# Efficiency and Effectiveness of a Practical Provenance and Probabilistic DBMS

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# In this talk

- What is a provenance-aware DBMS?
- What is a probabilistic DBMS?
- Is it possible to build such a DBMS, with:
  - Support for various forms of provenance
  - Support for a large, and practically useful, query language
  - Efficient computation of provenance and probabilities
- What to compare it with?
- Benchmarks

# Provenance in Databases

- A way to keep track of annotations through data processing tasks, that provide extra information about the results of these tasks
- Provenance framework:
  - A base data model (e.g., the relational model)
  - A query language (e.g., the positive relational algebra)
  - A data model for annotations (e.g., $\mathbb{K}$-annotated relations)
  - A semantics for queries over the annotation data model

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| Semimodule [Amsterdamer et al., 2011] | Extended relational algebra | Semimodule annotation on values |

# Some important results

- Many application semirings, most of which can be extended into m-semirings, capturing useful meta-information: shortest path lengths, top-$k$ shortest path lengths and top-$k$ shortest paths, why-provenance, Trio's lineage, temporal intervals, counting...
- For the relational algebra, Boolean provenance semantics coincides with m-semiring semantics
- (M-)Semiring provenance semantics commutes with (m-)semiring homomorphism
- Universal semiring ($\mathbb{N}[X]$) and m-semiring (free m-semiring)
- Provenance tracking is generally PTIME
- Provenance circuits are generally more compact than provenance formulas

# Probabilistic database

- Compact representation of a probability distribution over possible databases
- Distributions can be finite, continuous [Abiteboul et al., 2011], discrete but infinite [Benedikt et al., 2010, Grohe and Lindner, 2020]
- Correlations across data items may be disallowed (TID) [Dalvi and Suciu, 2004], limited (BID) [Dalvi and Suciu, 2013], arbitrary (pc-tables) [Green and Tannen, 2006]
- Main problem: probabilistic query evaluation, i.e., computing the (marginal) probability of a data item in the output of a query; or sometimes computing the distribution of data values in the output of a query

# Main results

- Probabilistic query evaluation is #P-hard
- In the relational setting, becomes tractable when:
  - the Boolean provenance has some tractable representation (read-once, d-D circuit...)
  - the query is a safe UCQ [Dalvi and Suciu, 2013] over TIDs
  - the query is a safe CQ without self-joins [Dalvi et al., 2011] over BIDs
  - the data has bounded treewidth over BIDs [Amarilli et al., 2015], for any MSO query
  - the data and correlations have joint bounded treewidth [Amarilli, 2016], for any MSO query
- TIDs or BIDs are not a strong representation system for the relational algebra; pc-tables are

# ProvSQL: Provenance within PostgreSQL

[Senellart et al., 2018]

- Provenance annotations stored as Universally Unique Identifiers (UUIDs), in an extra attribute of each provenance-aware relation
- UUIDs of base tuples randomly generated; UUIDs of query results generated in a deterministic manner
- A provenance circuit relating UUIDs of elementary provenance annotations and arithmetic gates persistently stored on disk in memory-mapped files
- Query rewriting (after parsing, before planning) to automatically compute output provenance attributes in terms of the query and input provenance attributes

# Other databases with provenance/probability support

- Older probabilistic database systems can compute some forms of provenance (especially, Boolean provenance); but tied to specific version of PostgreSQL (8.3), hard to deploy

  Trio: `http://infolab.stanford.edu/trio/` [Benjelloun et al., 2006]
  MayBMS: `http://maybms.sourceforge.net/` [Huang et al., 2009]

- Perm `https://github.com/IITDBGroup/perm` [Glavic and Alonso, 2009] now obsolete system for provenance management; also tied to PostgreSQL 8.3
- ORCHESTRA `https://www.cis.upenn.edu/~zives/orchestra/` [Green et al., 2010] Java front end to DBMS with provenance support; not maintained
- GProM `http://www.cs.iit.edu/~dbgroup/projects/gprom.html` [Arab et al., 2018] similar to ProvSQL (though no probabilistic database capabilities), overlap of features; middleware
- ProbLog `https://dtai.cs.kuleuven.be/problog/` [Kimmig et al., 2011] probabilistic logic reasoning system in Python; has a (SQLite) DB backend

# ProvSQL features as of 2025

- PostgreSQL extension, works for all versions of PostgreSQL $\geqslant 10$, tested on Linux, Mac OS (x86/ARM), WSL

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  - Monte-Carlo sampling
- Shapley value and expected Shapley value computation

# Benchmarking ProvSQL

- We want to know:
  - What is the overhead of provenance computation?
  - Does it scale to large databases?
  - Is probabilistic query evaluation feasible in practice despite #P-hardness?
- Competitors:
  - GProM for why-provenance computation
  - MayBMS for probabilsitic query evaluation
  - ProbLog for probabilistic query evaluation
- Database: TPC-H, from 1 GB to 10 GB
- Queries: (some) TPC-H queries + ad-hoc queries on the same schema

# The case of ProbLog

Unfortunately does not scale at all, all data is brought into RAM even if using the DB backend. Simplest query of our benchmark:

```
:- use_module(library(db)).
:- sqlite_load('TPC-H.db').

1 :: result(O,P,S,LN,LS) :- lineitem(O,P,S,LN,Q,_,_,_,_,LS,_,_,_,_,SM,_), SM='AIR', Q>10 .
1 :: result(O,P,S,LN,LS) :- lineitem(O,P,S,LN,_,_,D,_,_,LS,_,_,_,_,_,_), D > .05 .

query(result(_,_,_,_,_)) .
```

