VerdictDB

Universalizing Approximate Query Processing

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Universal

Approximate Query Processing

VerdictDB

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What is Approximate Query Processing (AQP)?

I/O + Computation → Exact Answer

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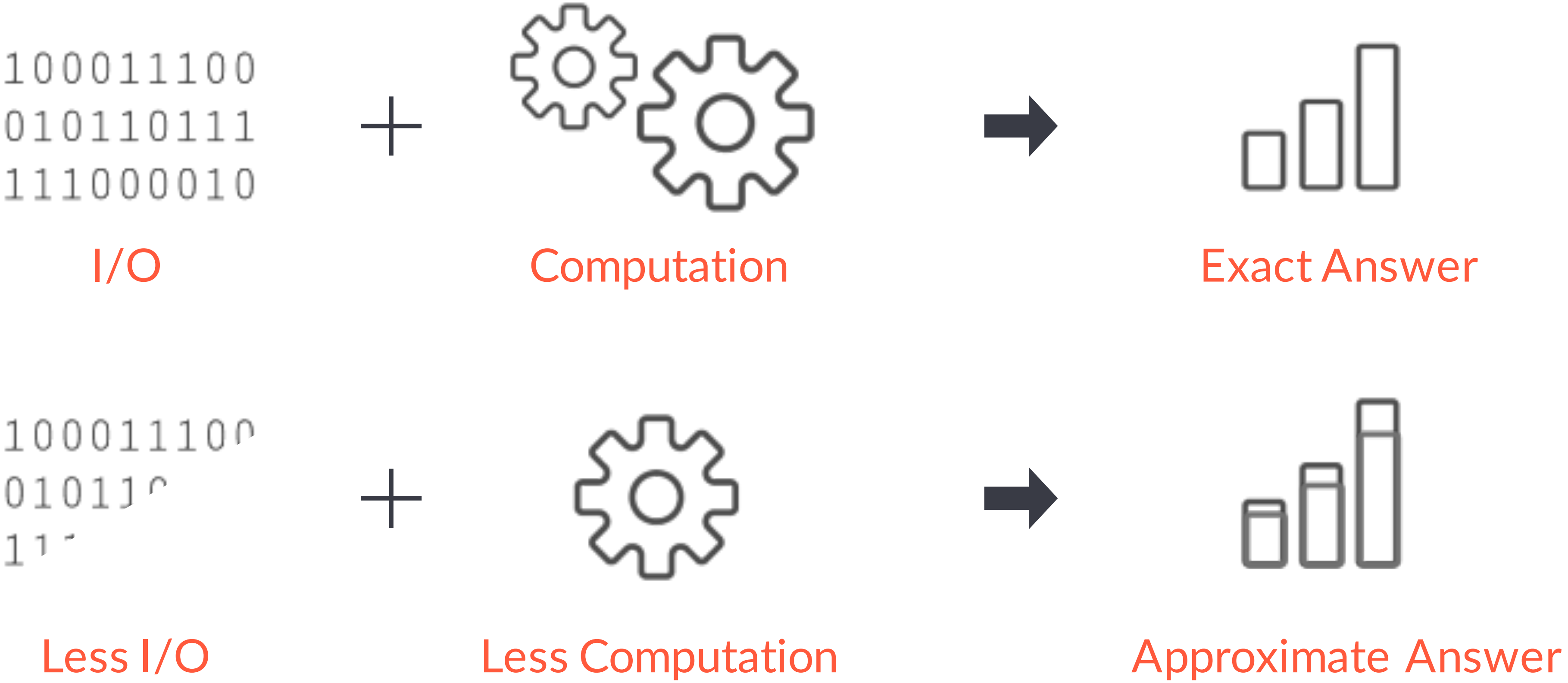

Why AQP?

Higher Productivity

Numerous studies:

A latency >2 seconds is no longer interactive and negatively affects creativity!

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Human time: Money

Machine time: No one loves their EC2 bill!

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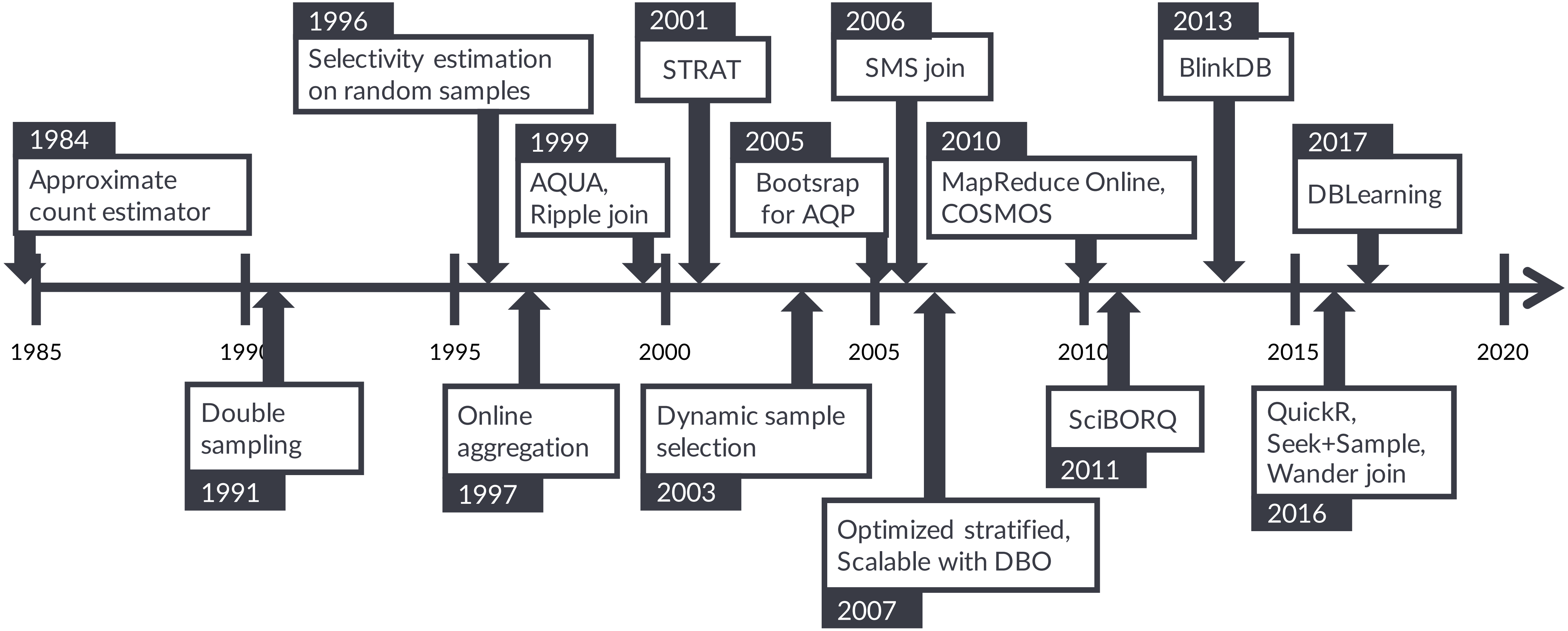
Jeff Bezos

AQP research in academia



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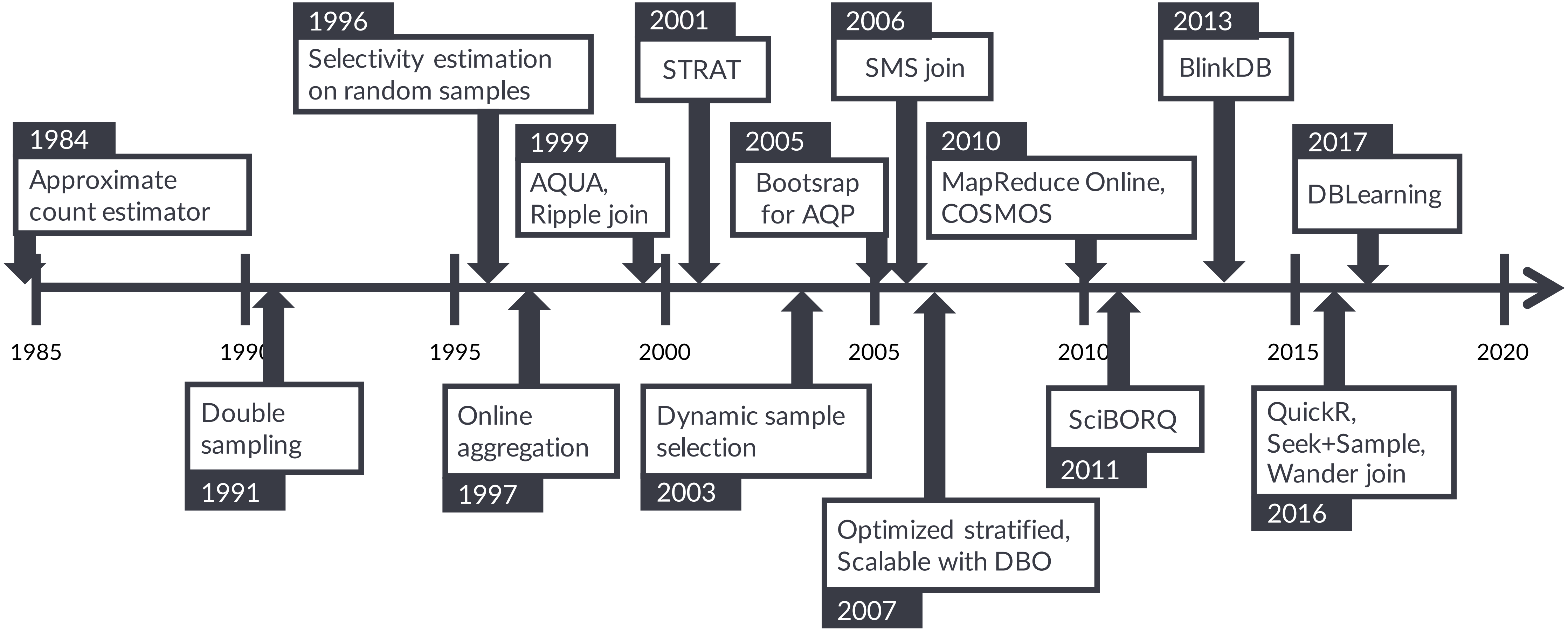

35 years of research, little industry adoption

AQP is hard to adopt

AQP typically requires significant modifications of DBMS internals

- **Error estimation:** [BlinkDB ‘13], [G-OLA ’15], …
- **Query evaluation:** [Online ‘97], [Join Synopses ‘99], …
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- Slow in adopting ANYTHING :-)

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Users won't abandon their existing DBMS just to use AQP.

Built-in AQP functions in OLAP engines

amazon REDSHIFT

APPROXIMATE
PERCENTILE_DISC

ORACLE

approx_count_distinct
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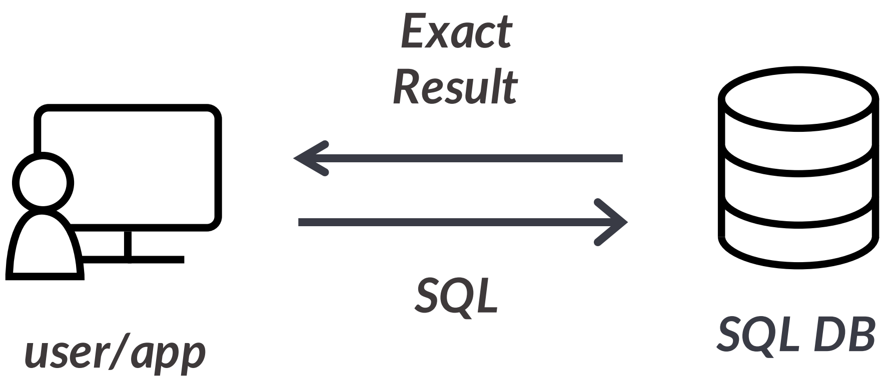
Need for complete AQP solutions that are easy to adopt

Our proposal: Universal AQP



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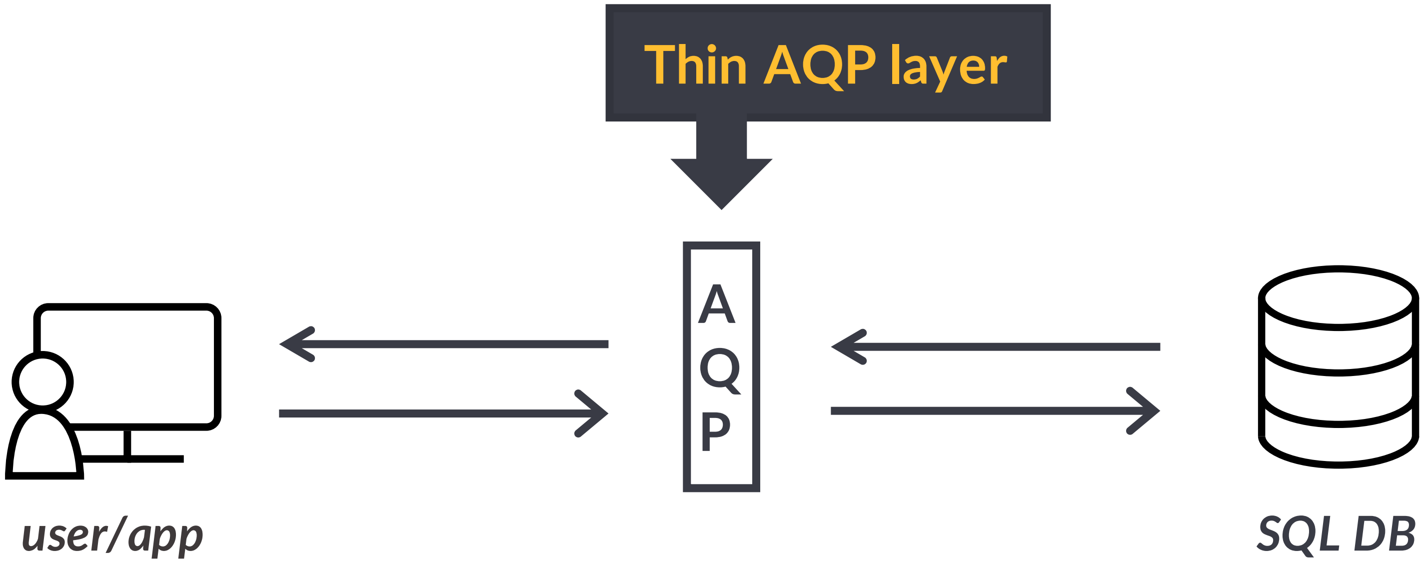

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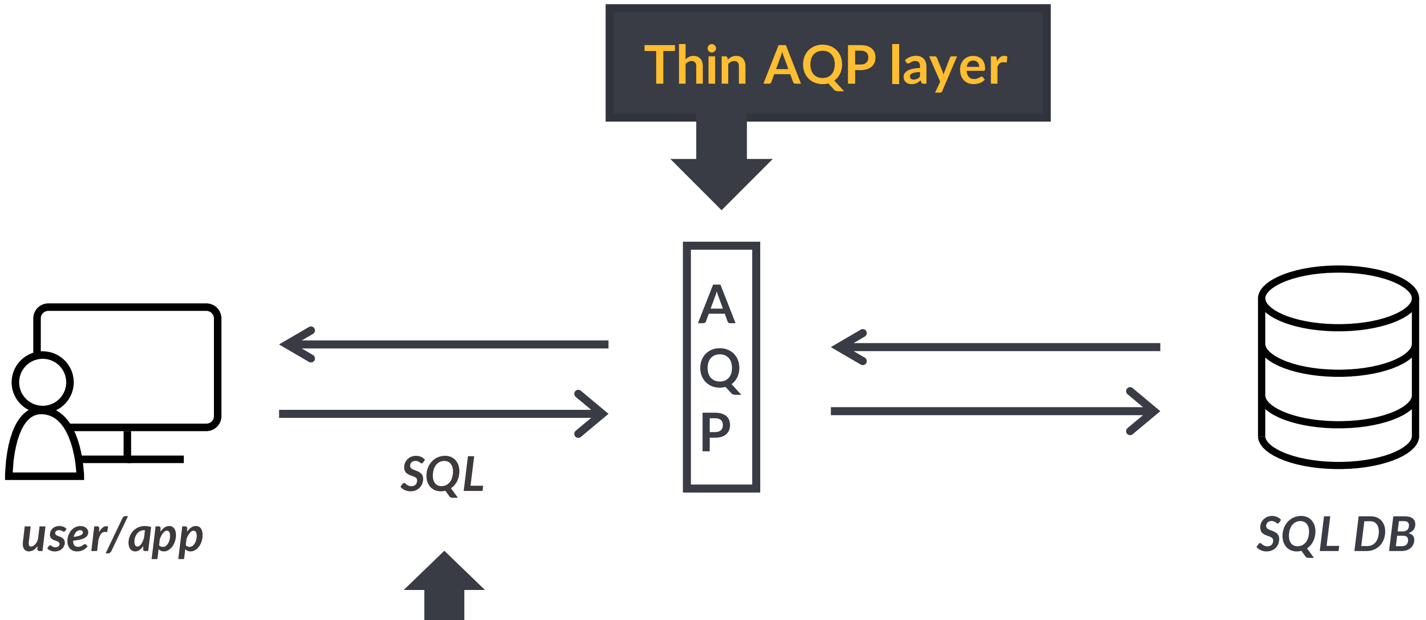


