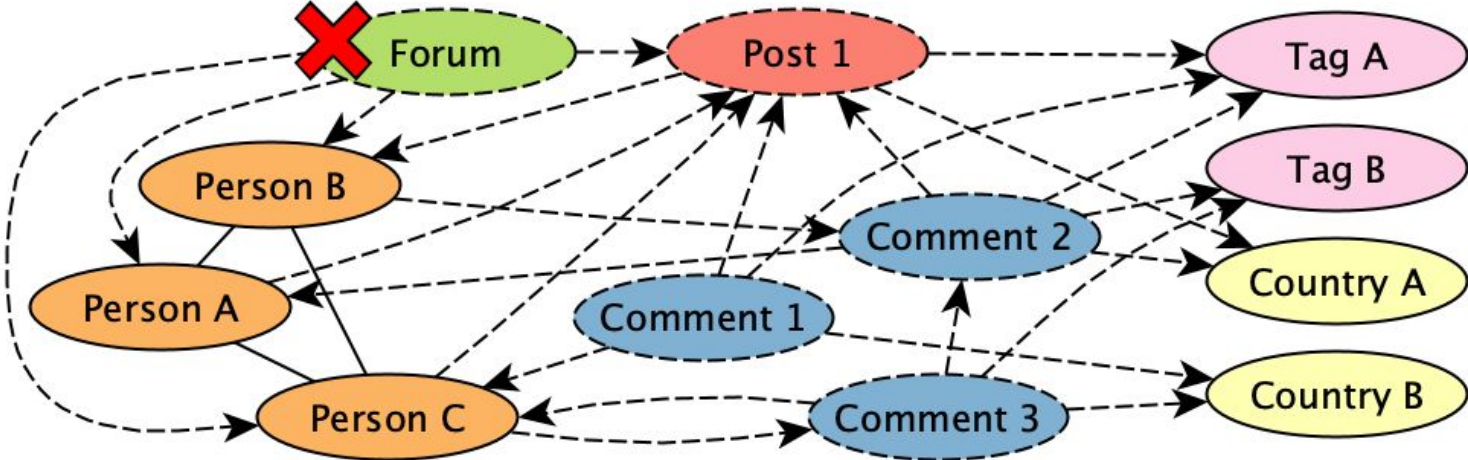


 [Supporting dynamic graphs in SNB Datagen,](#)

GRADES-NDA 2020

# Deleting a Forum

Deletes are heavy-hitting operations





# Workload

- Workload
- Parameter curation
- Example queries

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# Choke points

A choke point is a **difficult aspect of query processing** that has a significant impact on the performance of the query.

Examples:

- Join ordering
- Data access locality
- WCOJs
- Path queries



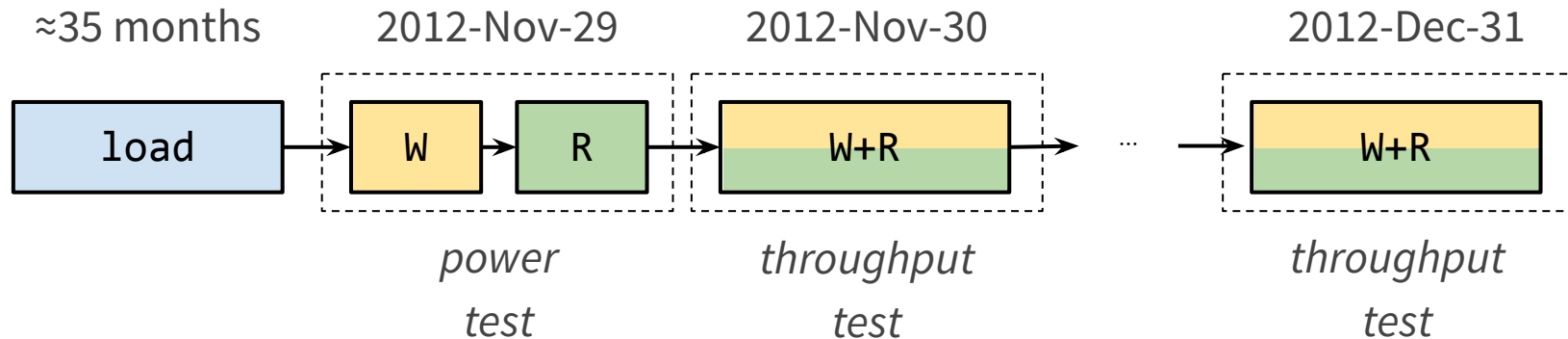
[TPCTC'12](#): experiences of implementing TPC-H on Vectorwise, Virtuoso, and HyPer