- For TPC-H 100 MB, 5 GB of RAM used, timeout after 5 hours
- For TPC-H 1 GB, out-of-memory

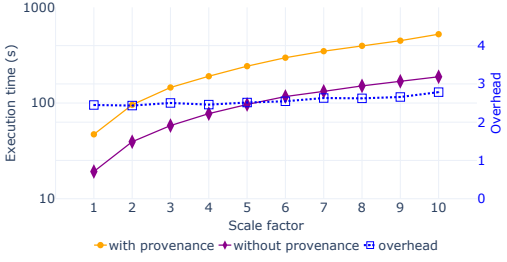
# Query support

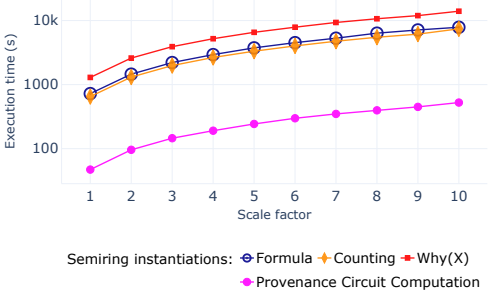
| | TPC-H | | | | | | TPC-H* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Query** | 1 | 6 | 7 | 9 | 12 | 19 | 1 | 3 | 4 | 12 | 15 |
| ProvSQL (prov.) | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| ProvSQL (prob.) | O | Y | O | Y | Y | Y | Y | Y | Y | Y | Y |
| GProM | N | N | N | N | N | N | Y | Y | O | Y | Y |
| MayBMS | N | N | N | N | N | N | Y | Y | Y | Y | Y |

| | Custom | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Query** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| ProvSQL (prov.) | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| ProvSQL (prob.) | Y | Y | Y | Y | Y | Y | Y | Y | O | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| GProM | O | Y | Y | Y | O | O | Y | O | T | Y | Y | O | Y | Y | Y | N | Y | N |
| MayBMS | Y | Y | Y | T | O | Y | Y | Y | O | Y | Y | Y | Y | Y | Y | N | Y | N |

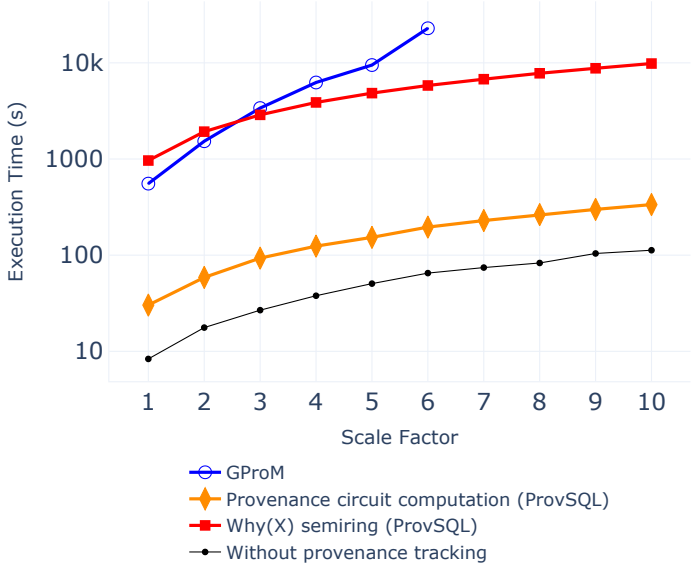
Not supported; Timeout after 3 000 s; Out-of-Memory Error

# Scalability of Provenance Computation in ProvSQL

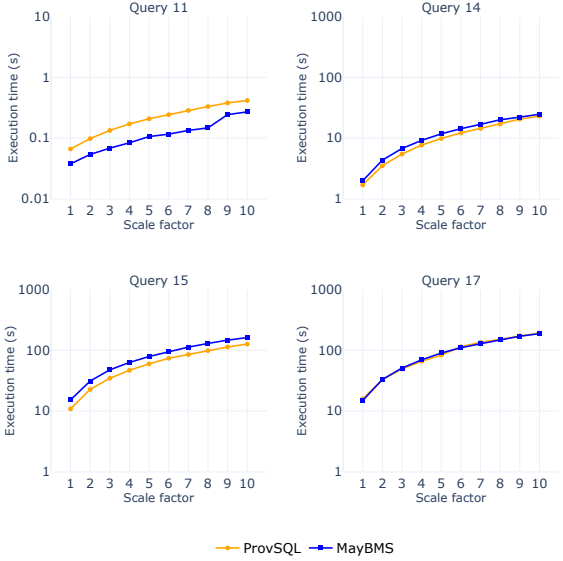


# Provenance Computation: ProvSQL vs GProM



# Probability Computation: ProvSQL vs MayBMS



# Missing and on-going features in ProvSQL

- Recursive query support: impossible because `WITH RECURSIVE` queries are very restricted in SQL (but see [Ramusat et al., 2021, Zhao et al., 2024] for how to implement provenance for Datalog within a Datalog evaluator)
- Updates: simple updates, following [Bourhis et al., 2020], in the process of being integrated; updates depending on multiple tables require more work
- Continuous distributions: prototype implementation available, in the spirit of [Abiteboul et al., 2011], hopefully can be integrated soon
- Extensional probabilistic query evaluation for safe queries: [Dalvi and Suciu, 2013] being considered, but requires architecture changes; ideally would be possible through compilation to a d-D circuit, but only known for particular cases [Monet, 2020]
- Plenty of optimizations still possible! (e.g., compiling isomorphic circuits only once for probabilistic query evaluation)

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