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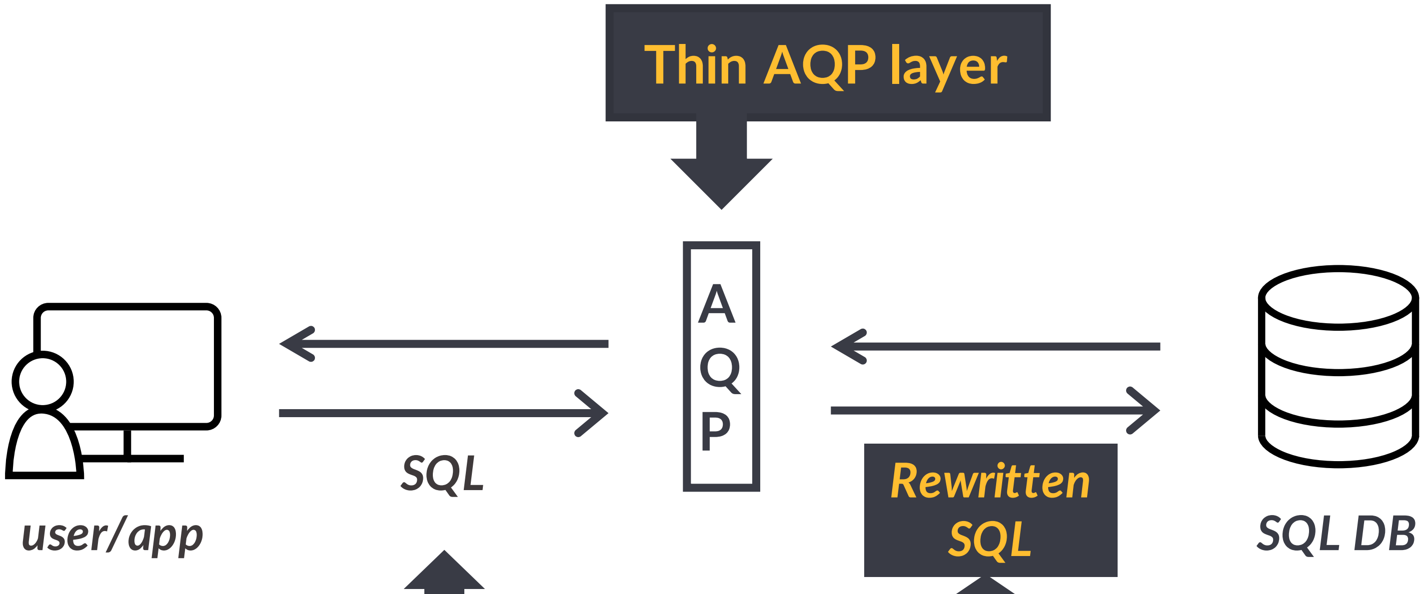


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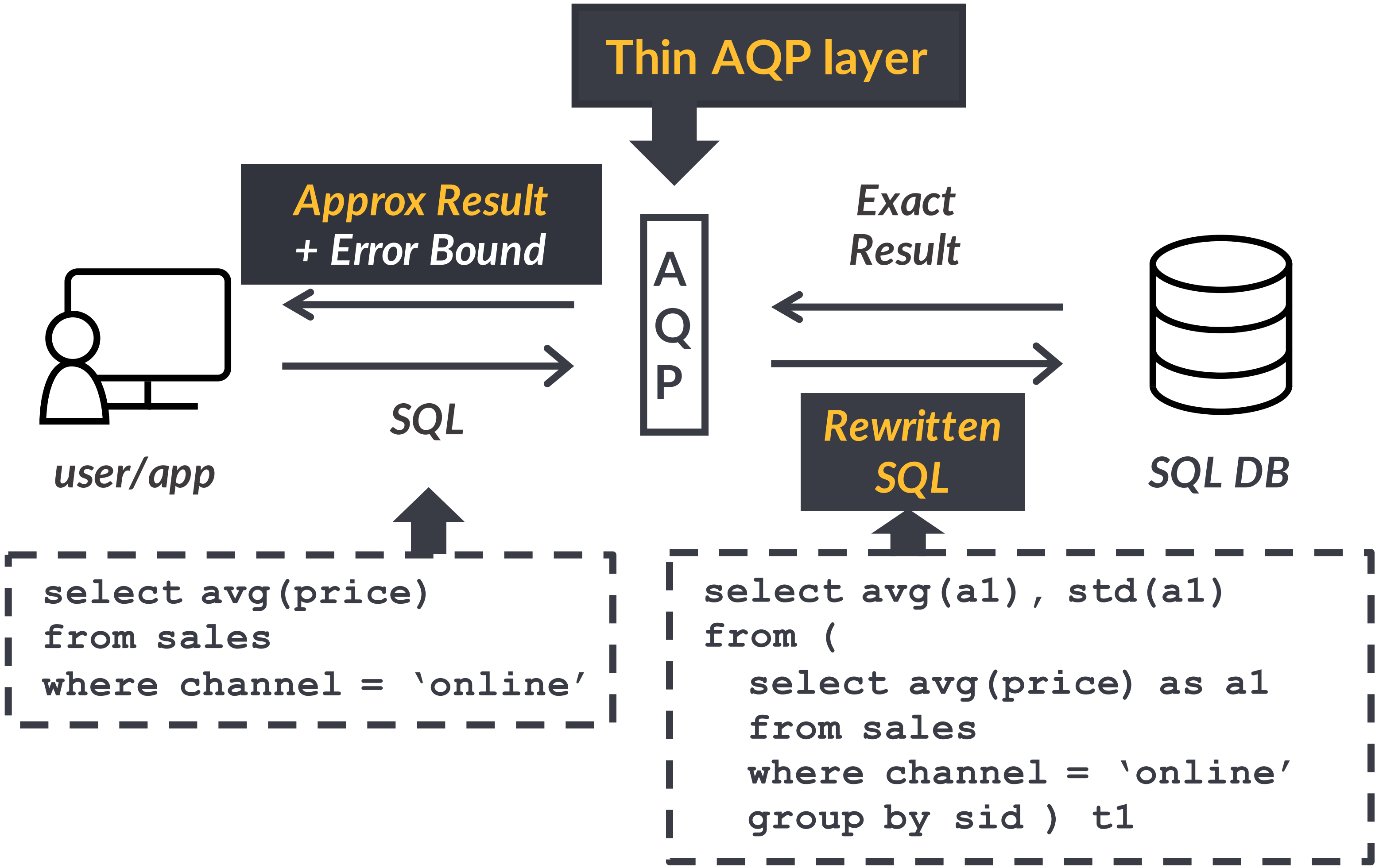

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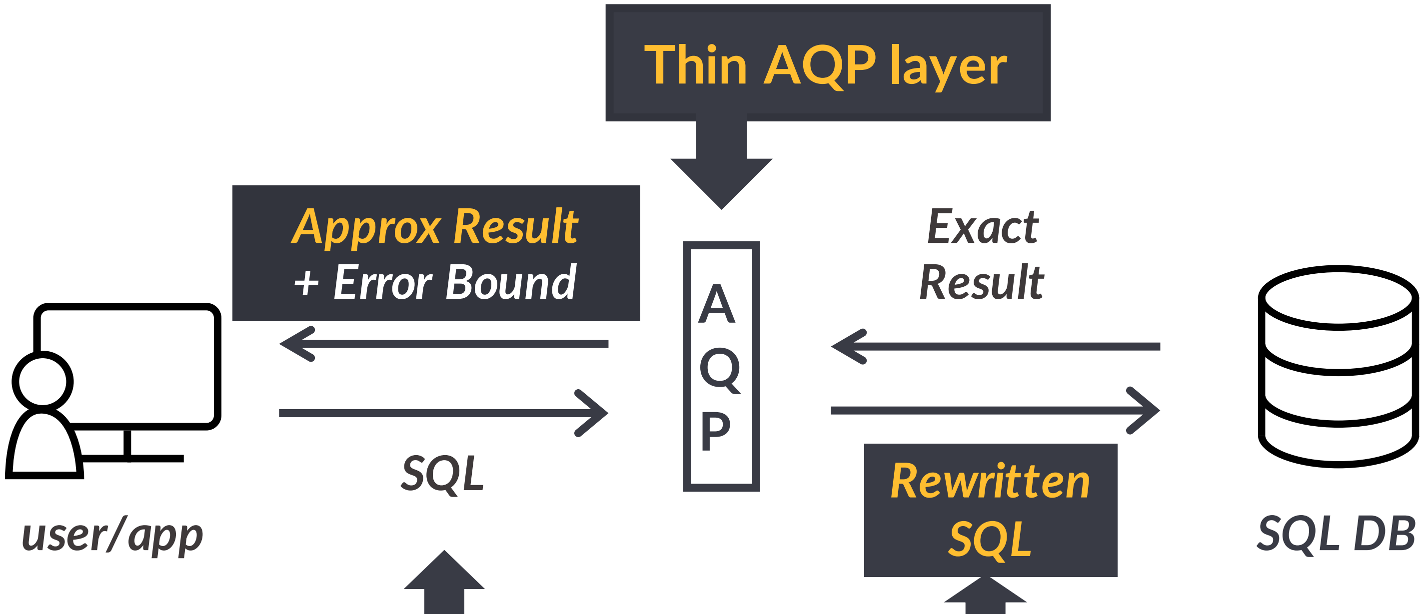


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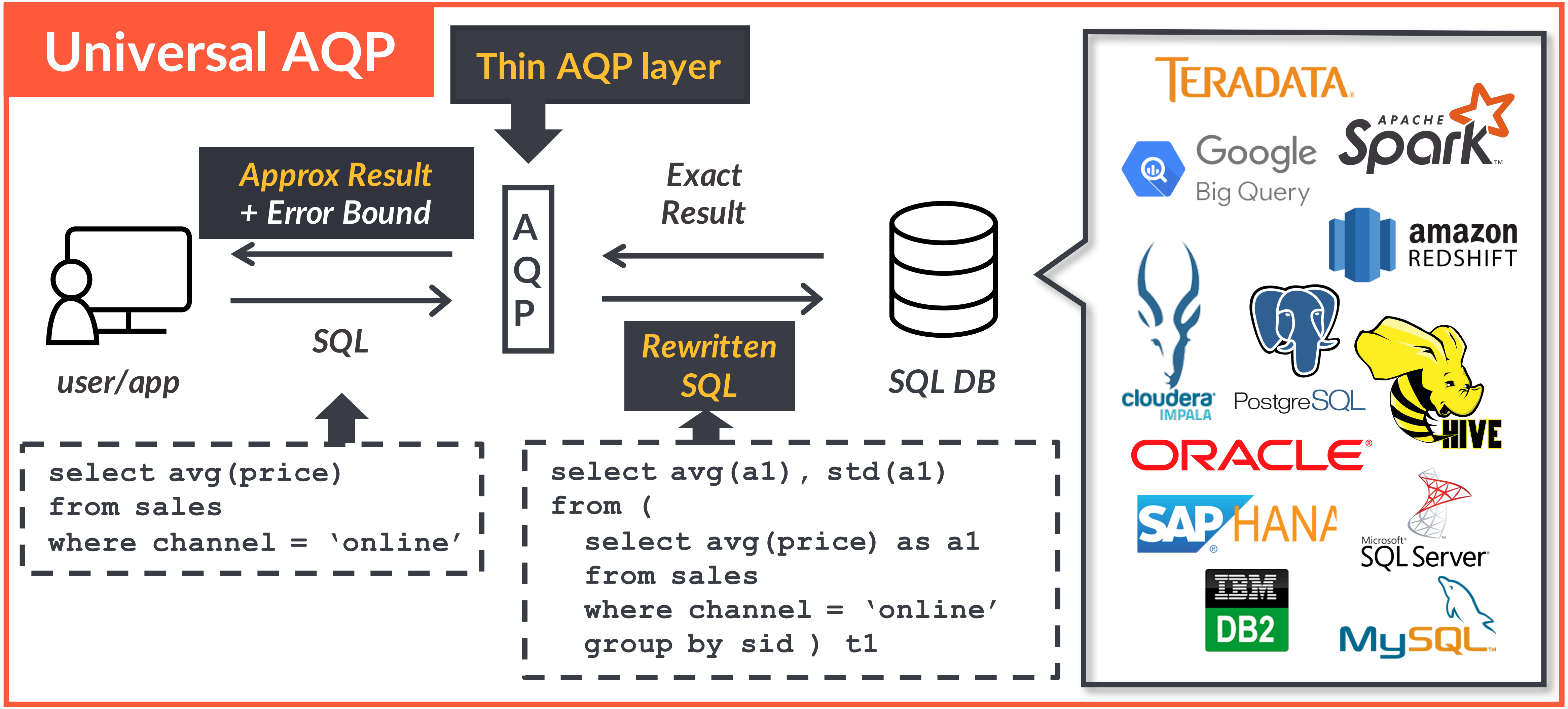

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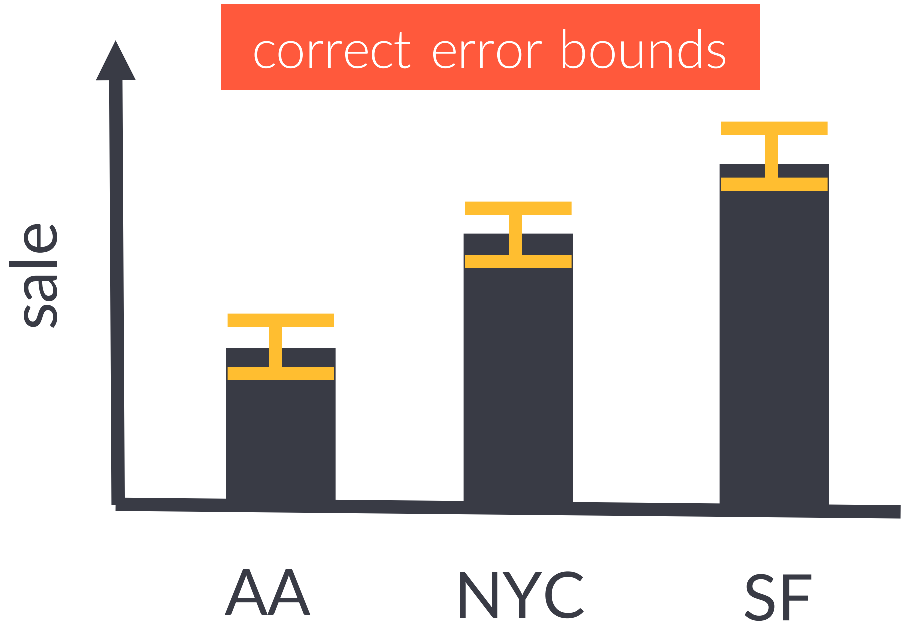

