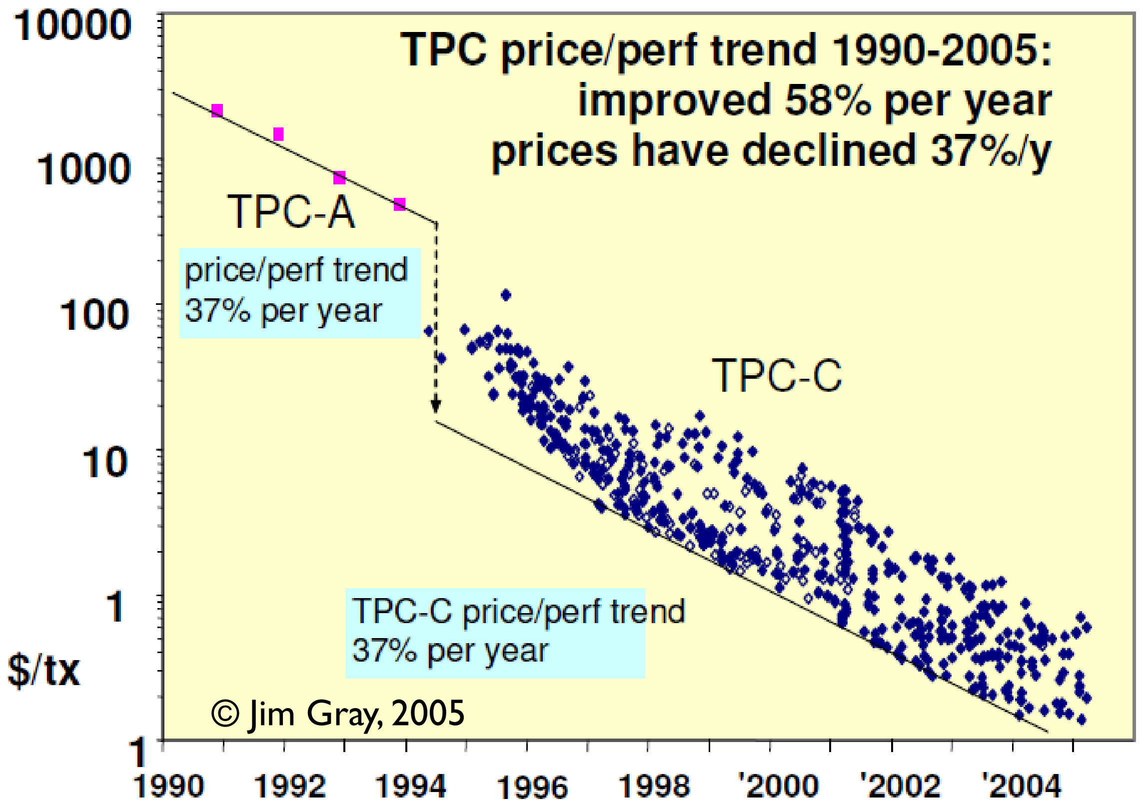
Industry-strength benchmarks for Graph and RDF Data Management

Peter Boncz

Why Benchmarking?



- make competing products comparable
- accelerate progress, make technology viable

What is the LDBC?

Linked Data Benchmark Council = LDBC

- Industry entity similar to TPC (www.tpc.org)
- Focusing on graph and RDF store benchmarking

Kick-started by an EU project

- Runs from September 2012 – March 2015
- 9 project partners:

- Will continue independently after the EU project

LDBC Benchmark Design

Developed by so-called "task forces"

- Requirements analysis and use case selection.
  - Technical User Community (TUC)
- Benchmark specification.
  - data generator
  - query workload
  - metrics
  - reporting format
- Benchmark implementation.
  - tools (query drivers, data generation, validation)
  - test evaluations
- Auditing
  - auditing guide
  - auditor training

LDBC: what systems?

Benchmarks for:

- RDF stores (SPARQL speaking)
  - Virtuoso, OWLIM, BigData, Allegrograph,…
- Graph Database systems
  - Neo4j, DEX, InfiniteGraph, …
- Graph Programming Frameworks
  - Giraph, Green Marl, Grappa, GraphLab,…
- Relational Database systems

LDBC: functionality

Benchmarks for:

- Transactional updates in (RDF) graphs
- Business Intelligence queries over graphs
- Graph Analytics (e.g. graph clustering)
- Complex RDF workload, e.g. including reasoning, or for data integration

Anything relevant for RDF and graph data management systems

Roadmap for the Keynote

Choke-point based benchmark design

- What are Choke-points?
  - examples from good-old TPC-H
  - → relational database benchmarking
- A Graph benchmark Choke-Point, in-depth:
  - Structural Correlation in Graphs
  - and what we do about it in LDBC
- Wrap up

Database Benchmark Design

Desirable properties:

- Relevant.
- Representative.
- Understandable.
- Economical.
- Accepted.
- Scalable.
- Portable.
- Fair.
- Evolvable.
- Public.

Jim Gray (1991) *The Benchmark Handbook for Database and Transaction Processing Systems*

Dina Bitton, David J. DeWitt, Carolyn Turbyfill (1993) *Benchmarking Database Systems: A Systematic Approach*

Multiple TPCTC papers, e.g.:
Karl Huppler (2009) *The Art of Building a Good Benchmark*

Stimulating Technical Progress

- An aspect of 'Relevant'
- The benchmark metric
  - depends on,
  - or, rewards:

solving certain technical challenges

(not commonly solved by technology at benchmark design time)

Benchmark Design with Choke Points

Choke-Point = well-chosen difficulty in the workload

- "difficulties in the workloads"
  - arise from Data (distribs)+Query+Workload
  - there may be different technical solutions to address the choke point
    - or, there may not yet exist optimizations (but should not be NP hard to do so)
    - the impact of the choke point may differ among systems

Benchmark Design with Choke Points

Choke-Point = well-chosen difficulty in the workload

- "difficulties in the workloads"
- "well-chosen"
  - the majority of actual systems do not handle the choke point very well
  - the choke point occurs or is likely to occur in actual or near-future workloads

Example: TPC-H choke points

- Even though it was designed without specific choke point analysis
- TPC-H contained a lot of interesting challenges
  - many more than Star Schema Benchmark
  - considerably more than Xmark (XML DB benchmark)
  - not sure about TPC-DS (yet)