# Workload

**Workload:** Ad-hoc graph OLAP queries with daily updates

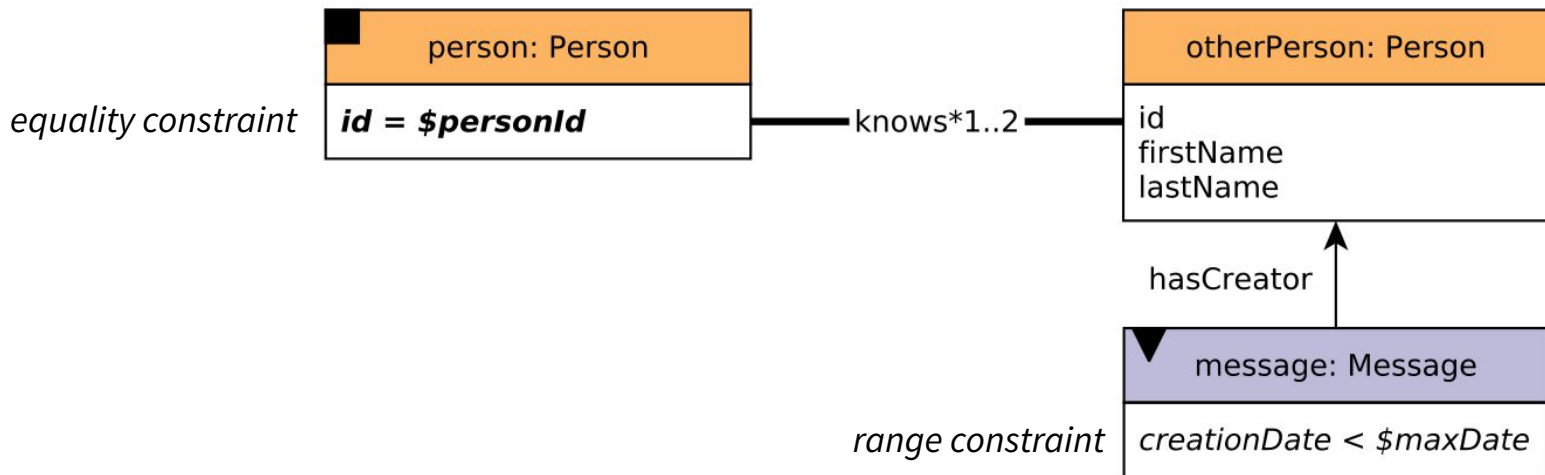
**Batches:** 33 days of W/R operations

- W: apply one day's worth of updates
- R: 20 complex read queries with different parameters