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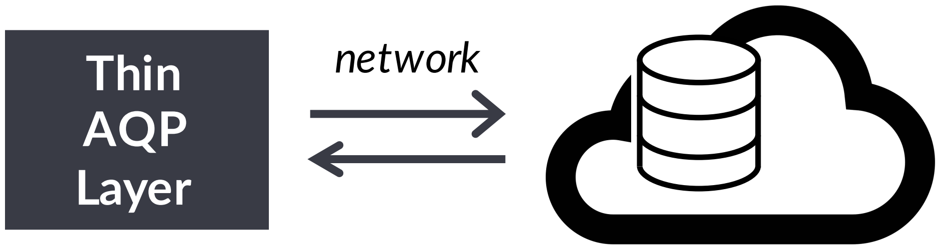

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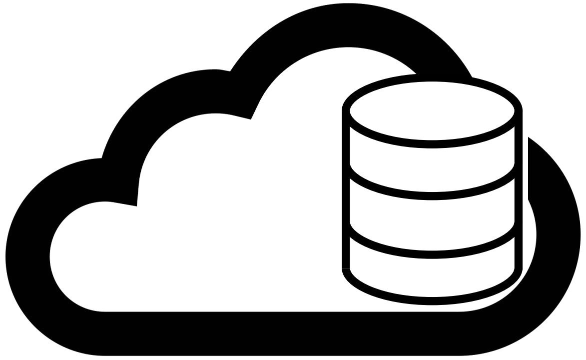
   - Lack of access to DBMS machinery
3. **Server efficiency**
   - Resampling-based techniques [Pol and Jermaine '05, BlinkDB '14]
   - Intimate integration of err est. logic into scan operators [Quickr '16, SnappyData]
   - Overriding the relational operators altogether [ABM '14]

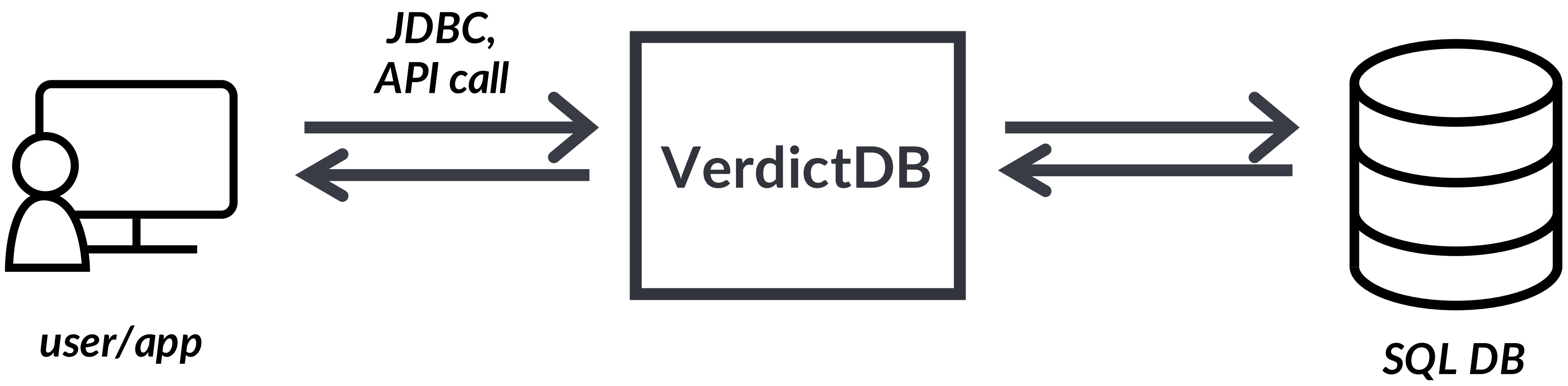


VerdictDB Overview

First Universal AQP system

Deployment

Deployment



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supported by almost any SQL engines

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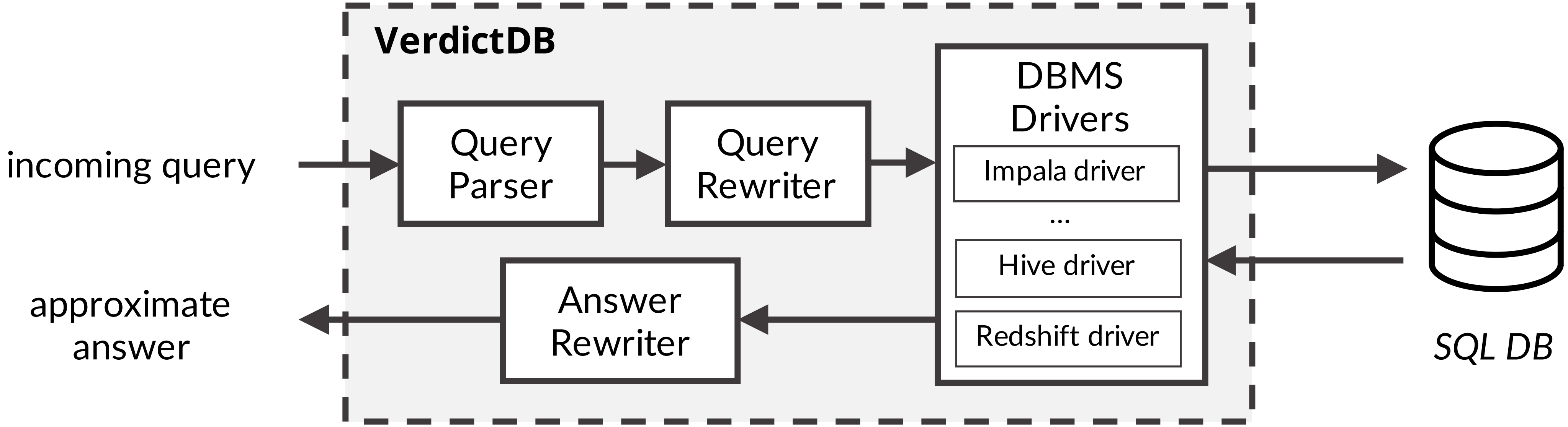

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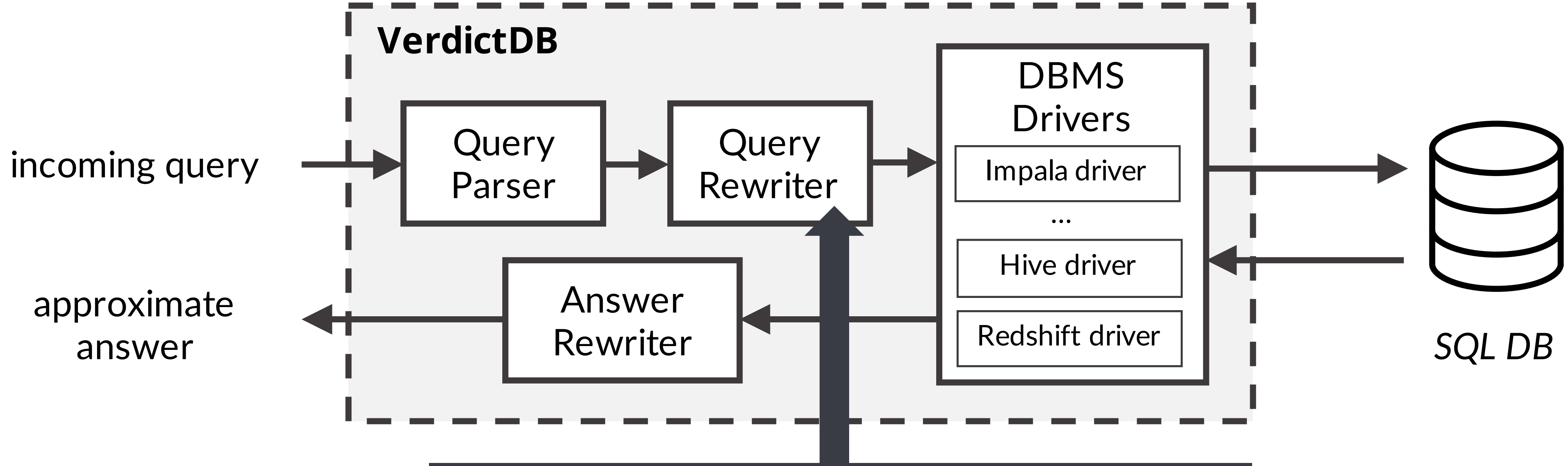

Crucial component

1. Chooses an optimal set of samples
2. Scales values appropriately
3. **Inserts an error estimation logic**

Error estimation in VerdictDB

Error estimation in general

User interested in $Q(T)$

We compute $Q(S)$ where S is a sample of T

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Recap: traditional subsampling

Q(T) is slow / expensive

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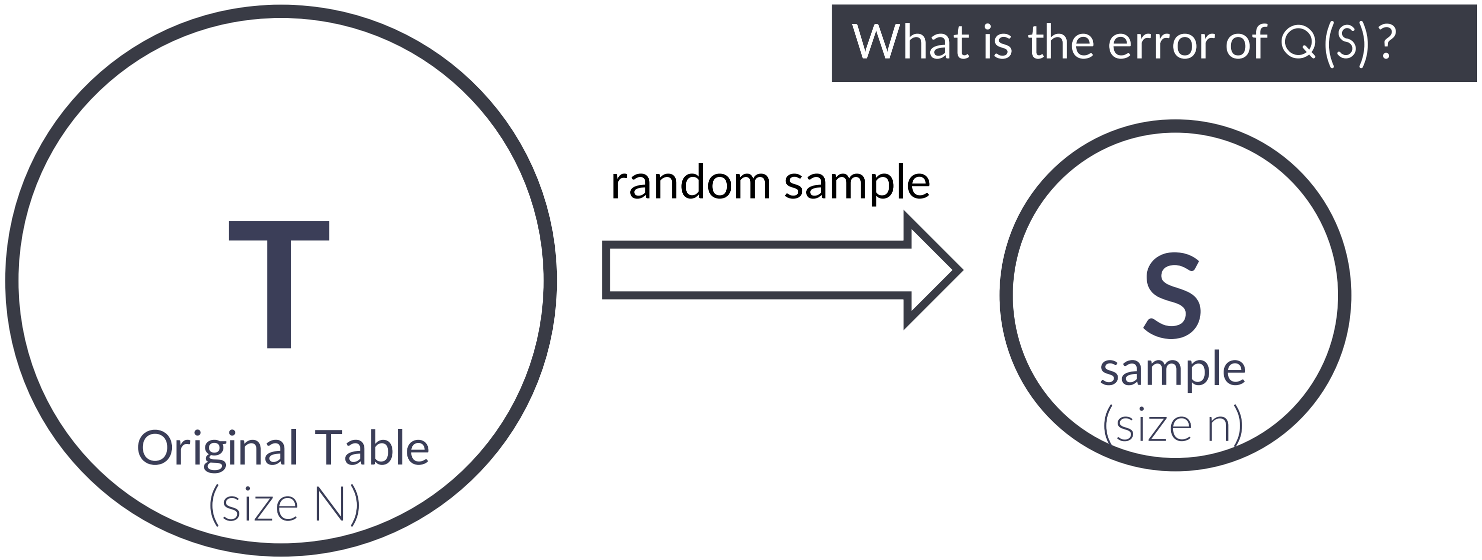

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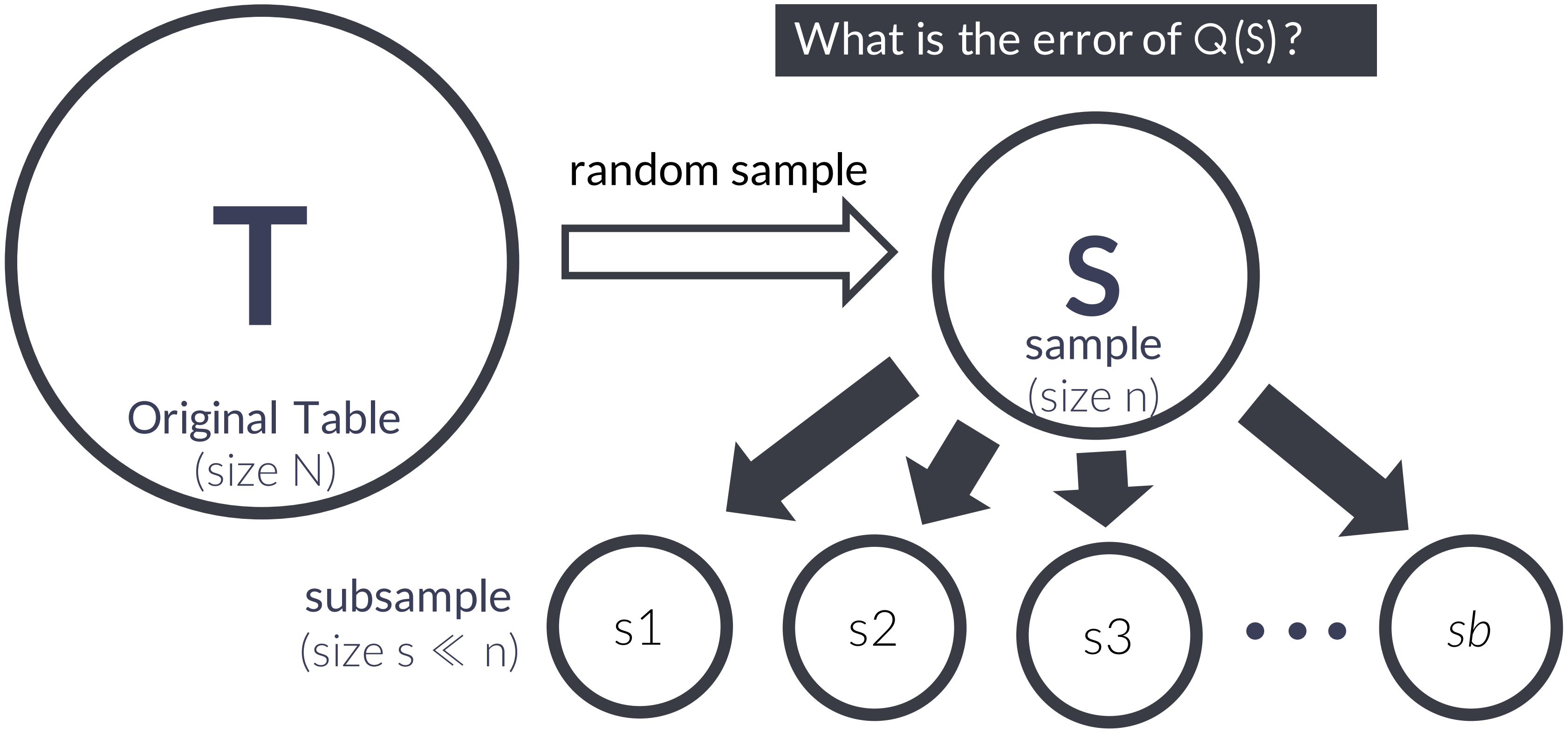