TPCTC 2013: www.cwi.nl/~boncz/tpctc2013_boncz_neumann_erling.pdf
"TPC-H Analyzed: Hidden Messages and Lessons Learned from an Influential Benchmark"

TPC-H choke point areas (1/3)

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22

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TPC-H choke point areas (2/3)

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22

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TPC-H choke point areas (3/3)

Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22

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CP1.4 Dependent GroupBy Keys

Q10

```
SELECT c_custkey,  c_name, c_acctbal,
   sum(l_extendedprice * (1 - l_discount)) as revenue,
   n_name,  c_address,  c_phone, c_comment
FROM  customer, orders,  lineitem,  nation
WHERE  c_custkey = o_custkey and l_orderkey = o_orderkey
   and o_orderdate >= date '[DATE]'
   and o_orderdate < date '[DATE]' + interval '3' month
   and l_returnflag = 'R` and c_nationkey = n_nationkey
GROUP BY
   c_custkey, c_name,   c_acctbal,  c_phone,  n_name,
   c_address, c_comment
ORDER BY revenue DESC
```

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ORDER BY revenue DESC
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Exasol:
"foreign key check" phase after load

CP1.4 Dependent GroupBy Keys

- Functional dependencies:

  `c_custkey ➔ c_name, c_acctbal, c_phone, c_address, c_comment, c_nationkey ➔ n_name`

- Group-by hash table should exclude the colored attrs ➔ less CPU+ mem footprint
- in TPC-H, one can choose to declare primary and foreign keys (all or nothing)
  - this optimization requires declared keys
  - Key checking slows down RF (insert/delete)

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CP2.2 Sparse Joins

- Foreign key (N:1) joins towards a relation with a selection condition
  - Most tuples will *not* find a match
  - Probing (index, hash) is the most expensive activity in TPC-H

- Can we do better?
  - Bloom filters!

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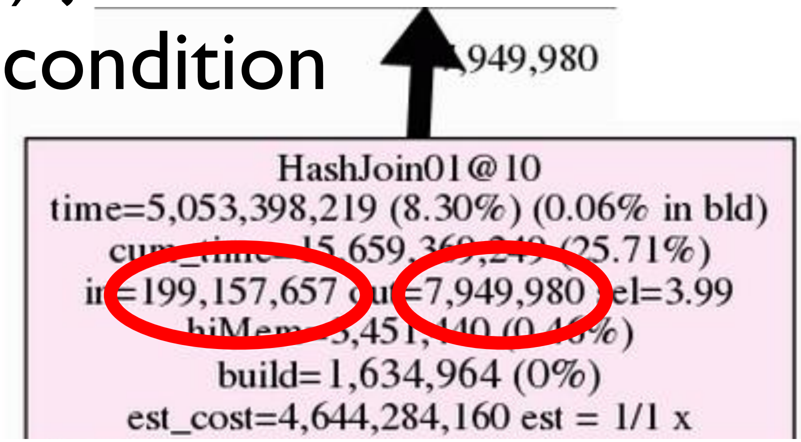
CP2.2 Sparse Joins

- Foreign key (N:1) joins towards a relation with a selection condition

Q21

probed: 200M tuples
result: 8M tuples
➔ 1:25 join hit ratio



Vectorwise:
TPC-H joins typically accelerate 4x
Queries accelerate 2x

2G cycles 29M probes ➔ cost would have been 14G cycles ~= 7 sec

```
#PROF 2021162220   OWN 28950172  9.8avg rdtsc  307565 calls vht_lookup_keys() "vht_lookup_keys" in con
#PROF 1575739535   OWN 199097581  7.9avg rdtsc  307534 calls sel_bitfiltercheck_uchr_col_slng_val_sint_
```

1.5G cycles 200M probes ➔ 85% eliminated

CP5.2 Subquery Rewrite

Q17

```
SELECT sum(l_extendedprice) / 7.0 as avg_yearly
FROM lineitem,  part
WHERE p_partkey = l_partkey
   and p_brand = '[BRAND]'
   and p_container = '[CONTAINER]'
   and l_quantity <( SELECT 0.2 * avg(l_quantity)
                     FROM lineitem
                     WHERE l_partkey = p_partkey)
```

This subquery can be extended with restrictions from the outer query.

Hyper:
CP5.1+CP5.2+CP5.3
results in 500x faster
Q17

```
SELECT 0.2 * avg(l_quantity)
FROM lineitem
WHERE l_partkey = p_partkey
   and p_brand = '[BRAND]'
   and p_container = '[CONTAINER]'
```

+ CP5.3 Overlap between Outer- and Subquery.

Choke Points

- Hidden challenges in a benchmark
  ➔influence database system design, e.g. TPC-H
    - Functional Dependency Analysis in aggregation
    - Bloom Filters for sparse joins
    - Subquery predicate propagation

- LDBC explicitly designs benchmarks looking at choke-point "coverage"
  - requires access to database kernel architects

Roadmap for the Keynote

Choke-point based benchmark design

- What are Choke-points?
  - examples from good-old TPC-H
- Graph benchmark Choke-Point, in-depth:
  - **Structural Correlation in Graphs**
  - and what we do about it in LDBC
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Data correlations between attributes

```
SELECT personID from person
WHERE firstName = 'Joachim' AND addressCountry = 'Germany'

SELECT personID from person
WHERE firstName = 'Cesare'  AND addressCountry = 'Italy'
```

Anti-Correlation

- Query optimizers may underestimate or overestimate the result size of conjunctive predicates

Joachim Loew **Cesare** / **Joachim** **Cesare Prandelli**

Data correlations **between attributes**

```
SELECT COUNT(*)
FROM paper pa1 JOIN conferences cn1 ON pa1.journal = jn1.ID
     paper pa2 JOIN conferences cn2 ON pa2.journal = jn2.ID
WHERE  pa1.author = pa2.author   AND
              cn1.name = 'VLDB'   AND  cn2.name = 'SIGMOD'
```