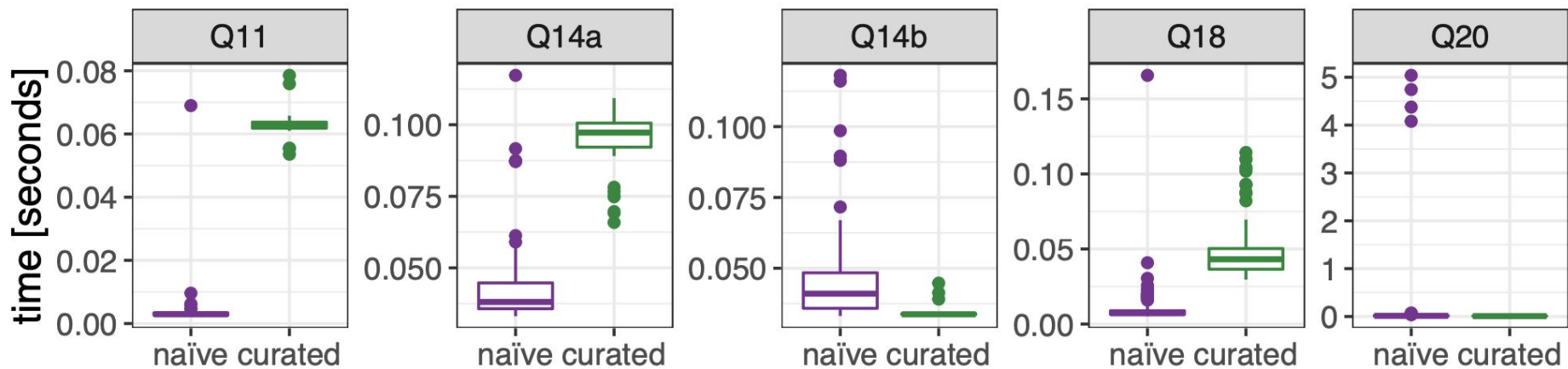
# Parameter curation

**Parameter selection** is particularly important for *skewed and correlated data sets*:

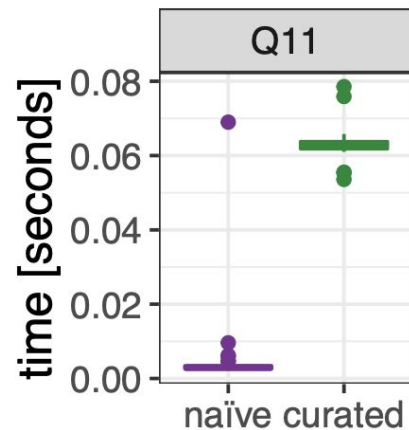
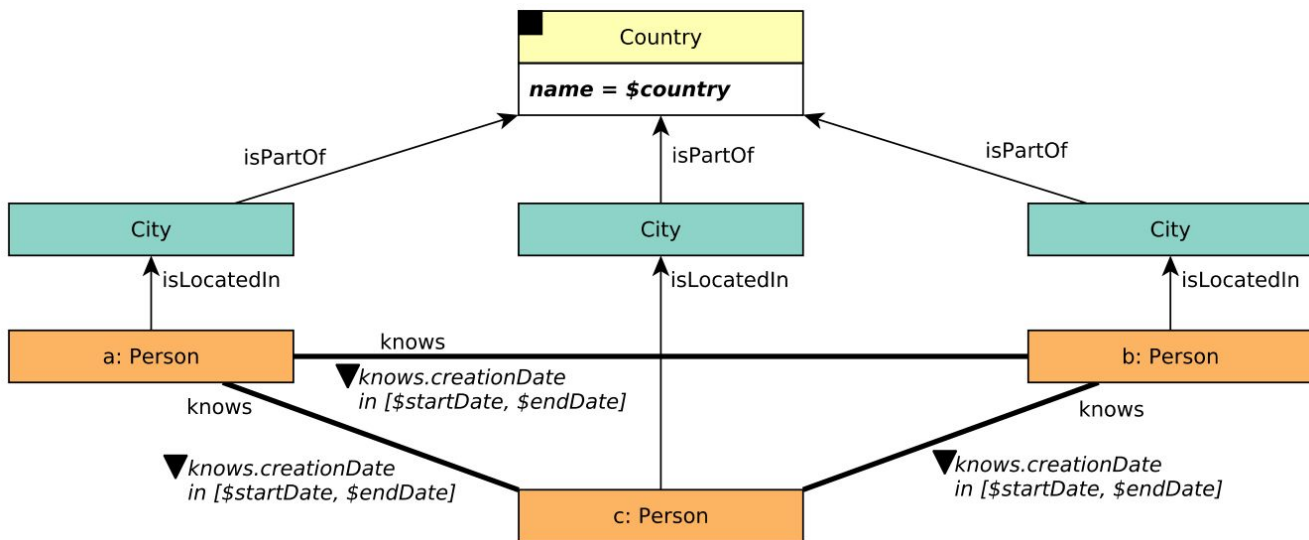


- starting a query from a person with a low degree vs. a high degree
- cost of reachability queries if there is a path vs. no path