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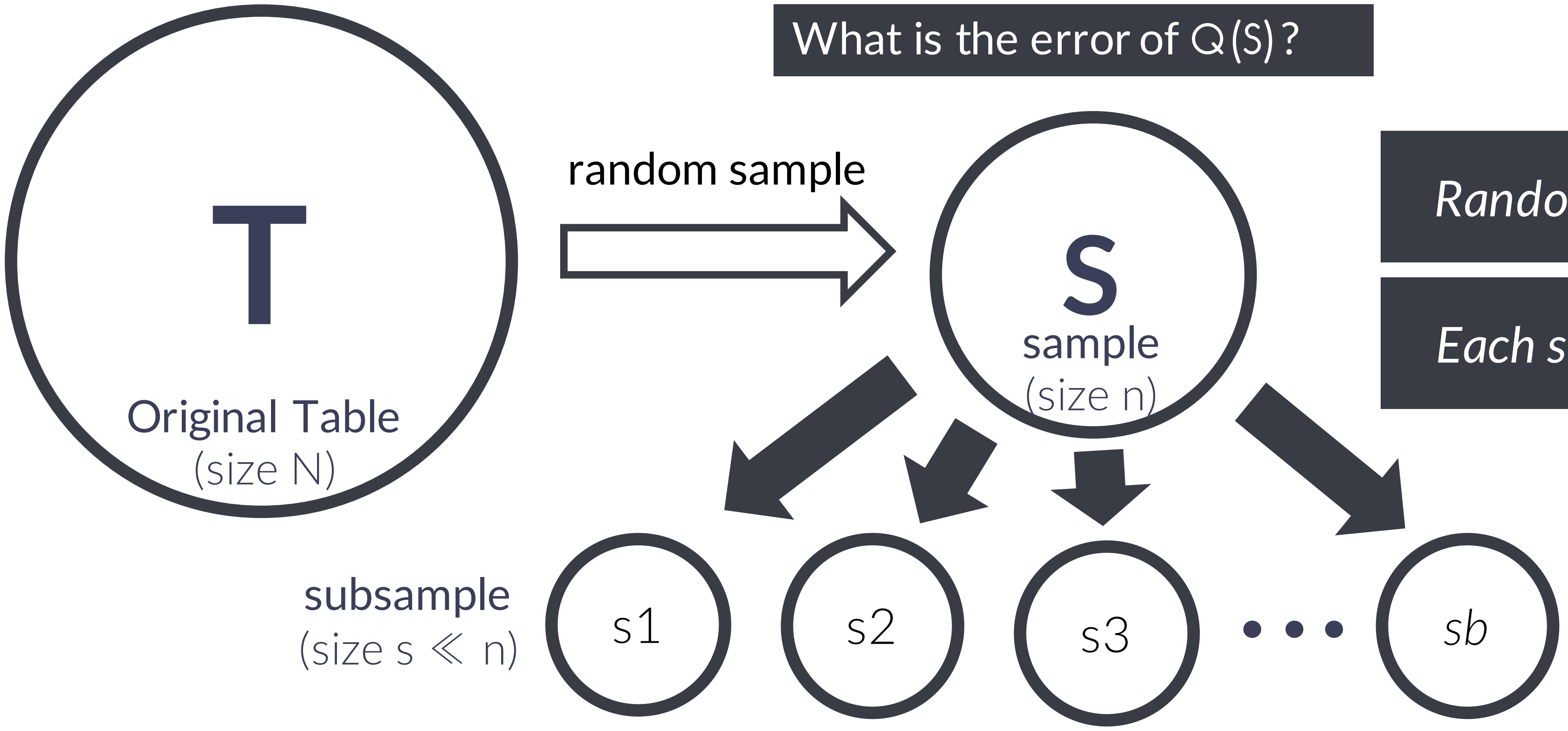

Random sample without replacement

Each subsample is independent

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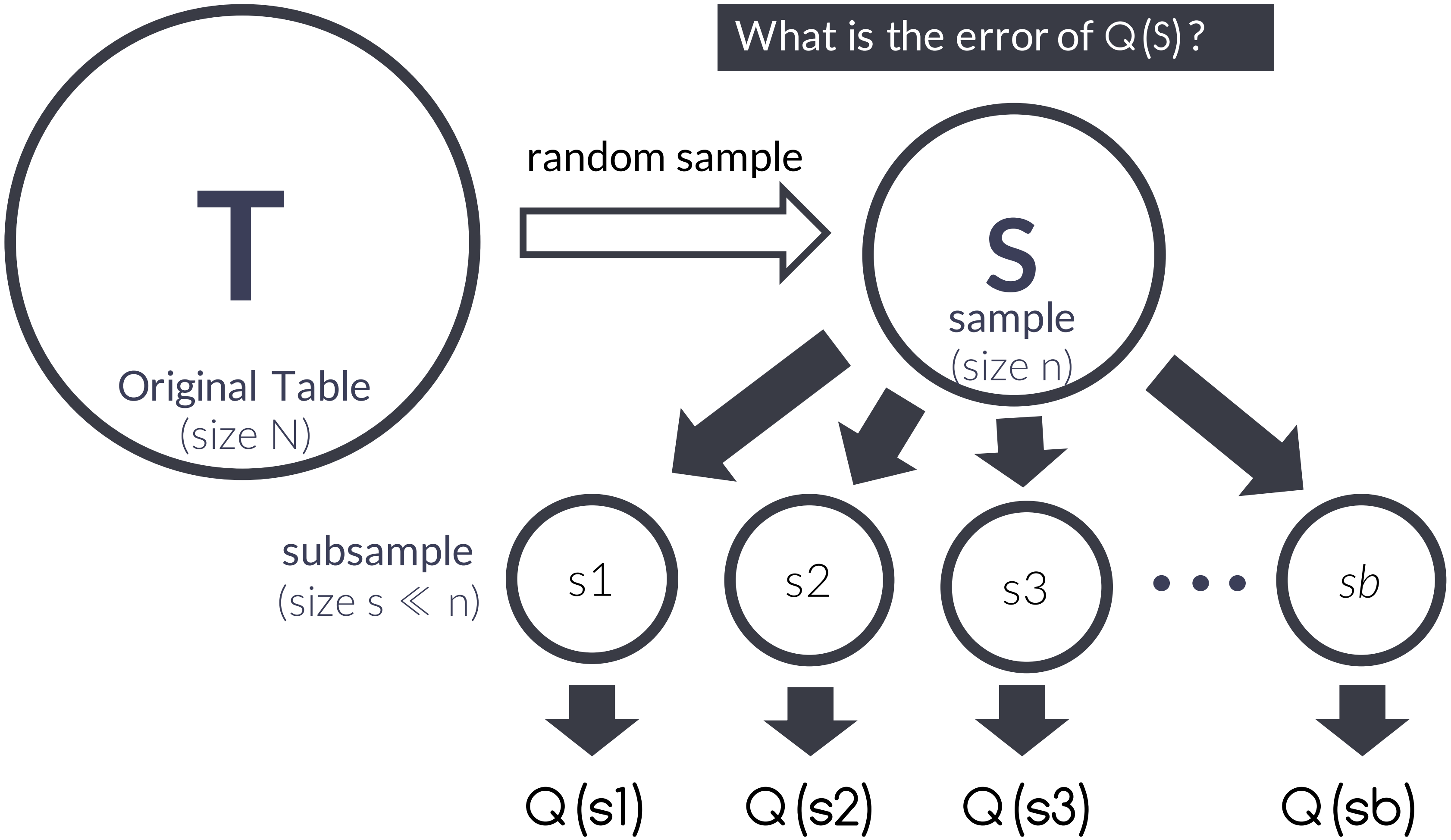

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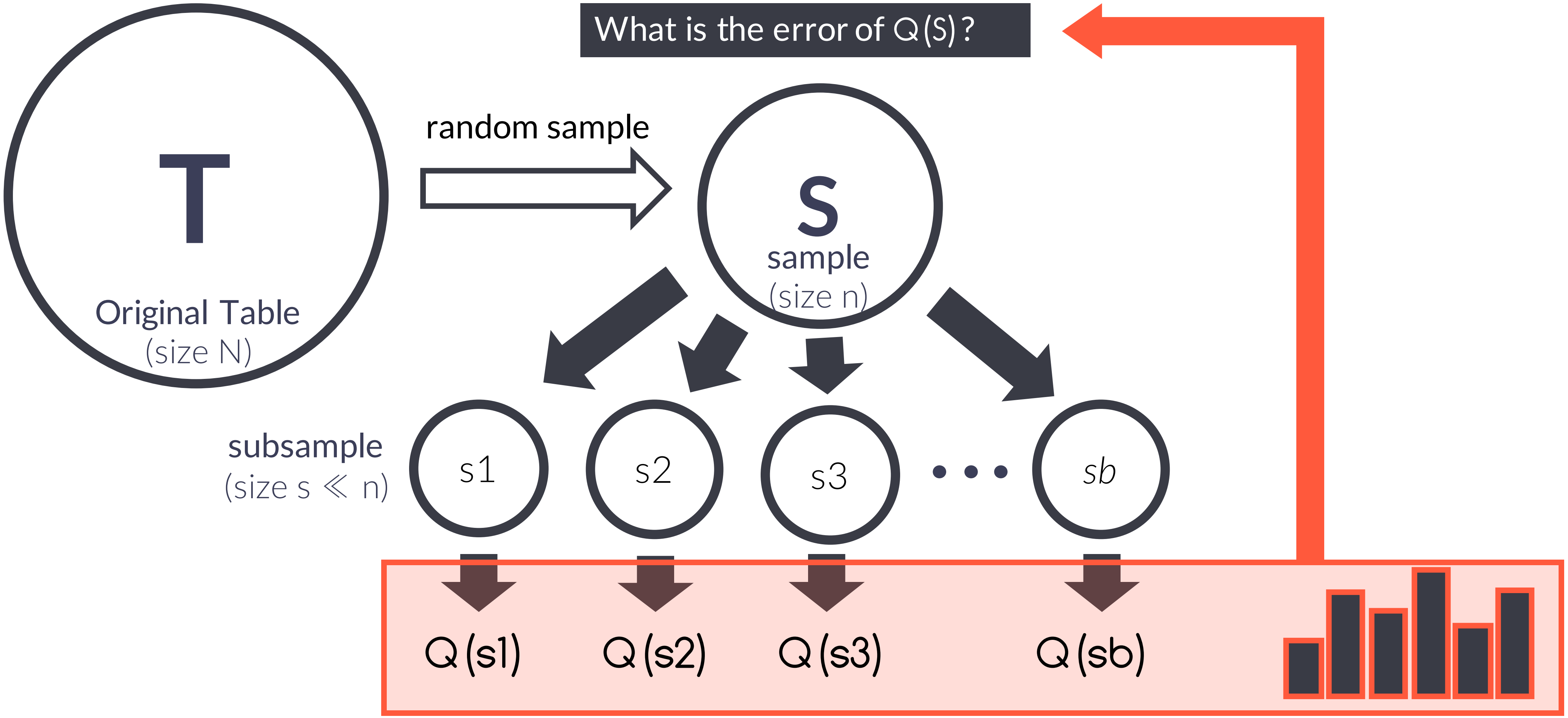

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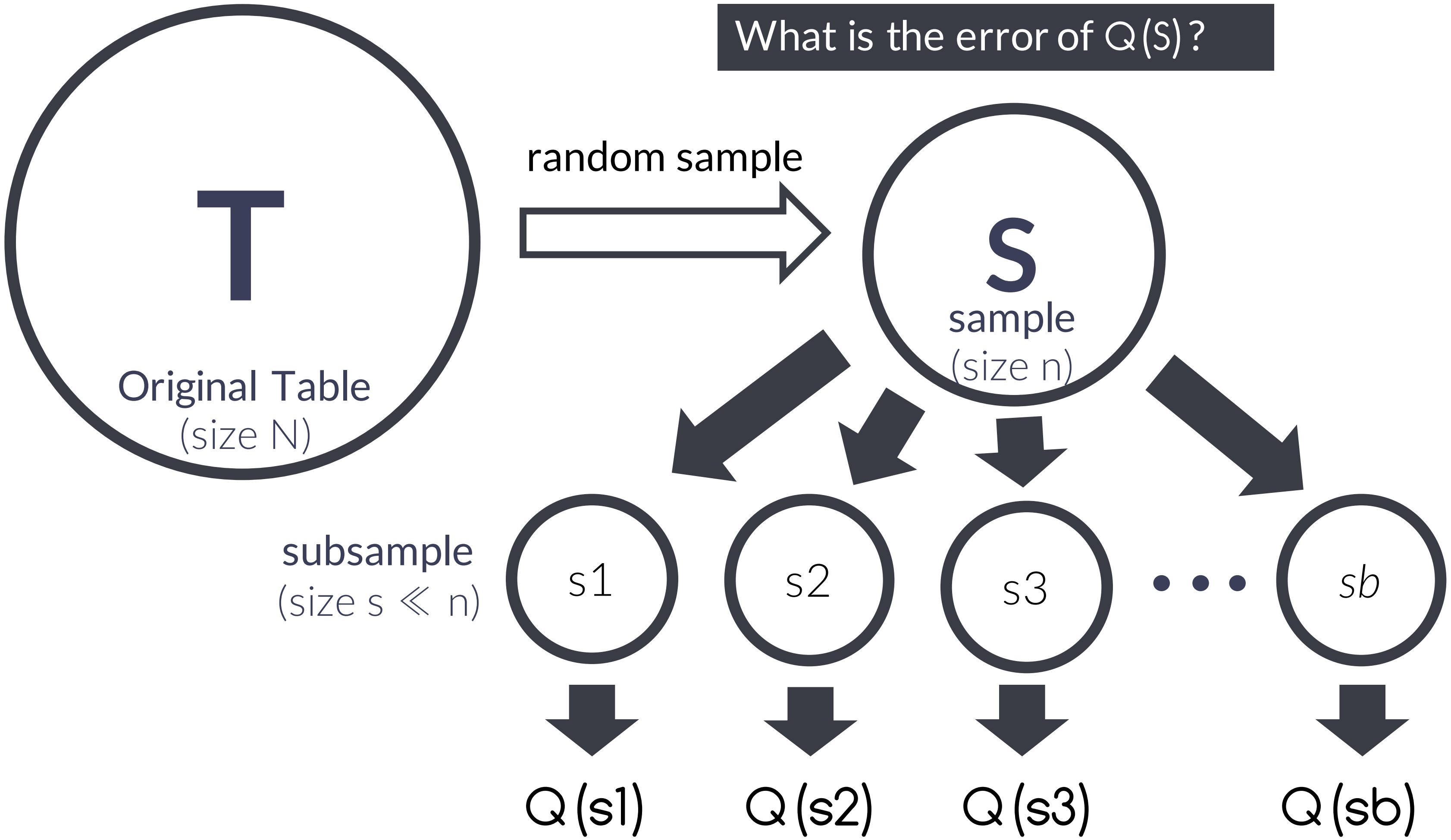

Important properties

1. A tuple may belong to multiple subsamples.
2. The size of every subsample is s.

Traditional subsampling in SQL is slow

subsample ID

n tuples

CITY	PRODUCT	PRICE	1	2	···	b
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AA	egg	$3.00	0	0		1
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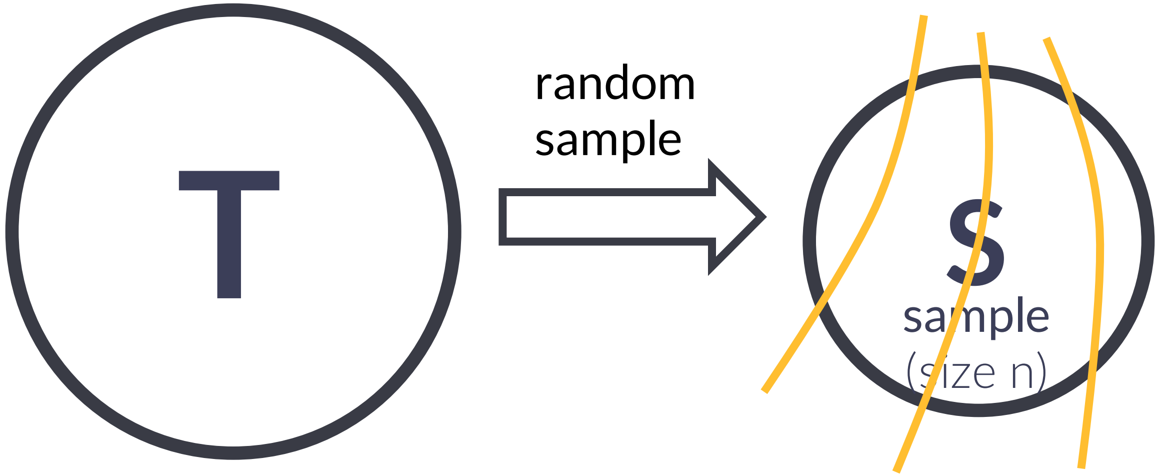
Time Complexity: O(n·b)

No error est: 0.35 sec
Trad. subsampling: 118 sec
337x slower

(based on 1G sample, Impala)