Data correlations **over joins**

```
SELECT COUNT(*)
FROM paper pa1 JOIN conferences cn1 ON pa1.journal = cn1.ID
     paper pa2 JOIN conferences cn2 ON pa2.journal = cn2.ID
WHERE  pa1.author = pa2.author   AND
             cn1.name = 'VLDB'   AND  cn2.name = 'SIGMOD'
```

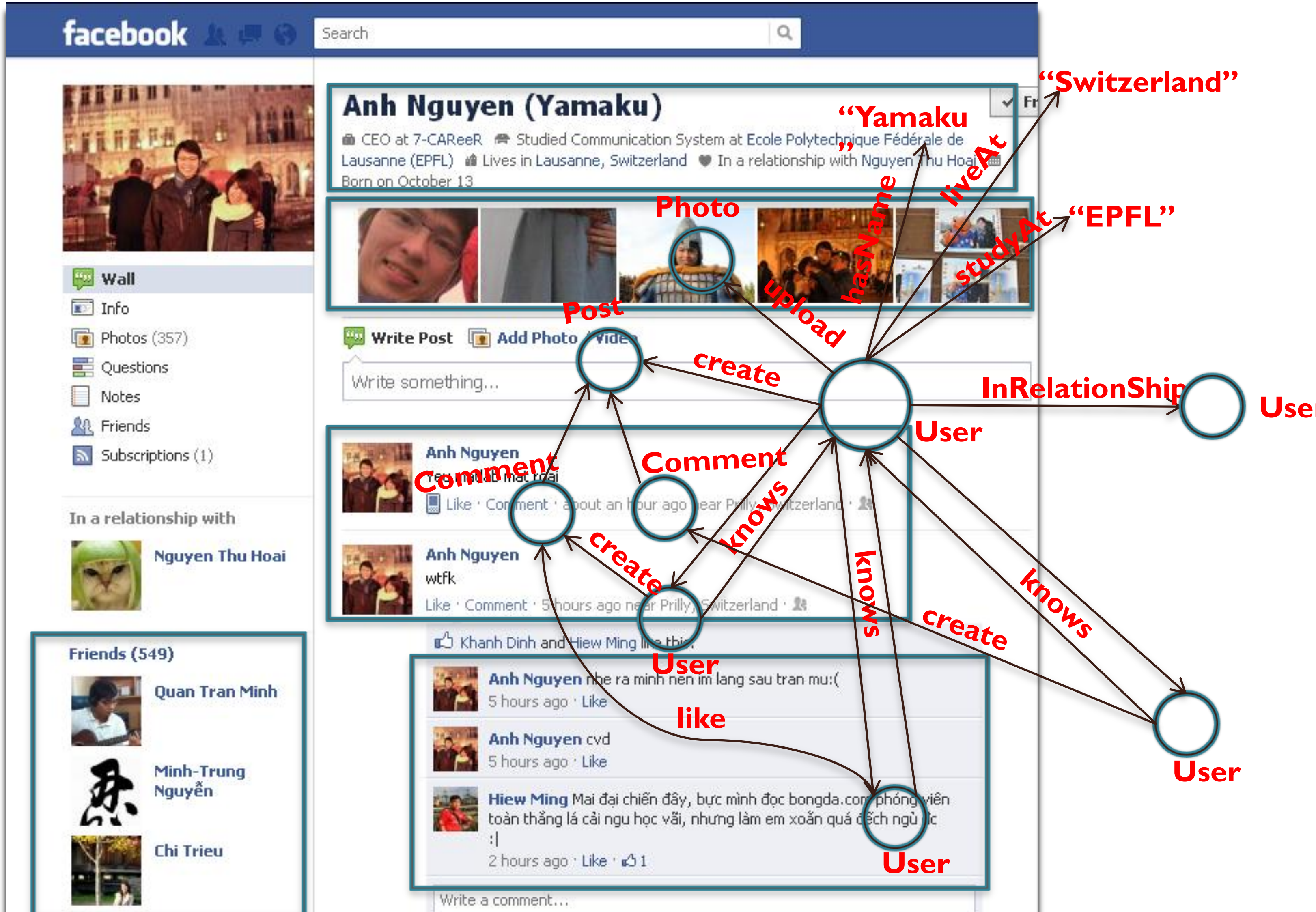
- A challenge to the optimizers to adjust estimated join hit ratio

  `pa1.author = pa2.author`

  depending on other predicates

Correlated predicates are still a frontier area in database research

LDBC Social Network Benchmark (SNB)



Handling Correlation: a choke point for Graph DBs

- What makes graphs interesting are the connectivity patterns
  - who is connected to who?
  - ➔ structure typically depends on the (values) attributes of nodes
- **Structural Correlation (➔ choke point)**
  - amount of common friends
  - shortest path between two persons

  search complexity in a social network varies wildly between
  - two random persons
  - e.g. colleagues at the same company
- No existing graph benchmark specifically tests for the effects of correlations
- Synthetic graphs used for benchmarking do not have structural correlations

➔ Need a data generator generating synthetic graph with data/structure correlations

TPCTC 2012: www.cwi.nl/~boncz/tpctc2012_pham_boncz_erling.pdf
"S3G2: A Scalable Structure-correlated Social Graph Generator"

Generating **Correlated** Property Values

- How do data generators generate values? E.g. **`FirstName`**

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Generating Property Values

- How do data generators generate values? E.g. `FirstName`

- **Value** Dictionary **D()**
  - a fixed set of values, e.g.,

    {"Andrea","Anna","Cesare","Camilla","Duc","Joachim", .. }

- **Probability** density function **F()**
  - steers how the generator chooses values
    - cumulative distribution over dictionary entries determines which value to pick
  - could be anything: uniform, binomial, geometric, etc…
    - geometric (discrete exponential) seems to explain many natural phenomena

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Generating **Correlated** Property Values

- How do data generators generate values? E.g. `FirstName`
- **Value** Dictionary **D()**
- **Probability** density function **F()**
- **Ranking** Function **R()**
  - Gives each value a unique rank between one and **|D|**
    - determines which value gets which probability
  - Depends on some parameters (parameterized function)
    - value frequency distribution becomes correlated by the parameters or **R()**

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Generating **Correlated** Property Values

- How do data generators generate values? E.g. `FirstName`
- **Value** Dictionar
  {"Andrea",
  'O
- **Probability** d
  geometric d
- **Ranking** Function **R(gender,country,birthyear)**
  - **gender, country, birthyear ➔ correlation parameters**

How to implement R()?