# Umbra SF10: naïve vs. curated parameters



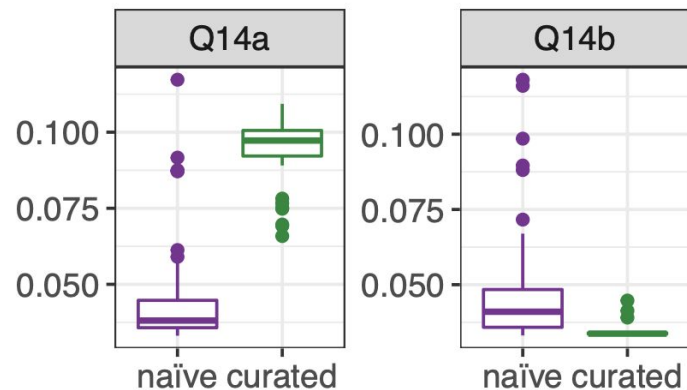
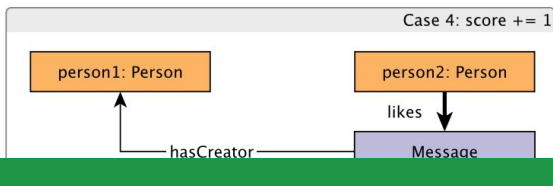
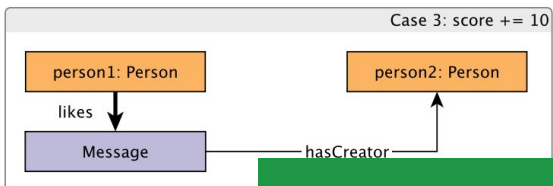
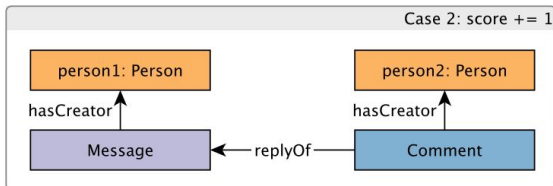
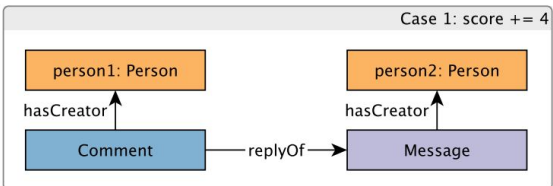
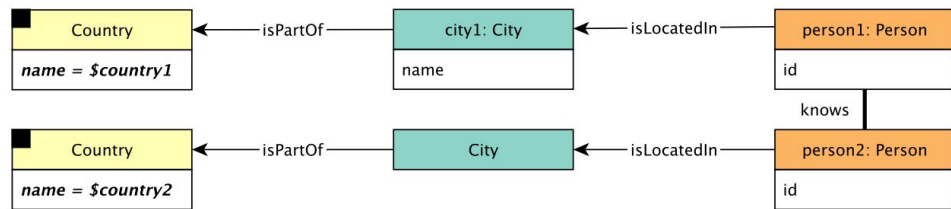
# Q11: Triangle query – WCOJs are beneficial



**Parameters: Only big countries, similar intervals**

# Q14: Correlations – Different runtimes/query plans

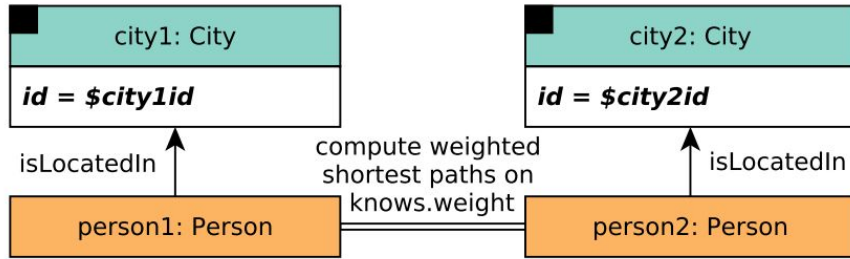
For each pair of countries, calculate the cost as a sum of cases #1-4. Cases that have a match add to the final score with the specified value. Each case only counts once, multiple matches do not increase to the score.