Our approach: variational subsampling



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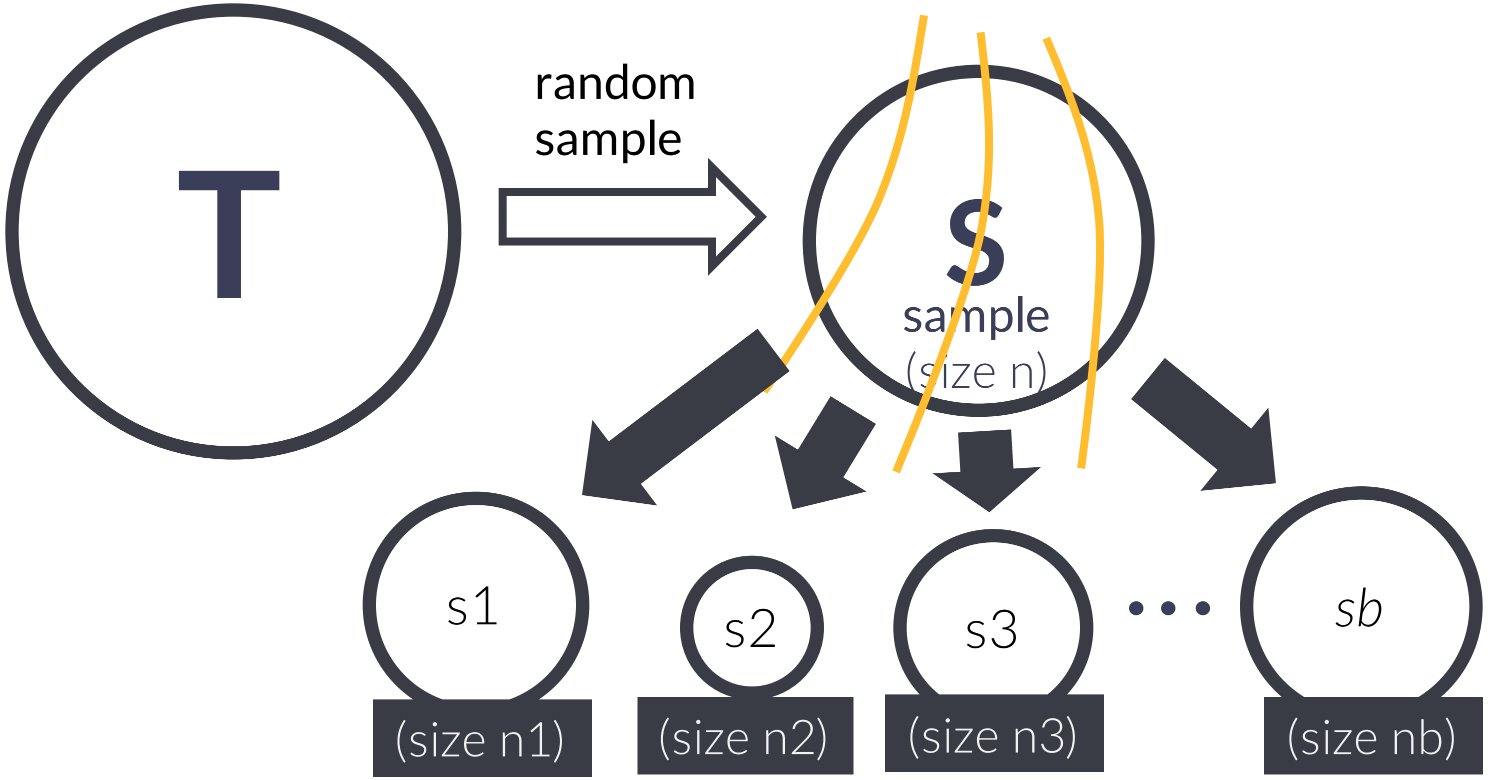

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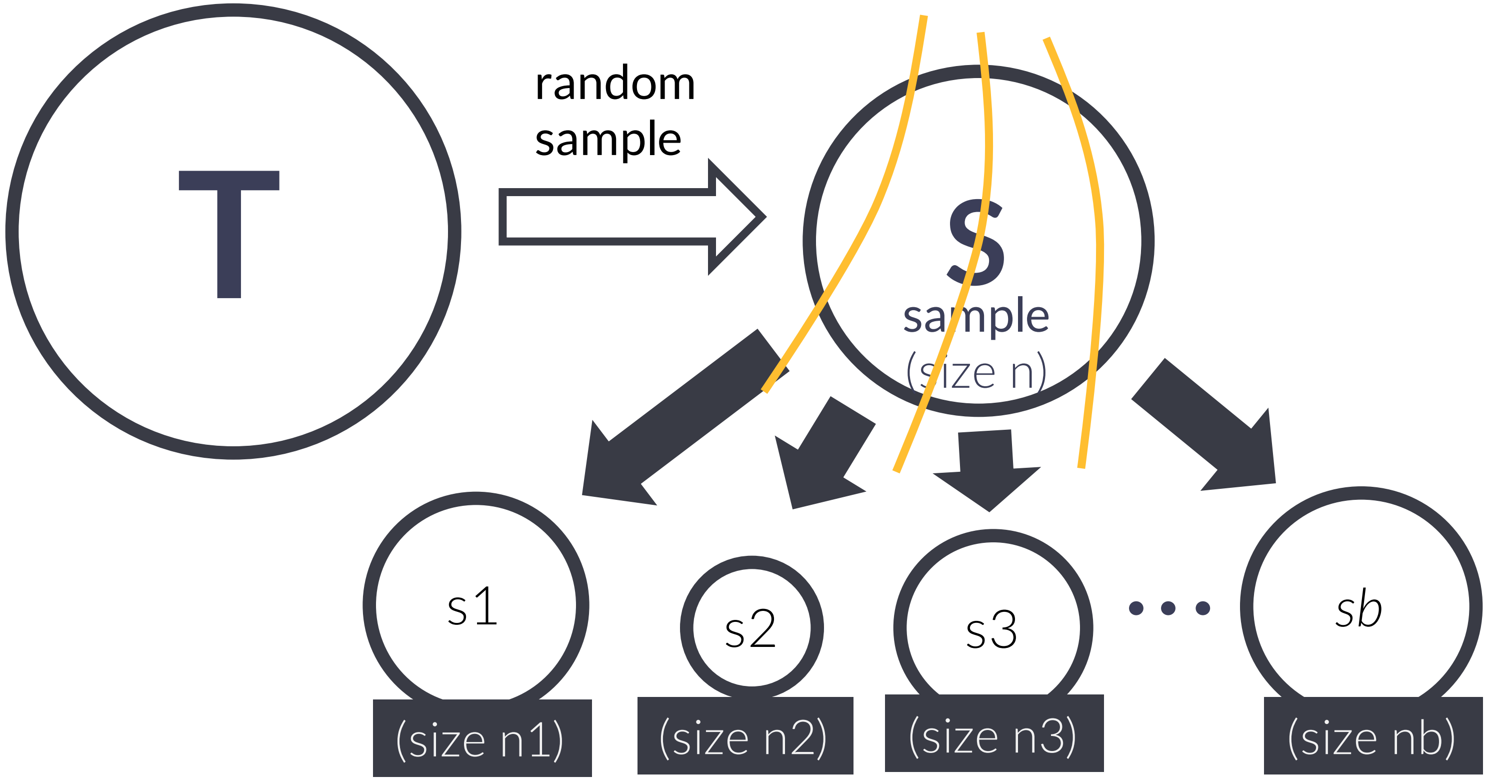

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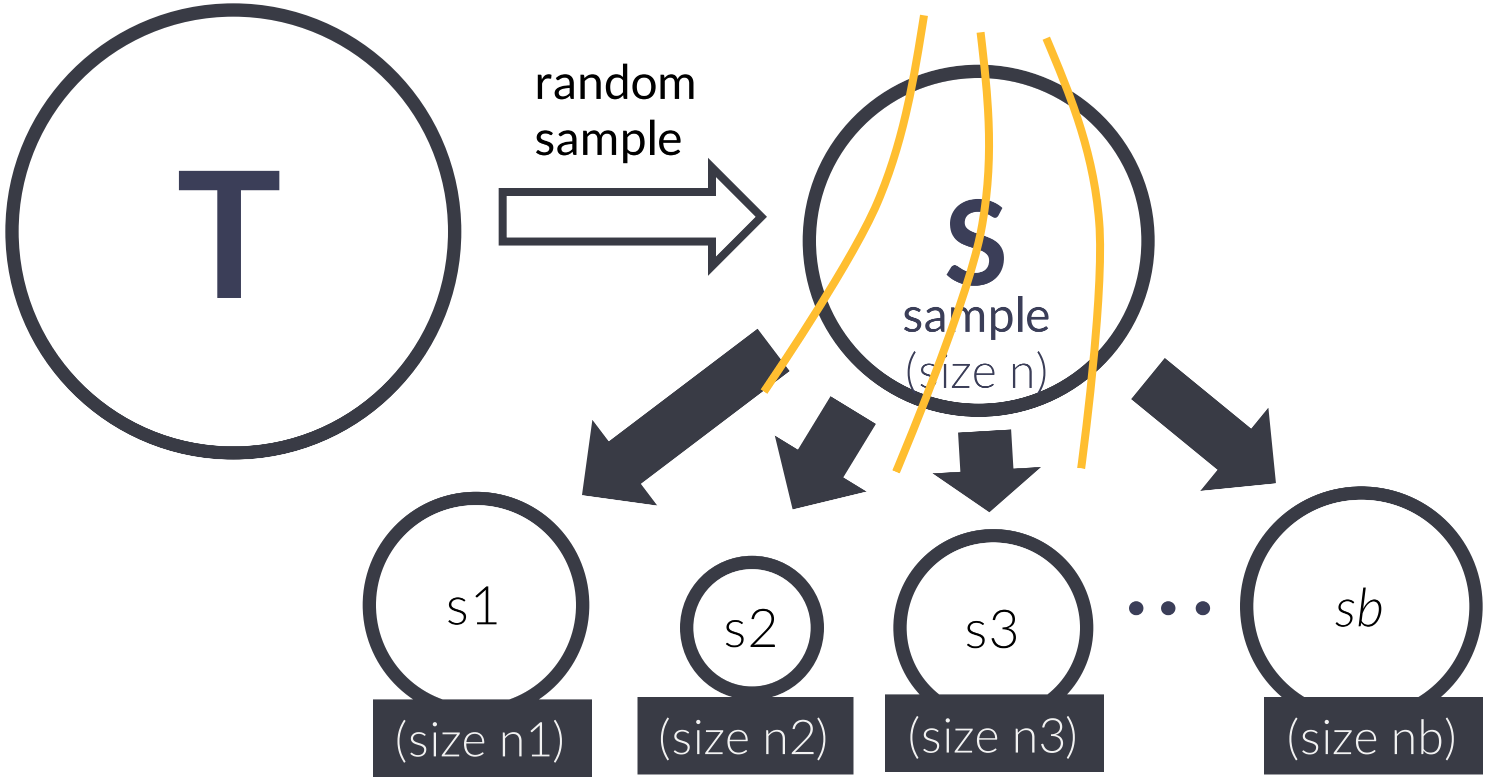

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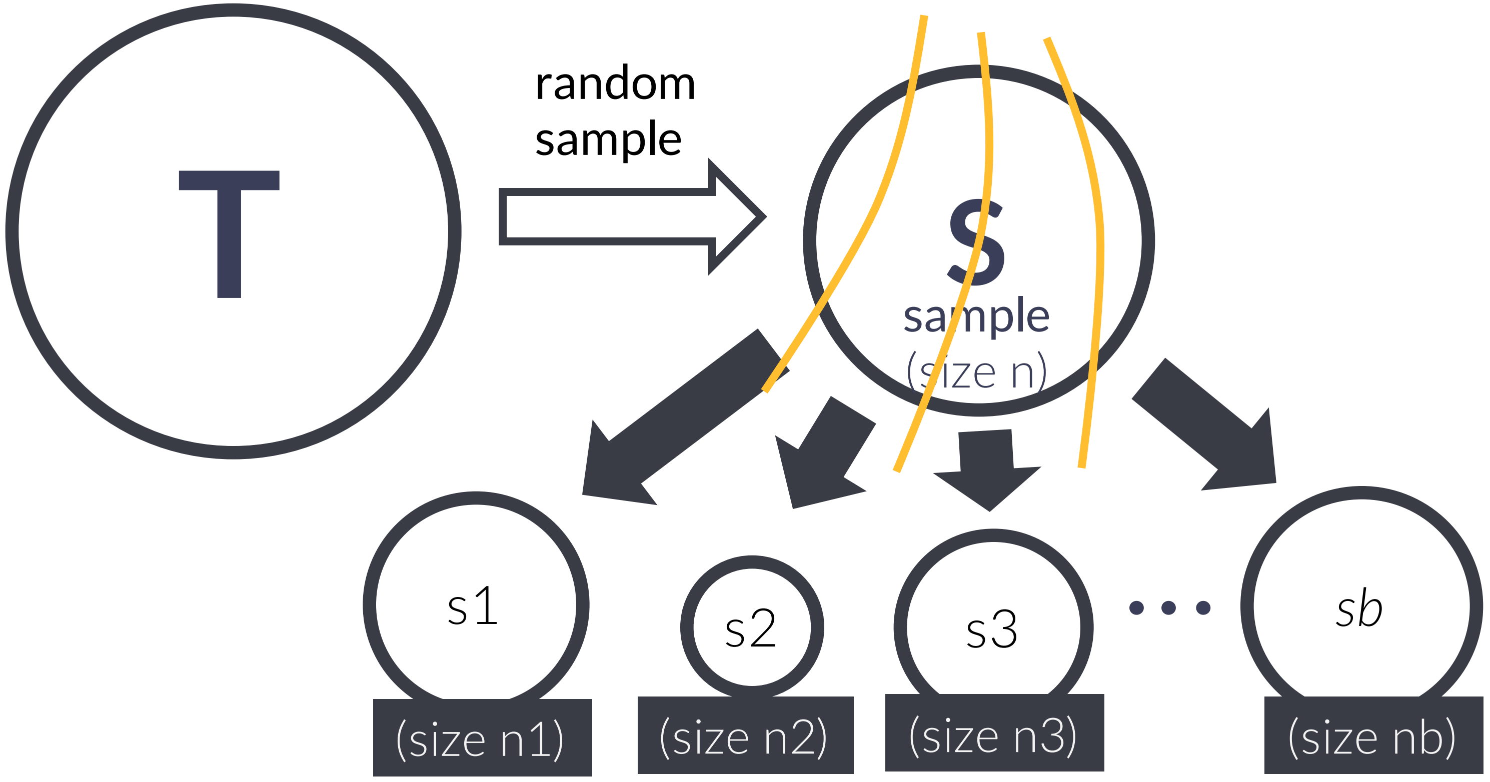

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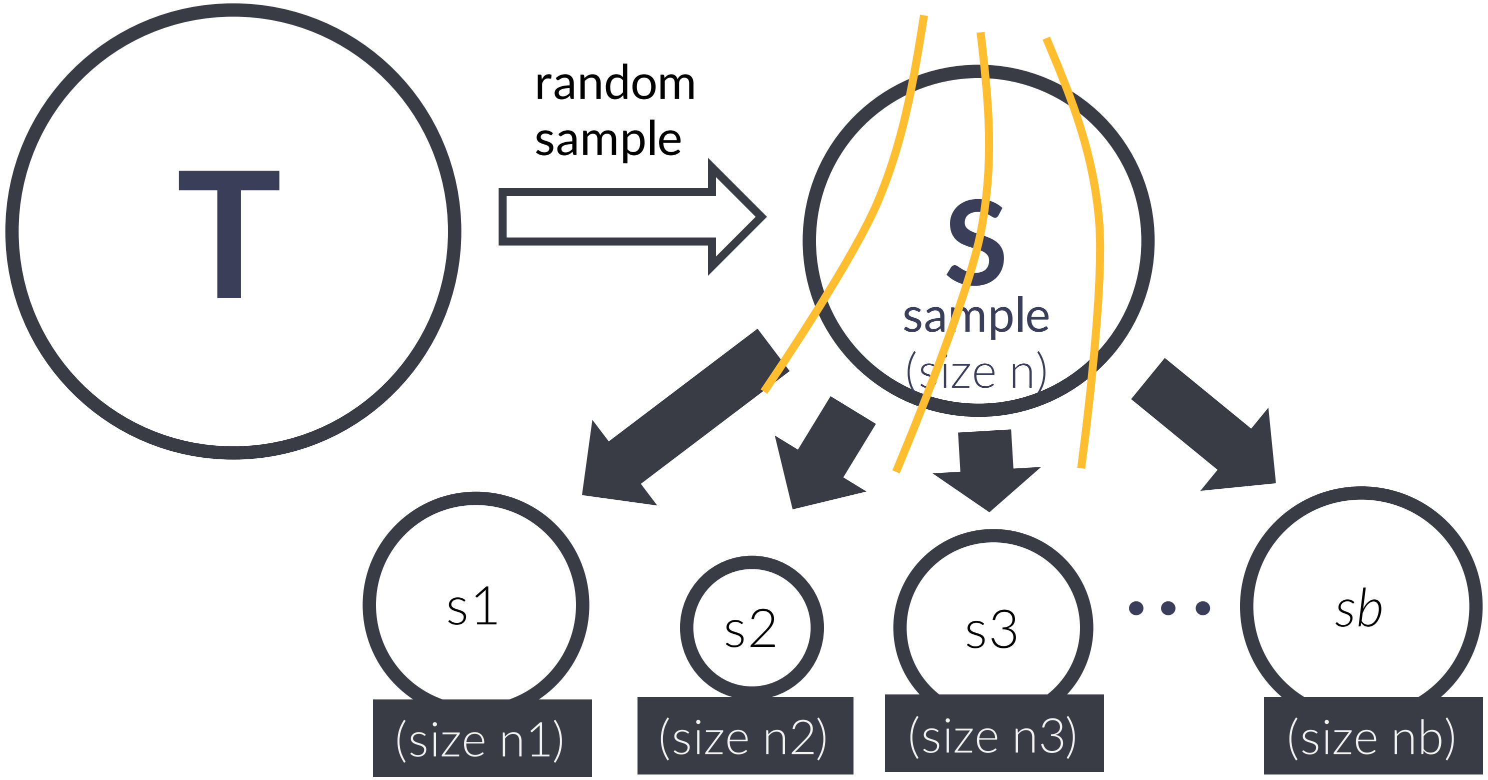

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*Can be implemented in SQL as **a single group-by query!***

Variational subsampling in SQL is fast

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n tuples

We call this augmented table, a variational table

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Main results

<u>Theorem 1 (Consistency)</u> ***The distribution*** *of the aggregates of* ***variational subsamples****, after appropriate scaling,* ***converges to the true distribution*** *of the aggregate of a sample as* $n \to \infty$.