We need a table storing

limited #combinations

|Gender| X |Country| X |BirthYear| X |D|

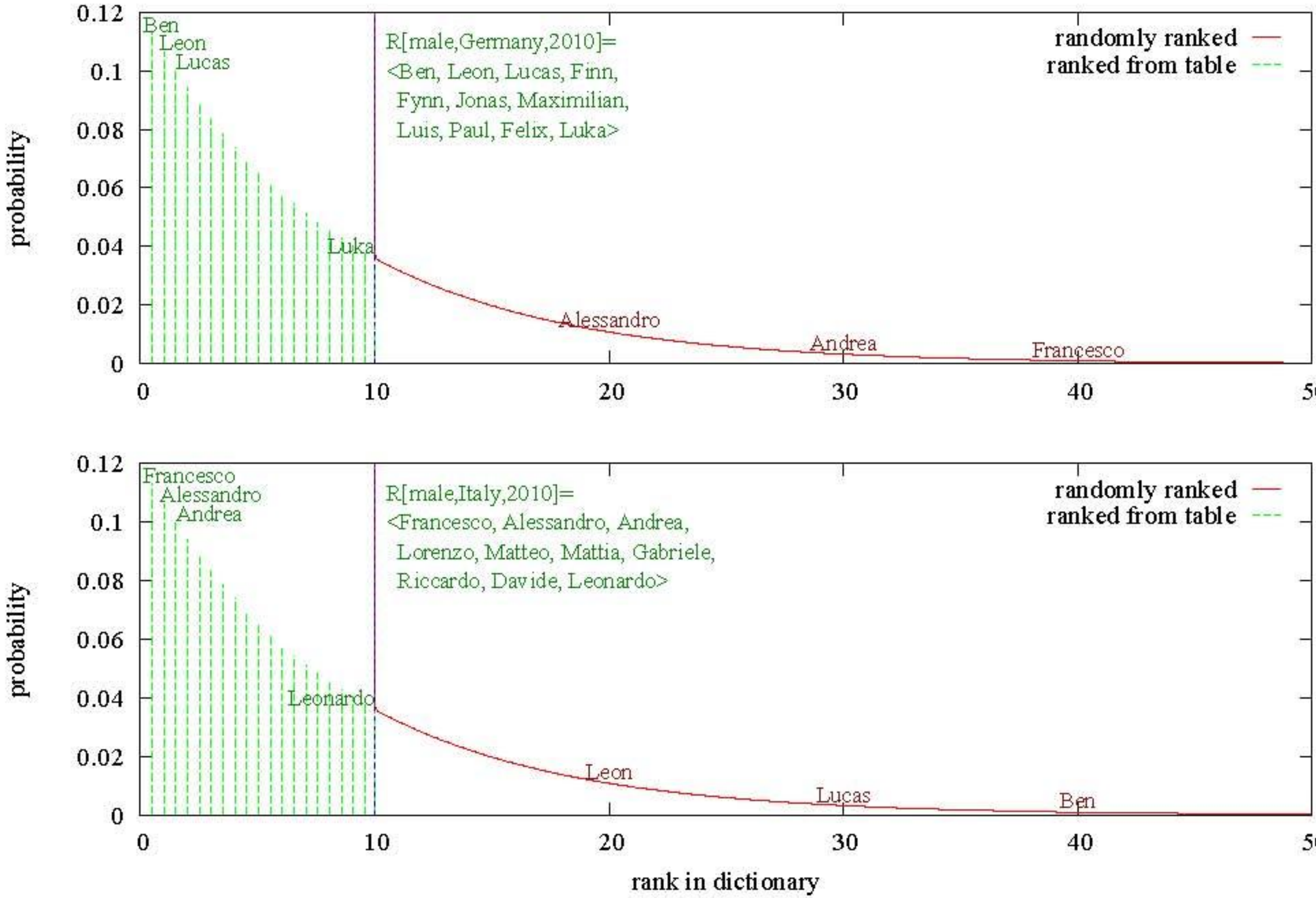
Potentially Many! ☹

Solution:

- Just store the rank of the **top-N** values, not all **|D|**
- Assign the rank of the other dictionary values randomly

Compact Correlated Property Value Generation

Using geometric distribution for function **F()**



Correlated Value Property in LDBC SNB

- Main source of dictionary values from DBpedia (http://dbpedia.org)

- Various realistic property value correlations (→)

  e.g.,

  (person.location,person.gender,person.birthDay) → person.firstName

  person.location → person.lastName

  person.location → person.university

  person.createdDate → person.photoAlbum.createdDate

  ….