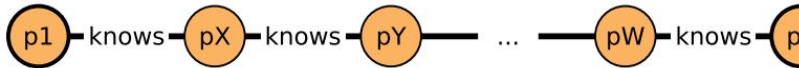
**Parameters: (A) close countries (B) far-away countries**

# Q19: Multi-source weighted shortest path

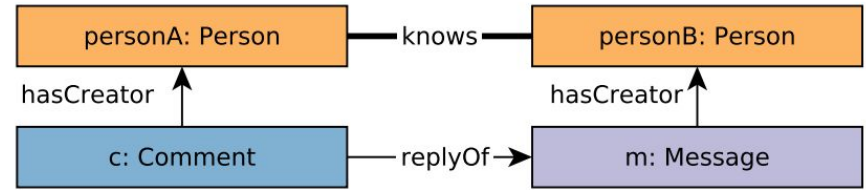
Find the shortest paths between all pairs of Persons in city1 and city2



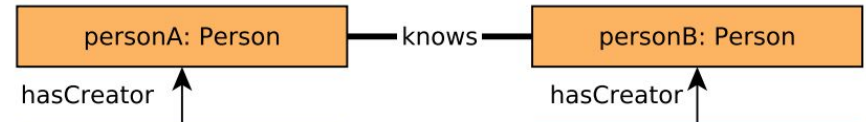
The weight of a knows edge is based on the number of interactions between its Persons:  
 $\text{knows.weight} = 1 / (\text{count}(i1) + \text{count}(i2))$



Case i1: Reply from personA to Person B's Message



Case i2: Reply from personB to personA's Message



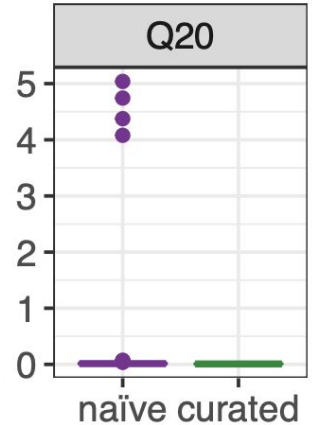
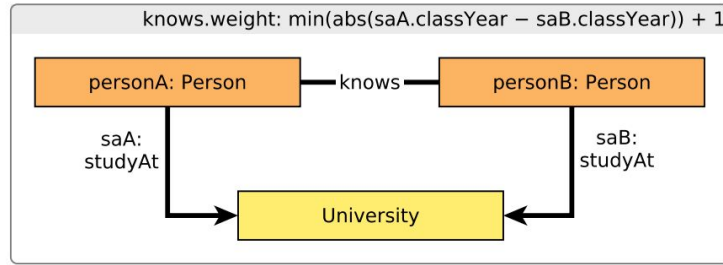
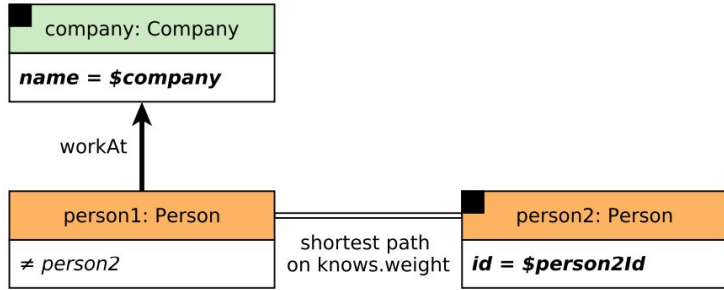
**Parameters:**

(A) Cities from the same country

(B) Cities from different countries






# Q20: Single-source weighted shortest path



## Parameters:

- (A) There is a path between `$company` employees and `$person2`
- (B) There is no path between `$company` employees and `$person2`

# BI implementations

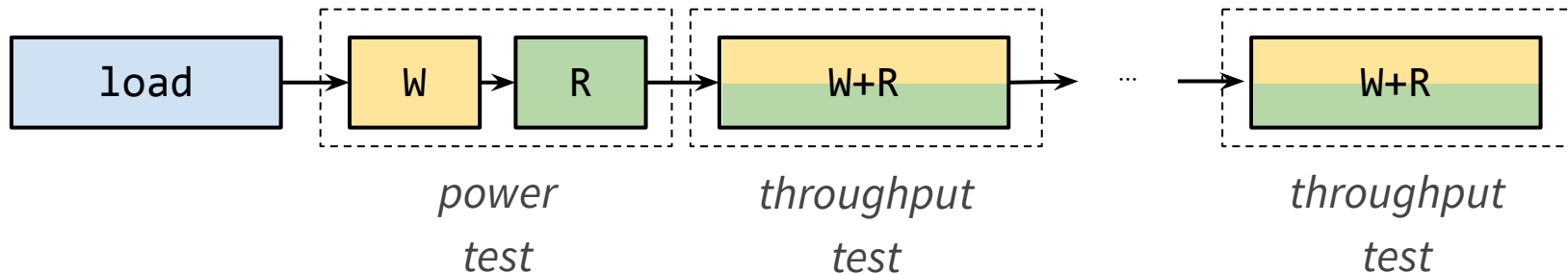
system	data model	language	LOC
 neo4j	graph	Cypher	495
 UMBRA	relational	SQL	755
 TigerGraph	graph	GSQL	832