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Theorem 2 (Convergence Rate) *The convergence rate of variational subsampling is equal to that of traditional subsampling* ***when b is finite***.

$$O\left(n_s^{-1/2} + \frac{n_s}{n} + \underline{b^{-1/2}}\right)$$

The error term from the finite b
(The Dvoretzky–Kiefer–Wolfowitz inequality)

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3. Is variational subsampling statistically correct?

Experiments

1. Does VerdictDB provide enough speedup?
2. Is VerdictDB (UAQP)'s performance comparable to a tightly-integrated AQP engine?
3. Is variational subsampling statistically correct?

Yes

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3. Is variational subsampling statistically correct?

Yes

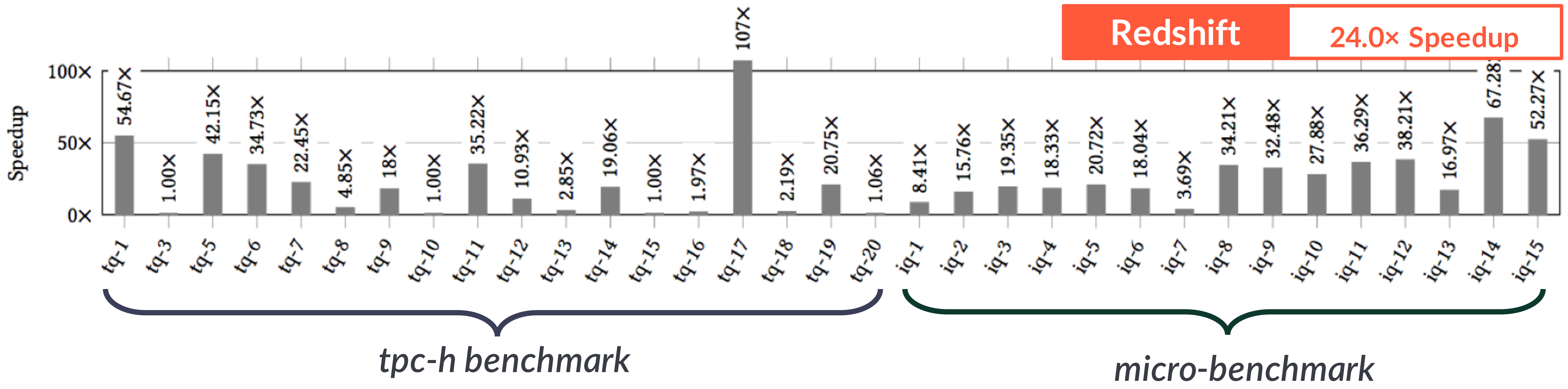
Datasets:

- 500GB TPC-H benchmark / 200GB Instacart dataset / synthetic datasets

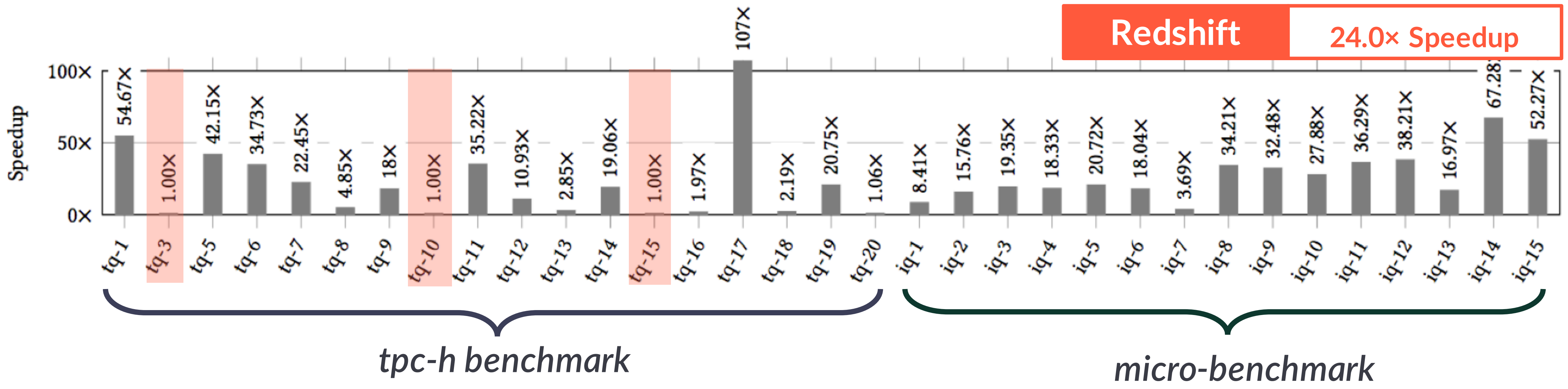
Underlying databases

- Amazon Redshift, Apache Spark SQL, Apache Impala on 10+1 r4.xlarge cluster

Speedup for Redshift



Speedup for Redshift



t3, t10, t15: no speedup (i.e., 1×) due to high-cardinality grouping attributes

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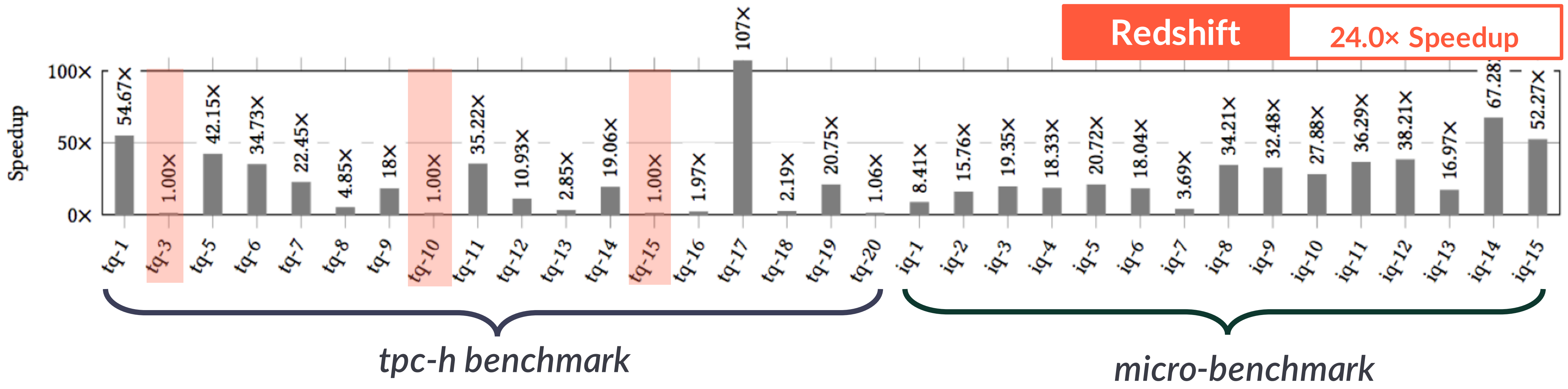
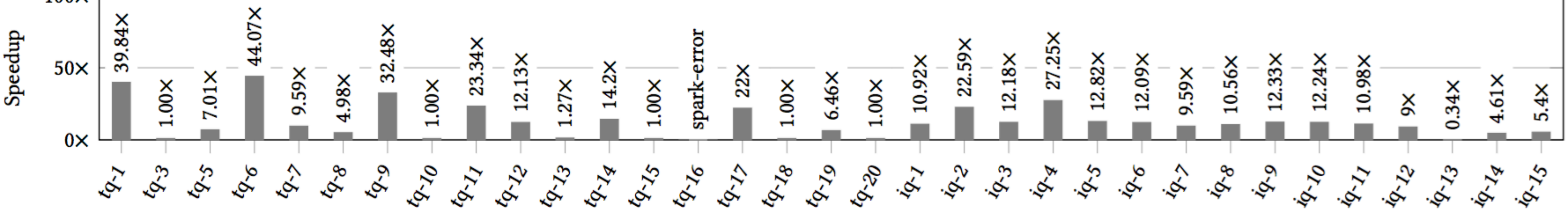


t3, t10, t15: no speedup (i.e., 1×) due to high-cardinality grouping attributes

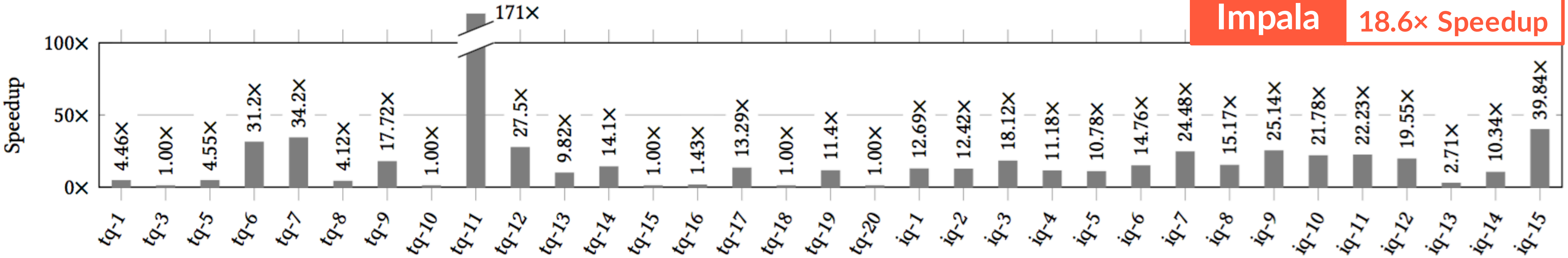
Other queries: 26.3× speedups (relative errors were 2%)

Speedup for Apache Spark & Impala

Spark SQL 12.0× Speedup



Impala 18.6× Speedup



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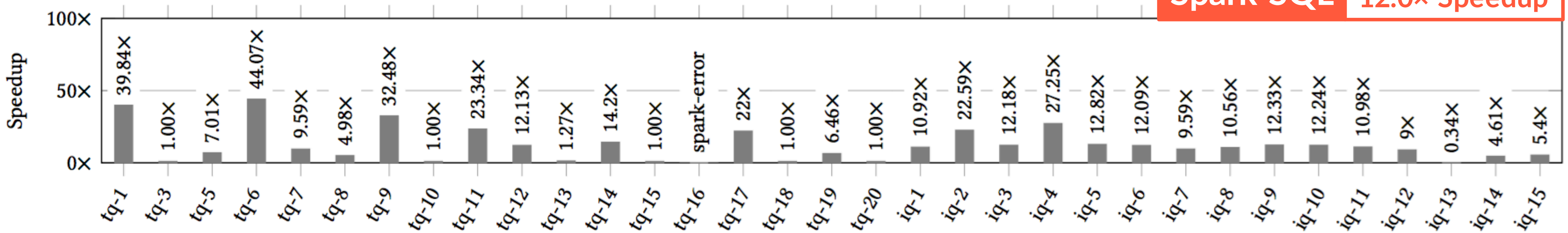

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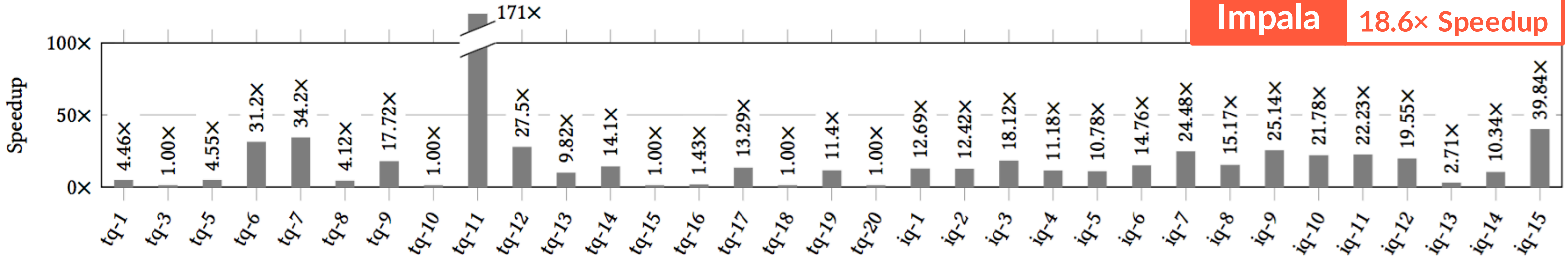
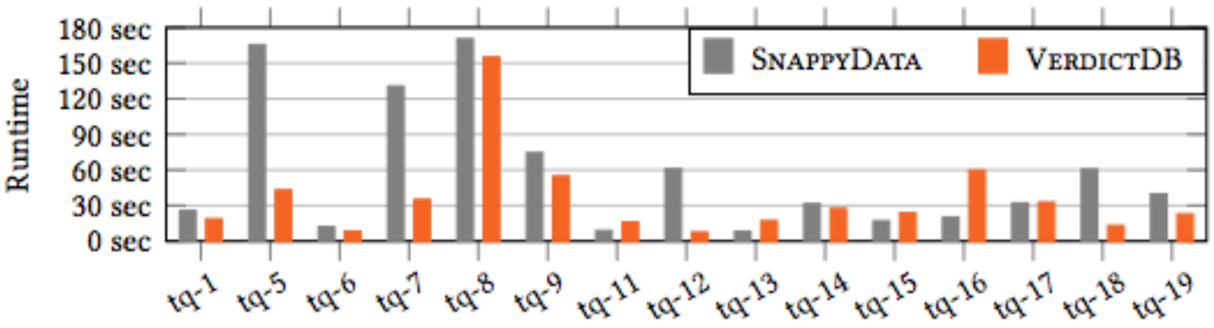
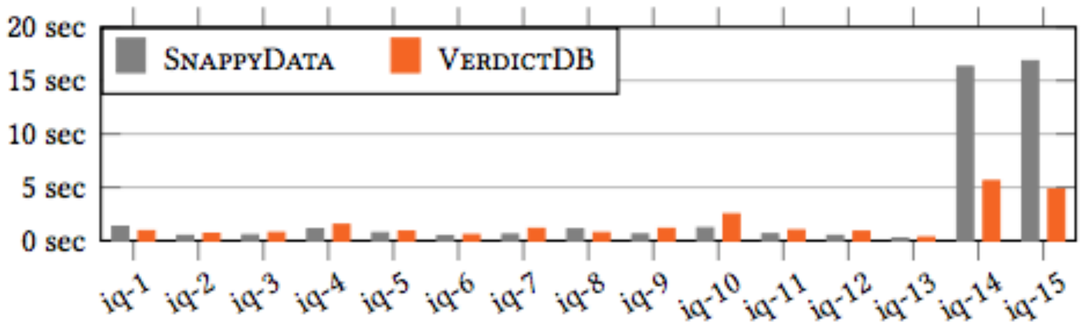


$$speedup = \frac{overhead + processing}{overhead + (sample\ processing)}$$

Lower overhead →
Larger speedup

UAQP vs. Tightly-integrated AQP





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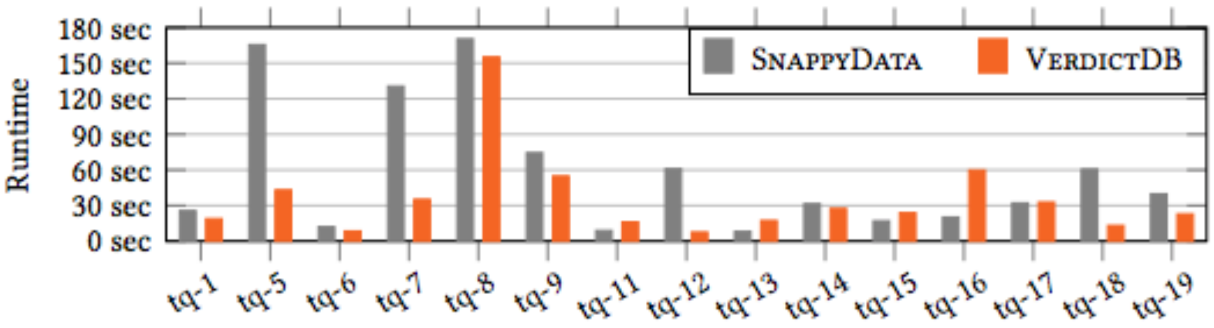