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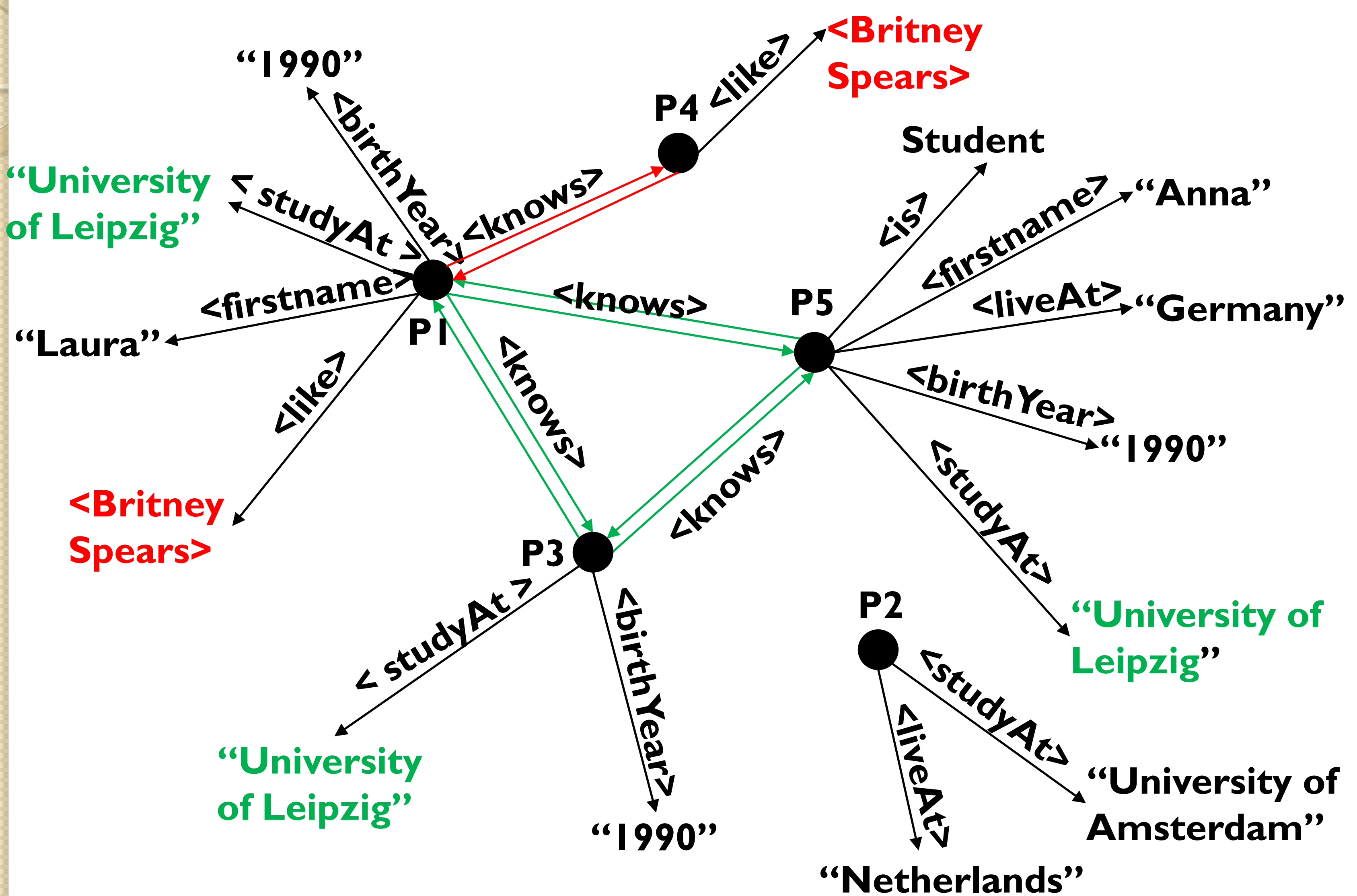