# Execution and scoring

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# Workload execution

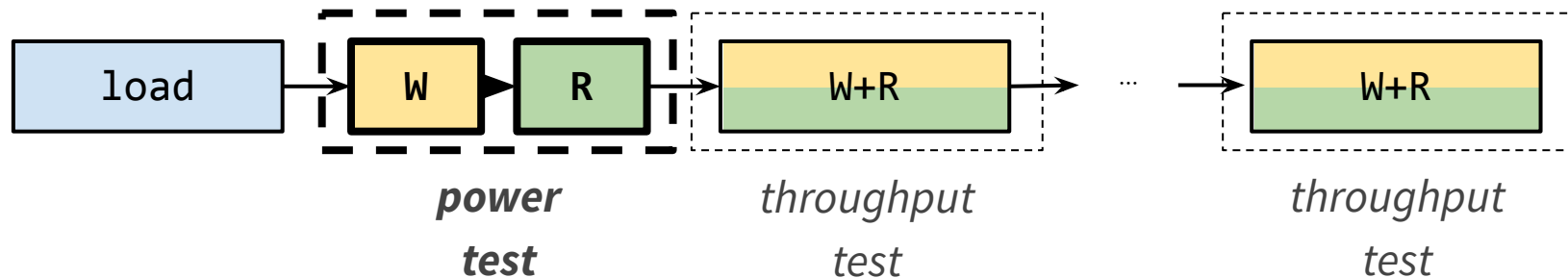
- Power test: sequential query execution
- Throughput tests: concurrent query execution
  - Concurrent RW
  - Disjoint RW



# Scoring metrics: Power

Geometric mean ensures all queries are of equal importance

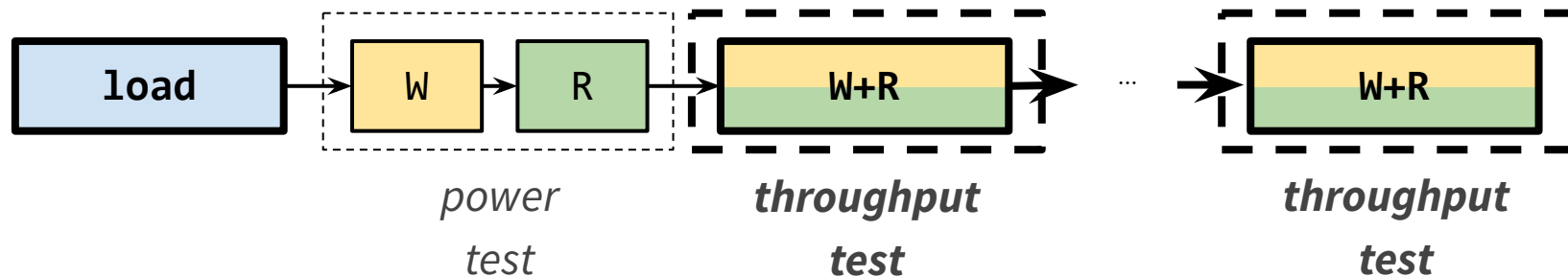
$$power@SF = \frac{3,600}{\sqrt[29]{w \cdot q_1 \cdot \dots \cdot q_{20a} \cdot q_{20b}}} \cdot SF$$



# Scoring metrics: Throughput

Run throughput batches for at least 1 hour and extrapolate to one day.

$$\text{throughput@SF} = (24 \text{ hours} - t_{\text{load}}) \cdot \frac{n_{\text{batches}}}{t_{\text{batches}}} \cdot SF$$



# Scoring metrics: Price-performance

Power and throughput metrics, taking the the total cost of ownership into account, using TPC's pricing.

$$power@SF/\$ = power@SF \cdot \frac{1,000}{TCO}$$

$$throughput@SF/\$ = throughput@SF \cdot \frac{1,000}{TCO}$$

# Scalability

BI workload scales up to SF10k: 10,000 GiB CSV data sets.