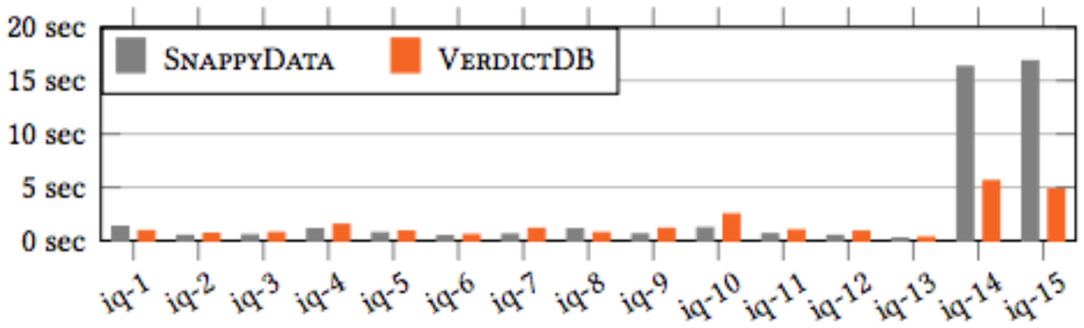

VerdictDB was comparable to SnappyData.

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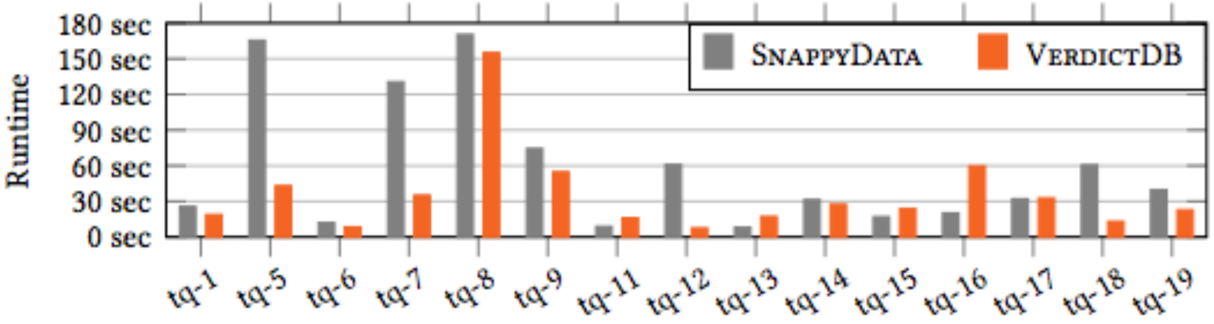
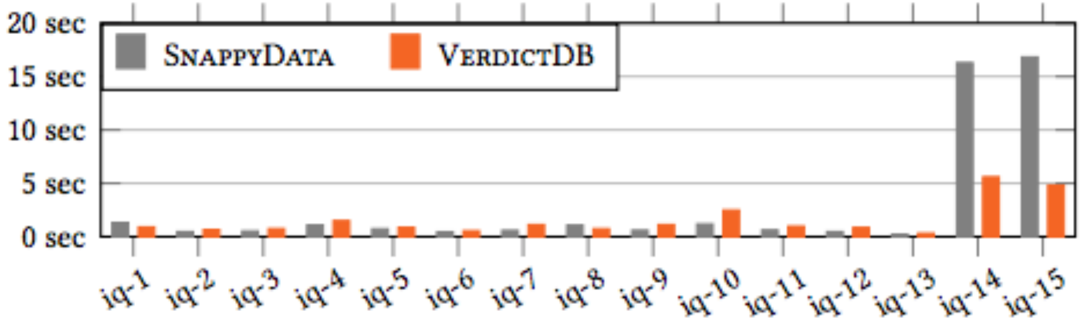


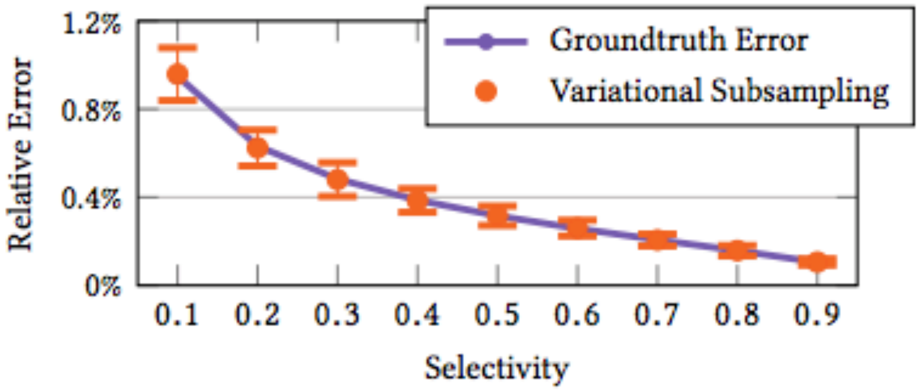


VerdictDB was comparable to SnappyData.

SnappyData ver 0.8 didn't support the join of two sample tables.

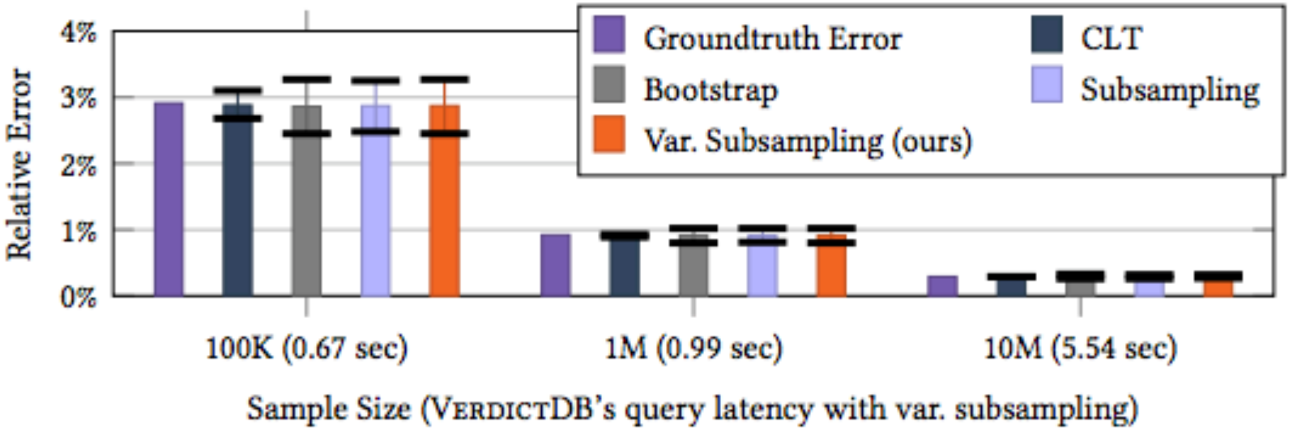
Variational subsampling: correctness

Rel. err. naturally become smaller for higher selectivity.



(a) Estimated error for different selectivity

The bars are 5th and 95th percentiles.



(b) Estimated error for different sample sizes

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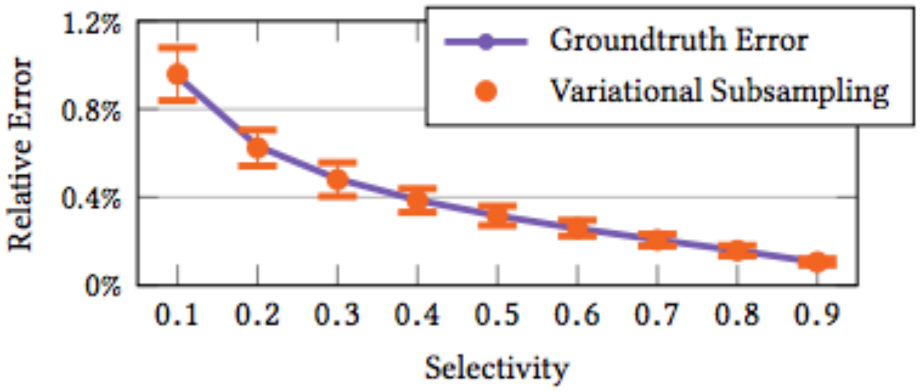

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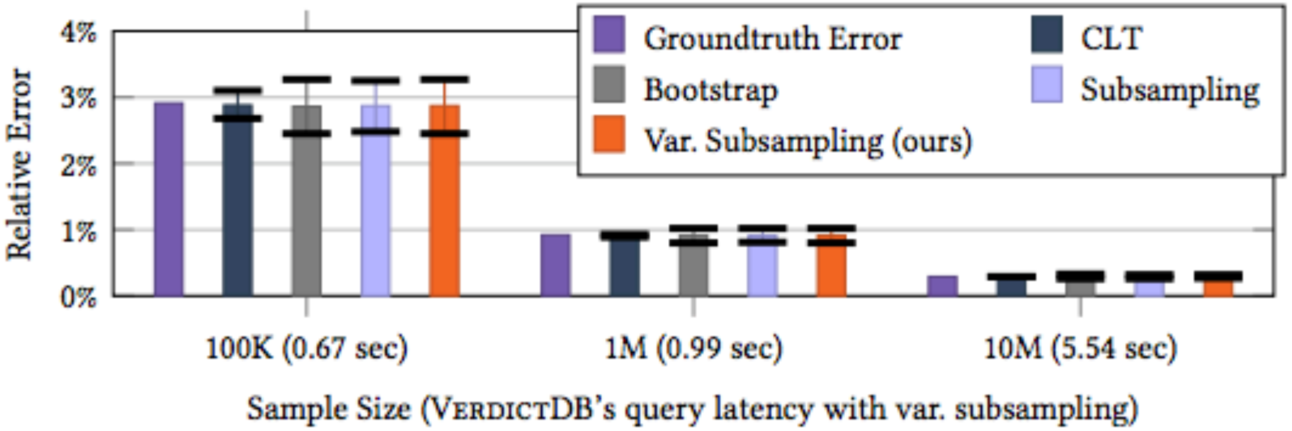

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The estimated errors close to true errors.

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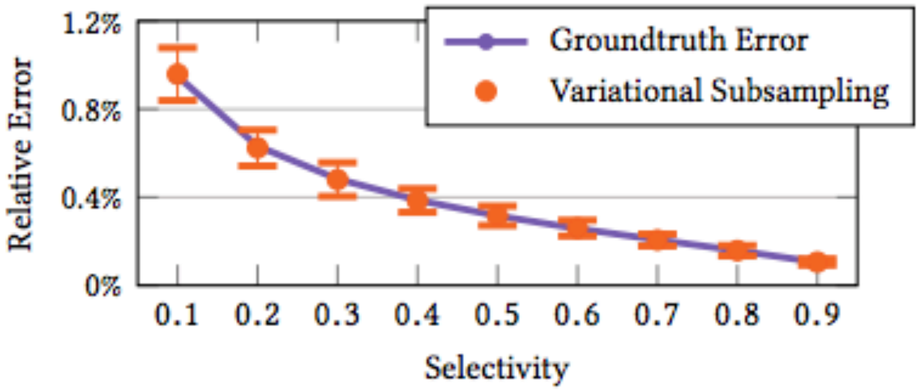

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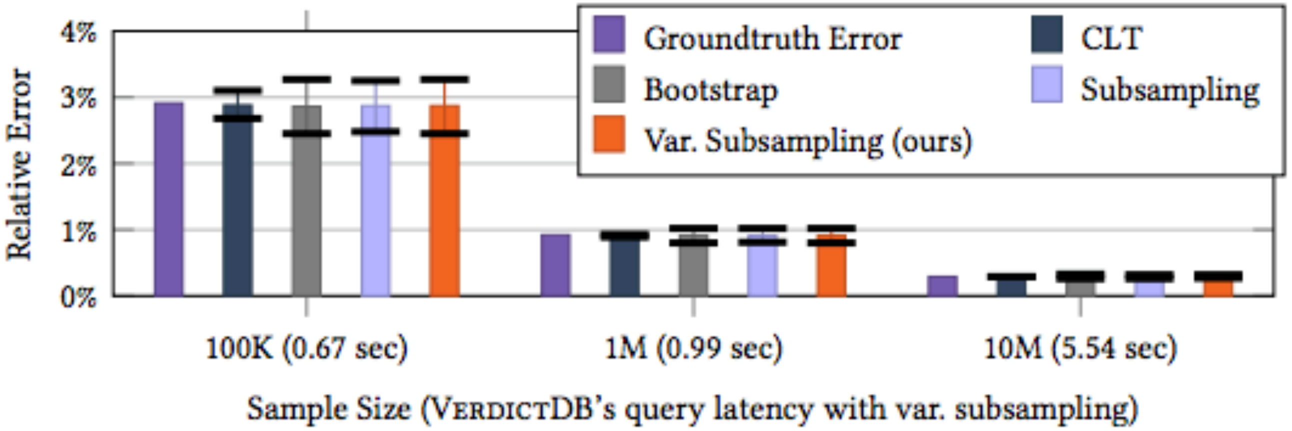

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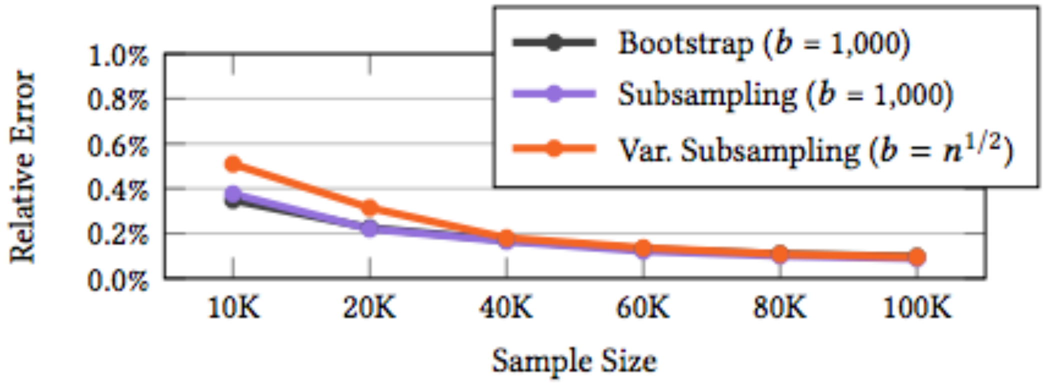
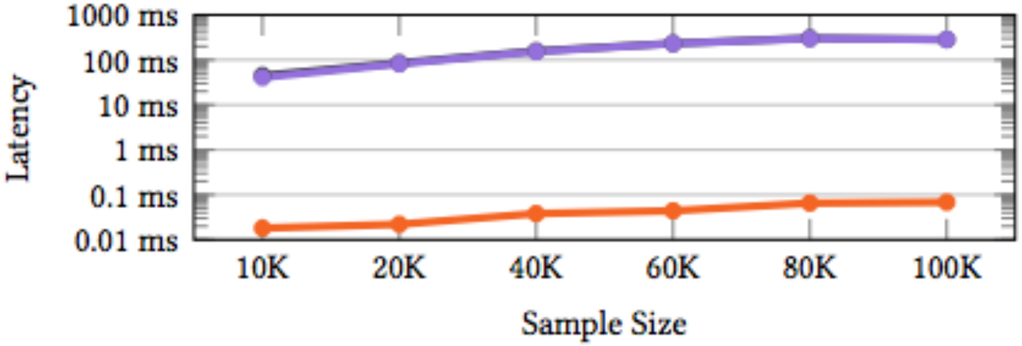
The estimated errors close to true errors.