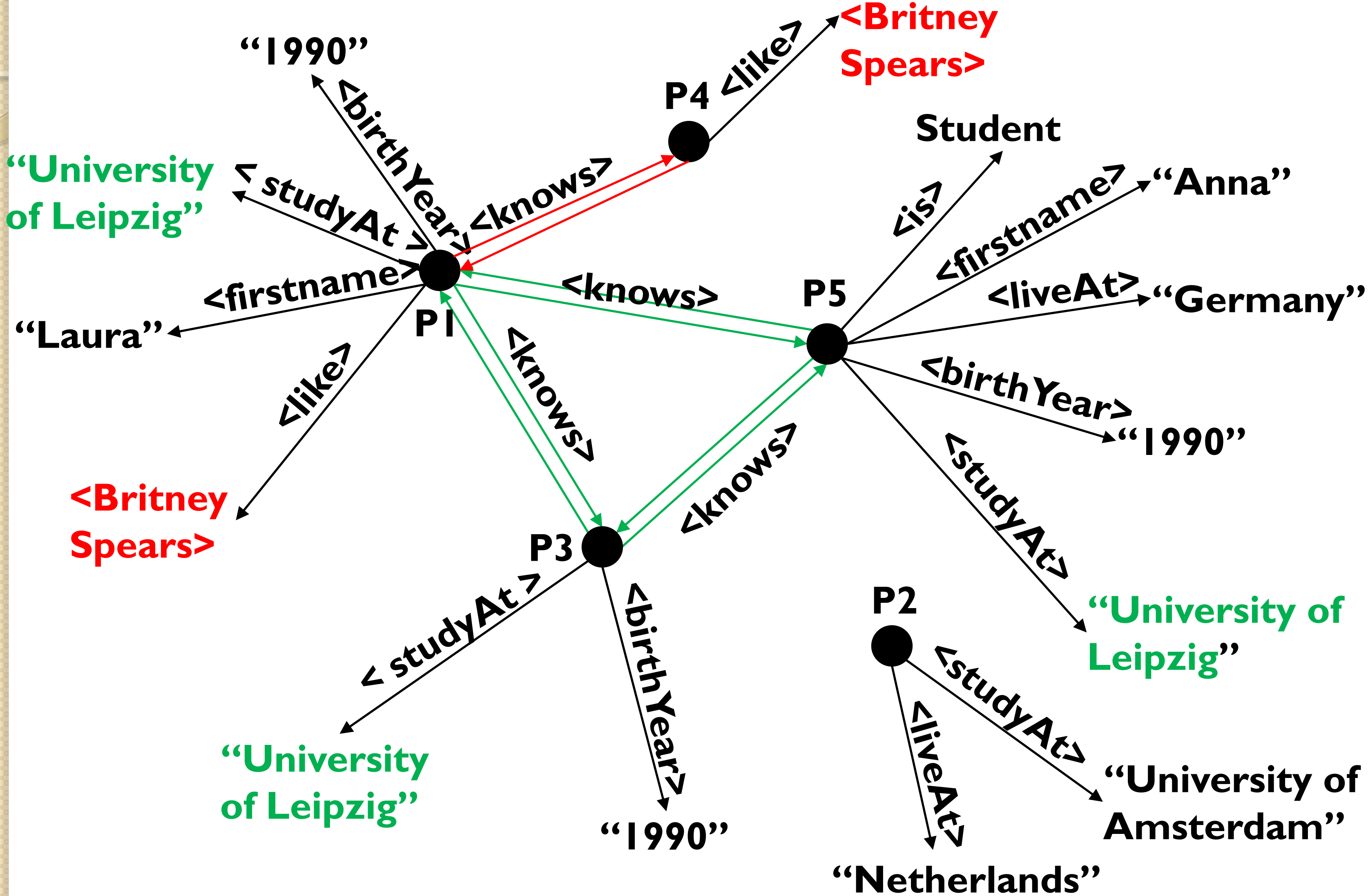
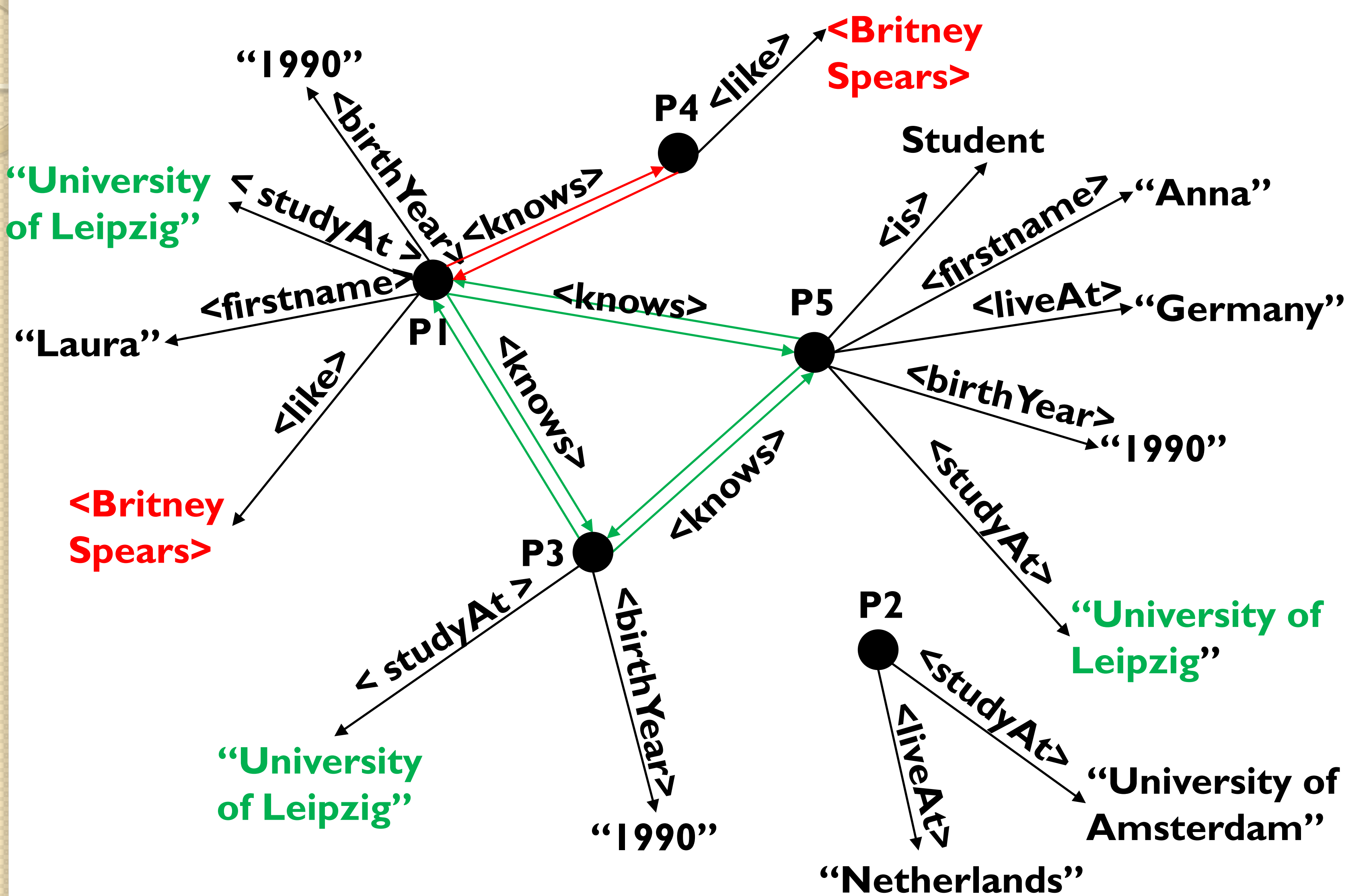
Correlated Edge Generation