- Larger than SF10k results are rare even for TPC-H (~14% in the last decade)

Economics of SF10k generation:

- Data generation: \$64
- Parameter generator: <20 minutes on a single machine



# Summary

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# Conclusion

State-of-the-art OLAP benchmark

- Scales to SF10k (10,000 GiB) graphs
- Paper with specification and experiments submitted

Plans:

- Start audits
- Generate SF30k+ data sets
- Backport improvements to SNB Interactive

***LDBC*** 

*The graph & RDF  
benchmark reference*

# Query design

Choke points and parameters

- Choke point analysis
  - Query templates
  - Parameter curation
-

# [ENSURE] Scalability

Spark-based data generator for increasing scale factors 1, 3, 10, ...

The benchmark *needs to be economical*.

Generating the SF10k data set:

- AWS Elastic MapReduce
- 100 instances with 128GiB RAM
- 1.5 hour runtime

**Cost:** \$74

# Comparison of workloads

	<b>Interactive v1.0</b>	<b>Business Intelligence v1.0</b>
<b>focus</b>	OLTP	OLAP
<b>typical query</b>	2-3 hop neighbourhood queries with filtering	multi-hop/path/subgraph queries with filtering & aggregation
<b>refresh operations</b>	inserts	inserts and deletes
<b>target metric</b>	total compression ratio, implying throughput (ops/s)	throughput (ops/day)

# Graph data management systems

GDMs provide a graph-aware UI and support graph processing features.



property graph  
data model



graph query  
language



graph  
visualization

relational  
queries

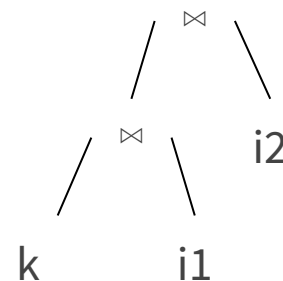
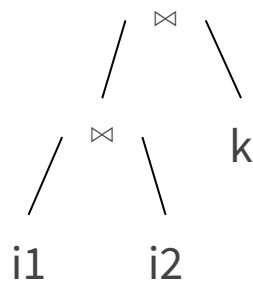
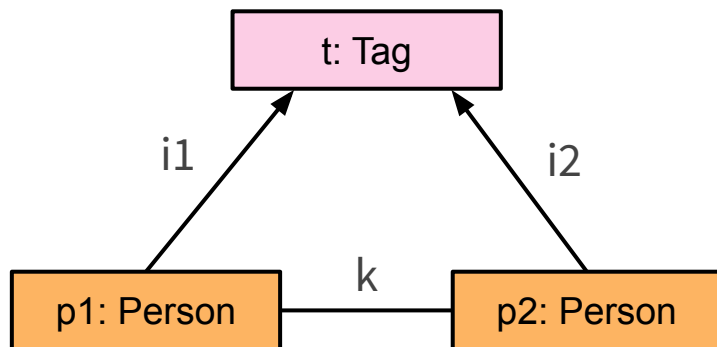
subgraph  
matching

path  
queries

graph  
algorithms

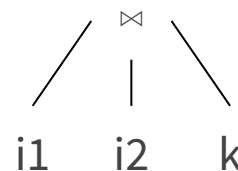
# Subgraph matching

The complexity of a **triangle query with binary joins** is provably suboptimal:  $O(|E|^2)$



Triggered by many-to-many edges and skewed distributions.

Worst-case optimal **multi-way join algorithms** are needed, which have a complexity of just  $O(|E|^{1.5})$  for this query.