The accuracy of var. subsampling ≈ (a) bootstrap and (b) trad. subsampling

Variational subsampling: convergence rate



(a) Accuracy of error bound estimation



(b) Latency of error bound estimation

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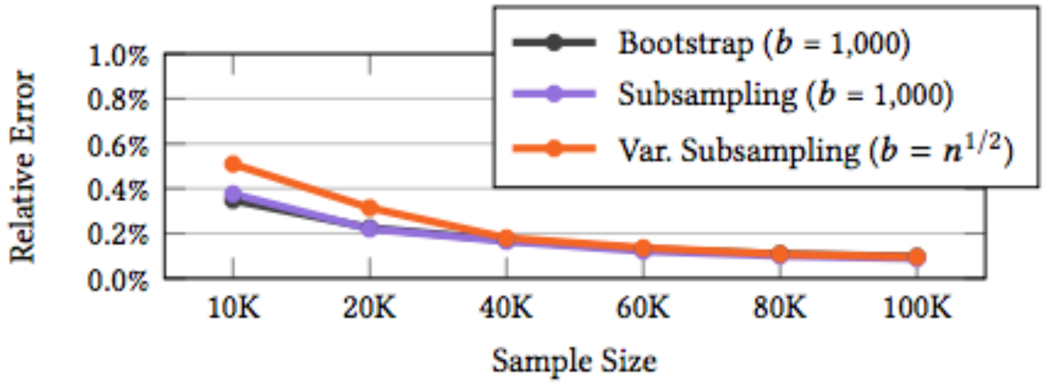

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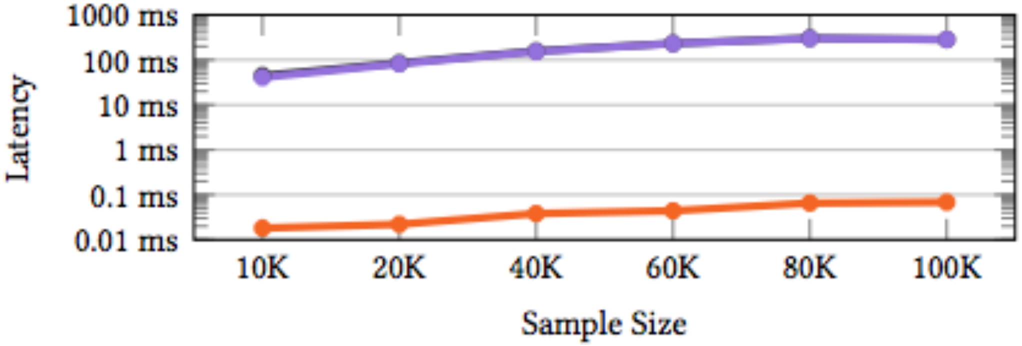

(b) Latency of error bound estimation

The accuracy was almost the same for relatively large samples.

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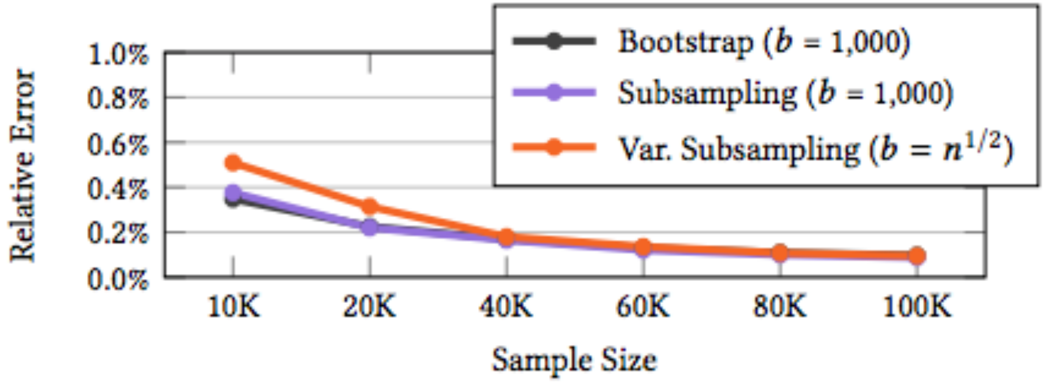

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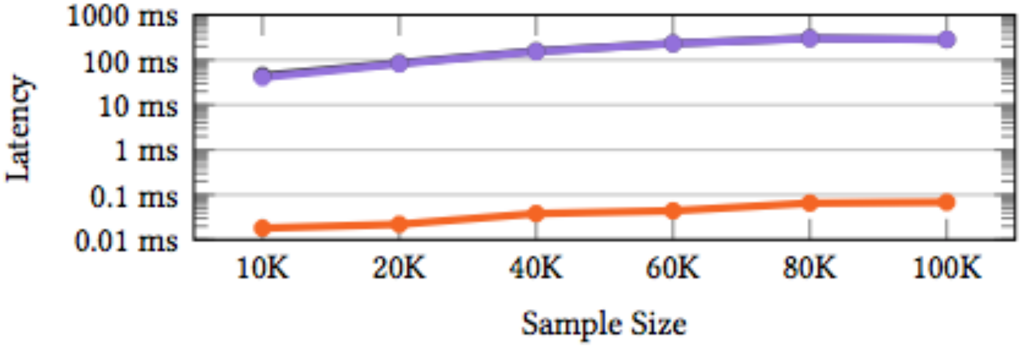

(b) Latency of error bound estimation

The accuracy was almost the same for relatively large samples.

Variational subsampling was significantly faster.

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Open-sourced (Apache v2.0): http://verdictdb.org

Future Work

Development

Research

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- Adding more drivers (Presto, Teradata, Oracle, SQL Server, …)

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- Robust physical designer (see CliffGuard @ SIGMOD 15)

Future Work

Development

- Adding more drivers (Presto, Teradata, Oracle, SQL Server, ...)

Research

- Support for online sampling
- Robust physical designer (see CliffGuard @ SIGMOD 15)
- Integration with ML libraries (sampling-based model tuning)

VerdictDB

http://verdictdb.org

Thank You

VerdictDB: current status

- We support
  - aggregates: sum, count, avg, count-distinct, quantiles, UDAs
  - sources: base table, derived table, equi-join
  - filters: comparison, some subquery
  - others: group-by, having, etc.

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- Upcoming features
  - Online sampling, automated physical designer

Example of query rewriting

original

```
select l_returnflag , count (*) as cc
from lineitem
group by l_returnflag ;
```

rewritten

```
select vt1 .` l_returnflag ` AS `l_returnflag `,
          round ( sum (( vt1 .`cc ` * vt1 .` sub_size `)) / sum ( vt1 .` sub_size `)) AS `cc `,
          (stddev ( vt1 .` count_order `) * sqrt ( avg ( vt1 .` sub_size `)))
          / sqrt ( sum ( vt1 .` sub_size `)) AS `cc_err `
from (select vt0 .` l_returnflag ` AS `l_returnflag `,
           (( sum ((1.0 / vt0 .` sampling_prob `)) / count (*))
           * sum ( count (*)) OVER ( partition BY vt0 .` l_returnflag `)) AS `cc `,
           vt0 .`sid ` AS `sid `, count (*) AS `sub_size `
        from lineitem_sample vt0
        GROUP BY vt0 .` l_returnflag `, vt0 .`sid `) AS vt1
GROUP BY vt1 .` l_returnflag `;
```

Bibliography

[Pol and Jermaine ‘05] Pol, Abhijit, and Christopher Jermaine. "Relational confidence bounds are easy with the bootstrap." In *Proceedings of the 2005 ACM SIGMOD international conference on Management of data*, pp. 587-598. ACM, 2005.

[BlinkDB ‘13] Agarwal, Sameer, Barzan Mozafari, Aurojit Panda, Henry Milner, Samuel Madden, and Ion Stoica. EuroSys, 2013.

[BlinkDB ‘14] Agarwal, Sameer, Henry Milner, Ariel Kleiner, Ameet Talwalkar, Michael Jordan, Samuel Madden, Barzan Mozafari, and Ion Stoica. "Knowing when you're wrong: building fast and reliable approximate query processing systems." SIGMOD, 2014.

[Quickr ‘16] Kandula, Srikanth, Anil Shanbhag, Aleksandar Vitorovic, Matthaios Olma, Robert Grandl, Surajit Chaudhuri, and Bolin Ding. "Quickr: Lazily approximating complex adhoc queries in bigdata clusters." SIGMOD, 2016.

Bibliography

[G-OLA ’15] Zeng, Kai, Sameer Agarwal, Ankur Dave, Michael Armbrust, and Ion Stoica. "G-ola: Generalized on-line aggregation for interactive analysis on big data." SIGMOD, 2015.

[ABM ‘14] Zeng, Kai, Shi Gao, Barzan Mozafari, and Carlo Zaniolo. "The analytical bootstrap: a new method for fast error estimation in approximate query processing." SIGMOD, 2014.

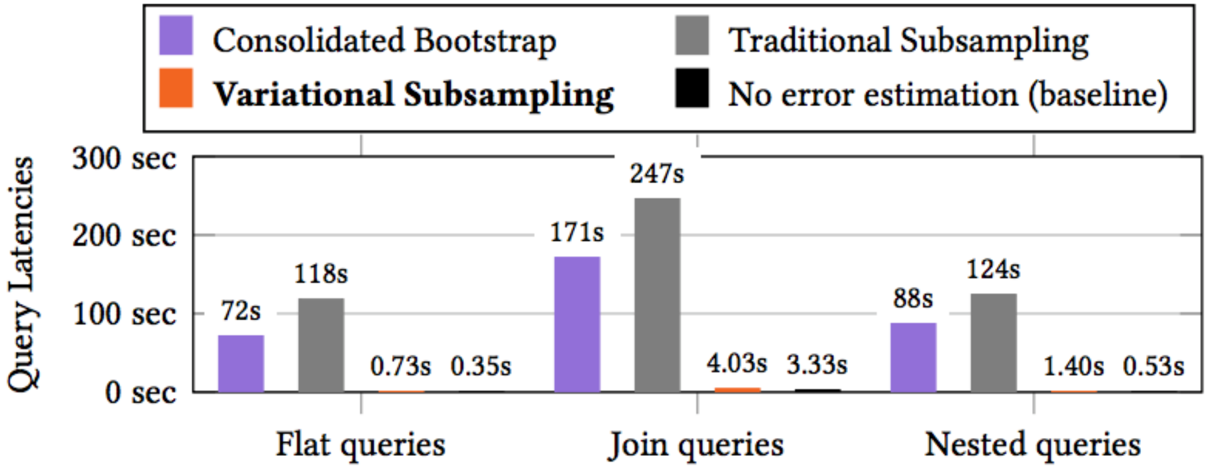
[Join Synopses ‘99] Acharya, Swarup, Phillip B. Gibbons, Viswanath Poosala, and Sridhar Ramaswamy. "Join synopses for approximate query answering." *SIGMOD Record*, 1999.

[Wander Join ‘16] Li, Feifei, Bin Wu, Ke Yi, and Zhuoyue Zhao. "Wander join: Online aggregation via random walks." SIGMOD, 2016.

[Online ‘97] Hellerstein, Joseph M., Peter J. Haas, and Helen J. Wang. "Online aggregation." SIGMOD, 1997.

[Politis ‘94] Politis, Dimitris N., and Joseph P. Romano. "Large sample confidence regions based on subsamples under minimal assumptions." *The Annals of Statistics*, 1994

Variational subsampling: overhead



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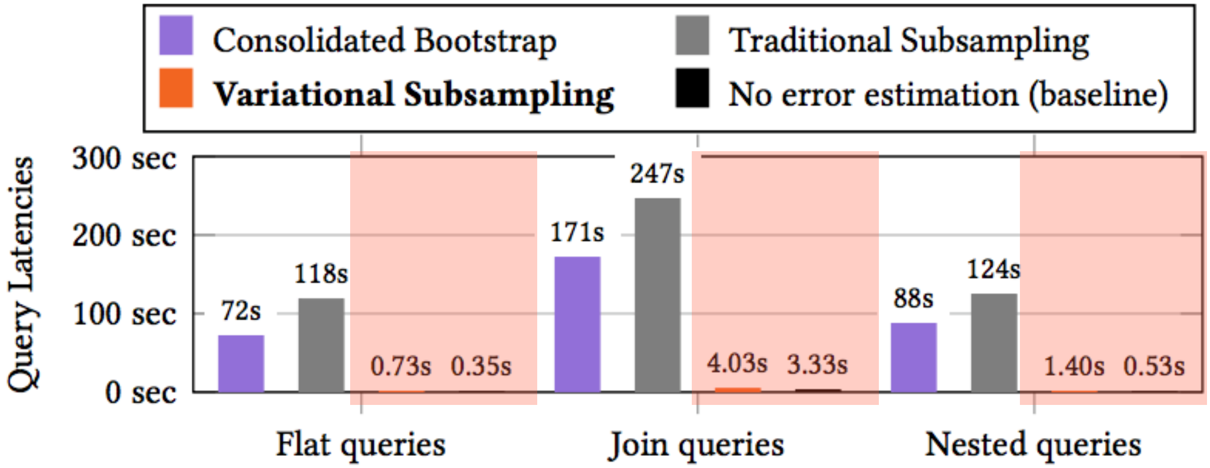

Overhead of *variational subsampling*: 0.38–0.87 *seconds*

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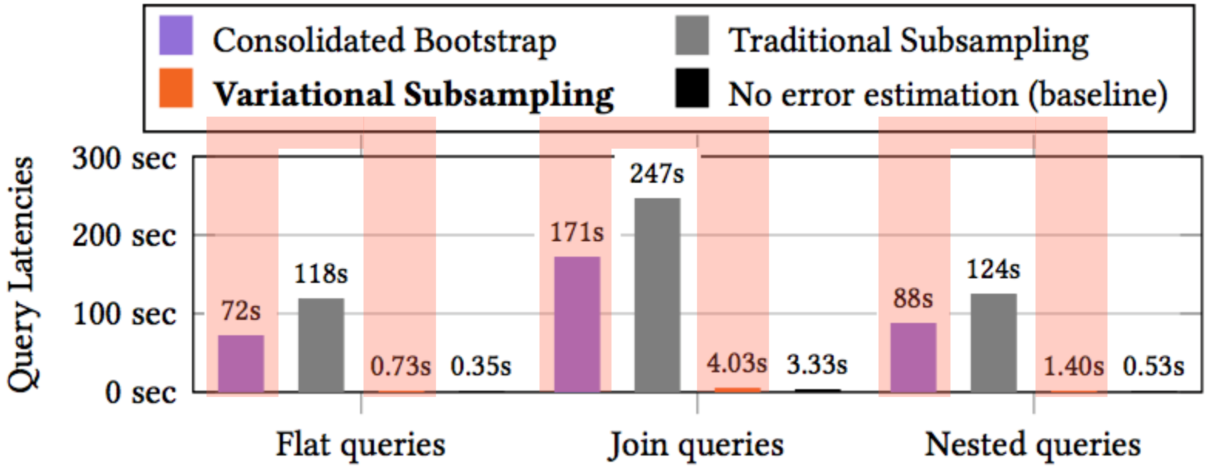

Overhead of *variational subsampling*: 0.38–0.87 seconds

Variational subsampling was 100×–237× faster compared to Consolidated Bootstrap.