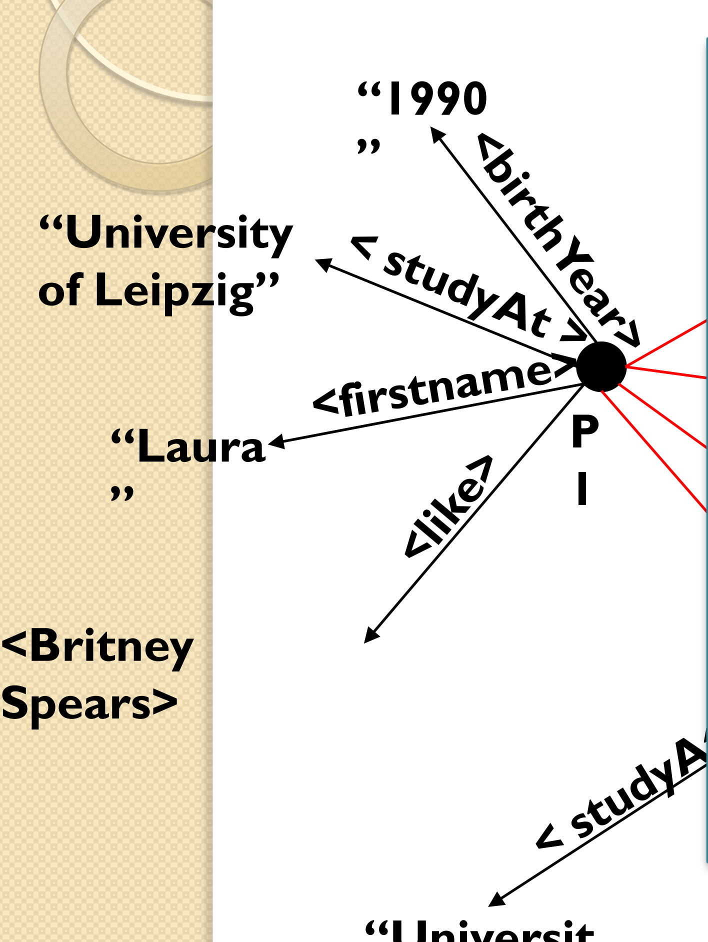
Correlated Edge Generation



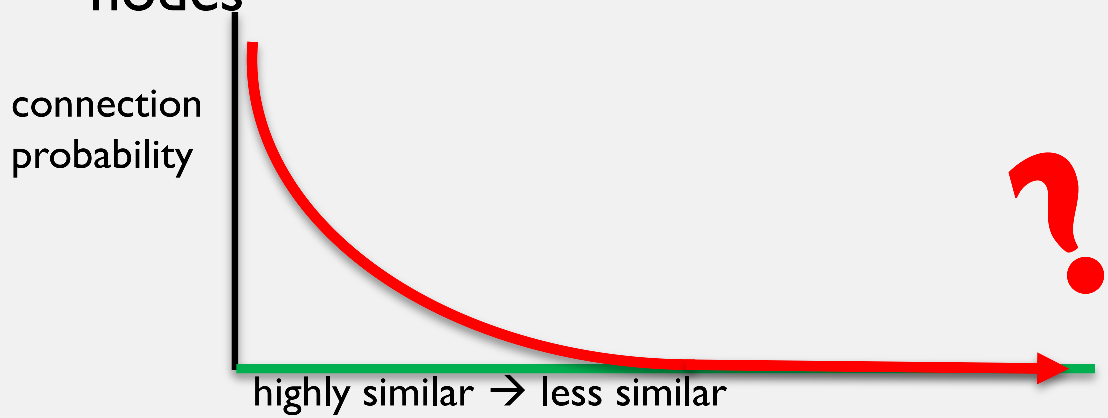
Correlated Edge Generation



Simple approach

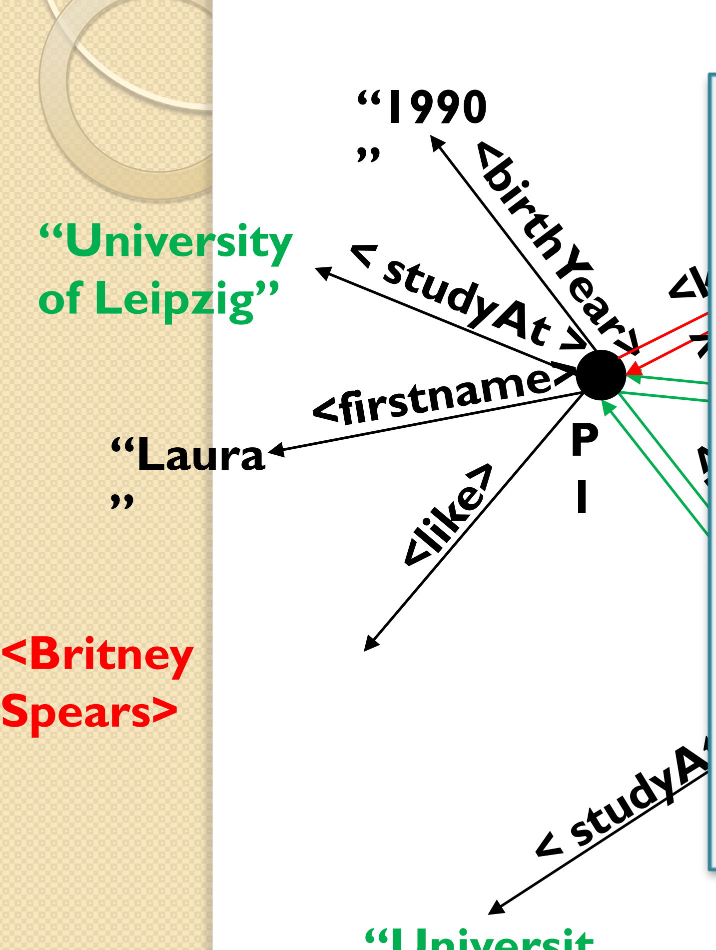


- Compute **similarity** of two nodes based on their (correlated) **properties**.
- Use a **probability density function** wrt to this similarity for connecting nodes

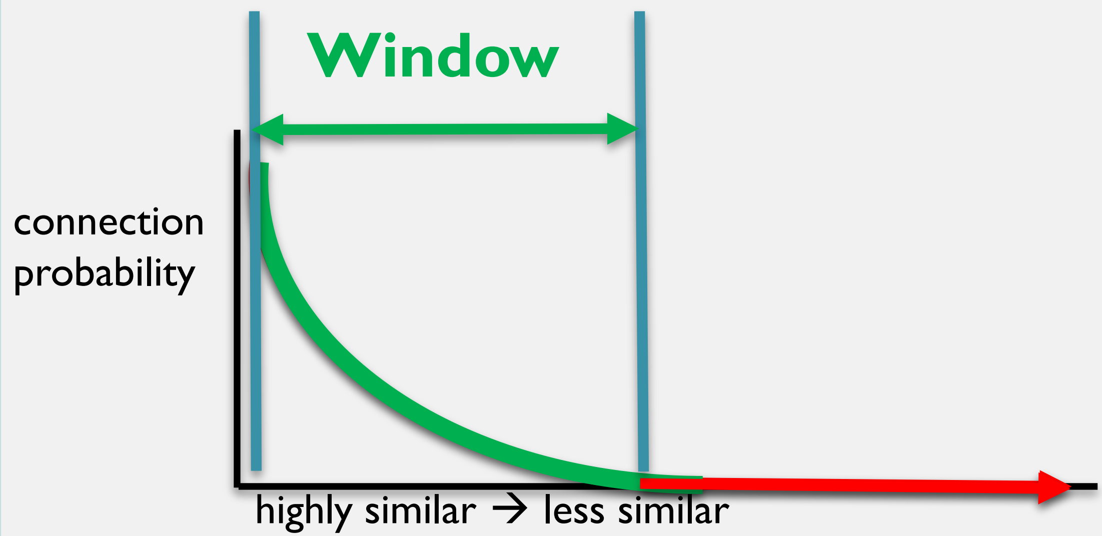


Danger: this is very expensive to compute on a large graph! (quadratic, random access)

Our observation



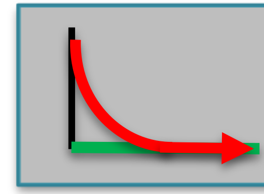
Trick: disregard nodes with too large similarity distance (only connect nodes in a **similarity window**)



Probability that two nodes are connected is **skewed** *w.r.t* the **similarity** between the nodes (due to probability distr.)