# Path queries

Implementing an efficient BFS/shortest path algorithm is non-trivial:

- direction optimizing BFS (push-pull) SC 2012
- landmark labelling for distance queries SIGMOD 2013
- multi-source batched BFS VLDB 2014

## Direction-Optimizing Breadth-First Search

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University of California, Berkeley  
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**Abstract**—Breadth-First Search is an important kernel used by many graph-processing applications. In many of these emerging applications of BFS, such as analyzing social networks, the input graphs are low-diameter and scale-free. We propose a hybrid approach that is advantageous for low-diameter graphs, which combines a conventional top-down algorithm along with a novel bottom-up algorithm. The bottom-up algorithm can dramatically reduce the number of edges examined, which in turn accelerates the search as a whole. On a multi-socket server, our hybrid approach demonstrates speedups of 3.3–7.8 on a range of standard synthetic graphs and speedups of 2.4–4.6 on graphs from real social networks when compared to a strong baseline. We also typically double the performance of prior leading shared memory (multicore and GPU) implementations.

### I. INTRODUCTION

Graph algorithms are becoming increasingly important, with applications covering a wide range of scales. Warehouse-scale computers run graph algorithms that reason about vast amounts of data, with applications including analytics and recommendation systems [16, 19]. On mobile clients, graph algorithms are important components of recognition and machine-learning applications [18, 28]. Unfortunately, due to a lack of locality, graph applica-

The bottom-up approach is not always advantageous, so we combine it with the conventional top-down approach, and use a simple heuristic to dynamically select the appropriate approach to use at each step of BFS. We show that our dynamic on-line heuristic achieves performance within 25% of the optimum possible using an off-line oracle. Our hybrid implementation also provides typical speedups of 2 or greater over prior state-of-the-arts for multicore [1, 10, 15] and GPUs [20] when utilizing the same graphs and the same or similar hardware. An early version of this algorithm [5] running on a stock quad-socket Intel server was ranked 17<sup>th</sup> in the Graph November 2011 rankings [14], achieving the fastest node implementation and the highest per-core process and outperforming specialized architectures and clusters with more than 150 sockets.

### II. GRAPH PROPERTIES

Graphs are a powerful and general abstraction that can represent a large number of problems to be represented and solved using the same algorithmic machinery. However, there is often substantial performance to be gained by optimizing algorithms for the types of graph present in a particular target workload.

## Fast Exact Shortest-Path Distance Queries on Large Networks by Pruned Landmark Labeling

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Yoichi Iwata The University of Tokyo Tokyo, 113-0033, Japan y.iwata@is.s.u-tokyo.ac.jp  
Yuichi Yoshida National Institute of Informatics, Preferred Infrastructure, Inc. Tokyo, 101-8430, Japan yyoshida@nii.ac.jp

### ABSTRACT

We propose a new exact method for shortest-path distance queries on large-scale networks. Our method precomputes distance labels for vertices by performing a breadth-first search from every vertex. Seemingly too obvious and too inefficient at first glance, the key ingredient introduced here is pruning during breadth-first searches. While we can still

analyze influential people and communities [19, 6]. On web graphs, distance between web pages is one of indicators of relevance, and used in context-aware search to give higher ranks to web pages more related to the currently visiting web page [30, 29]. Other applications of distance queries include top-*k* keyword queries on linked data [16, 37], discovery of optimal pathways between compounds in metabolic networks [31, 32], and management of resources in computer

# GDMs rarely support these optimizations

### Categories and Subject Descriptors

E.1 [Data]: Data Structures—Graphs and networks

## The More the Merrier: Efficient Multi-Source Graph Traversal

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† New York University

### ABSTRACT

Graph analytics on social networks, Web data, and communication networks has been widely used in a plethora of applications. Many graph analytics algorithms are based on breadth-first search (BFS) graph traversal, which is not only time-consuming for large datasets but also involves much

have influence on others and, as a consequence, are of great importance to spread information, e.g., for marketing purposes [20].

In a wide range of graph analytics algorithms, including shortest path computation [13], graph centrality calculation [9, 27], and *k*-hop neighborhood detection [12], breadth-first search (BFS) is used. In parallel, however, elementary

our synchronization costs. We demonstrate how a real graph analytics application—all-vertices closeness centrality—can be efficiently solved with MS-BFS. Furthermore, we present an extensive experimental evaluation with both synthetic and real datasets, including Twitter and Wikipedia, showing

graph, i.e., a graph from a large number of nodes, load-balanced in a distributed fashion, and mentioned in previous work had to address not only parallelization-specific and real datasets, including Twitter and Wikipedia, showing

# BI implementations

system	data model	language	LOC
Neo4j	graph	Cypher	495
TigerGraph	graph	GSQL	832
Umbra	relational	SQL	755