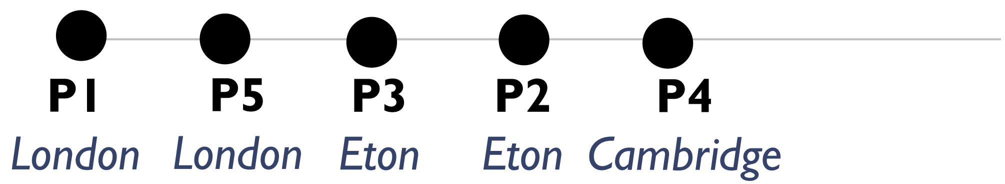
Correlation Dimensions

Similarity metric + Probability function



- **Similar metric**

  Sort nodes on similarity (similar nodes are brought near each other)



  <Ranking along the "*Having study together*" dimension>

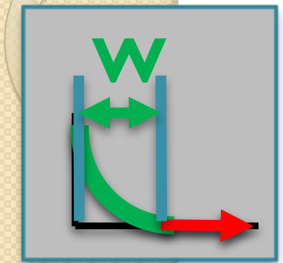
  we use ***space filling curves*** *(e.g. Z-order) to get a linear dimension*

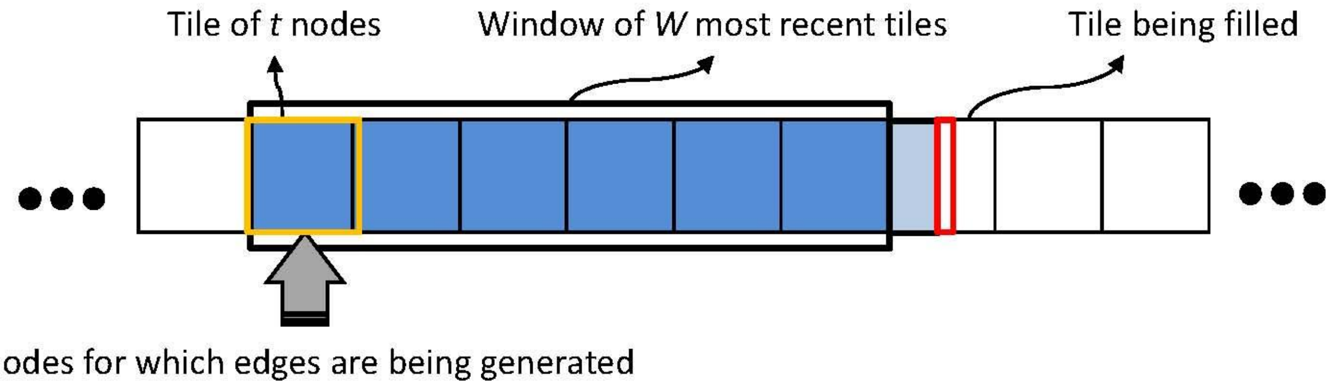
- **Probability function**

  Pick edge between two nodes based on their **ranked distance**

  (e.g. geometric distribution, again)

Generate edges along correlation dimensions





- Sort nodes using **MapReduce** on similarity metric
- Reduce function keeps a **window** of nodes to generate edges
  - Keep low memory usage (sliding window approach)

- Slide the window for **multiple passes**, each pass corresponds to one correlatio
dimension (multiple MapReduce jobs)
  - for each node we choose **degree** per pass (also using a prob. function)

steers how many edges are picked in the window for that node

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Correlation Dimensions in LDBC SNB

- Having studied together
- Having common interests (hobbies)
- Random dimension
  - motivation: not all friendships are explainable (…)

(of course, these two correlation dimensions are still a gross simplification of reali
but this provides some interesting material for benchmark queries)

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Evaluation (… see the TPCTC 2012 paper)

- **Social graph characteristics**
  - Output graph has similar characteristics as observed in real social network (i.e., *"small-world network"* characteristics)

    - Power-law social degree distribution

    - Low average path-length

    - High clustering coefficient

- **Scalability**
  - Generates up to **1.2 TB** of data (1.2 million users) in **half an hour**

    - Runs on a cluster of 16 nodes

    (part of the SciLens cluster, www.scilens.org)

  - **Scales** out **linearly**

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Summary

- correlation between values ("properties") and connection pattern in graphs affects many real-world data management tasks

  ➔use as a choke point in the Social Network Benchmark

- generating huge correlated graphs is hard!

  ➔MapReduce algorithm that approximates correlation probabilities with windowed-approach

  See: for more info

  - https://github.com/ldbc
  - SNB task-force wiki http://www.ldbc.eu:8090/display/TUC

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- What are Choke-points?
  - examples from good-old TPC-H
- Graph Choke-Point In depth
  - Structural Correlation in Graphs
  - And what we do about it in LDBC
- **Wrap up**

LDBC Benchmark Status

- Social Network Benchmark
  - Interactive Workload
    - Lookup queries + updates
    - Navigation between friends and posts

    ➔Graph DB, RDF DB, Relational DB
  - Business Intelligence Workload
    - Heavy Joins, Group-By + navigation!

    ➔ Graph DB, RDF DB, Relational DB
  - Graph Analytics
    - Graph Diameter, Graph Clustering, etc.

    ➔ Graph Programming Frageworks, Graph DB (RDF DB?, Relational DB?)

LDBC Benchmark Status

- Social Network Benchmark
- Semantic Publishing Benchmark
  - BBC use case (BBC data + queries)
    - Continuous updates
    - Aggregation queries
    - Light-weight RDF reasoning

LDBC Next Steps

- Benchmark Interim Reports
  - November 2013
  - SNB and Semantic Publishing

- Meet LDBC @ GraphConnect
  - 3rd Techical User Community (TUC) meeting
  - London, November 19, 2013

Conclusion

- LDBC: a new graph/RDF benchmarking initiative
  - EU initatiated, Industry supported
  - benchmarks under development (SNB, SPB)
    - more to follow
- Choke-point based benchmark development
  - Graph Correlation

thank you very much.
Questions?