Computations with Bounded Errors and Response Times on Very Large Data

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(joint work with: Sameer Agarwal, Ariel Kleiner, Henry Milner, Barzan Mozafari, Ameet Talwalkar, Purnamrita Sarkar, Michael Jordan, Sam Madden)

Paris, May 15, 2013

Problem

Support **interactive ad-hoc** exploration queries over **very large** datasets

Why is This a Problem?

100 TB on 1000 cores/disks

1-2 Hours

Hard Disks

10-15 Minutes

Memory

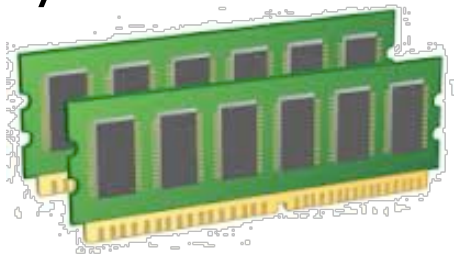
1 second

?

Why is This a Problem?

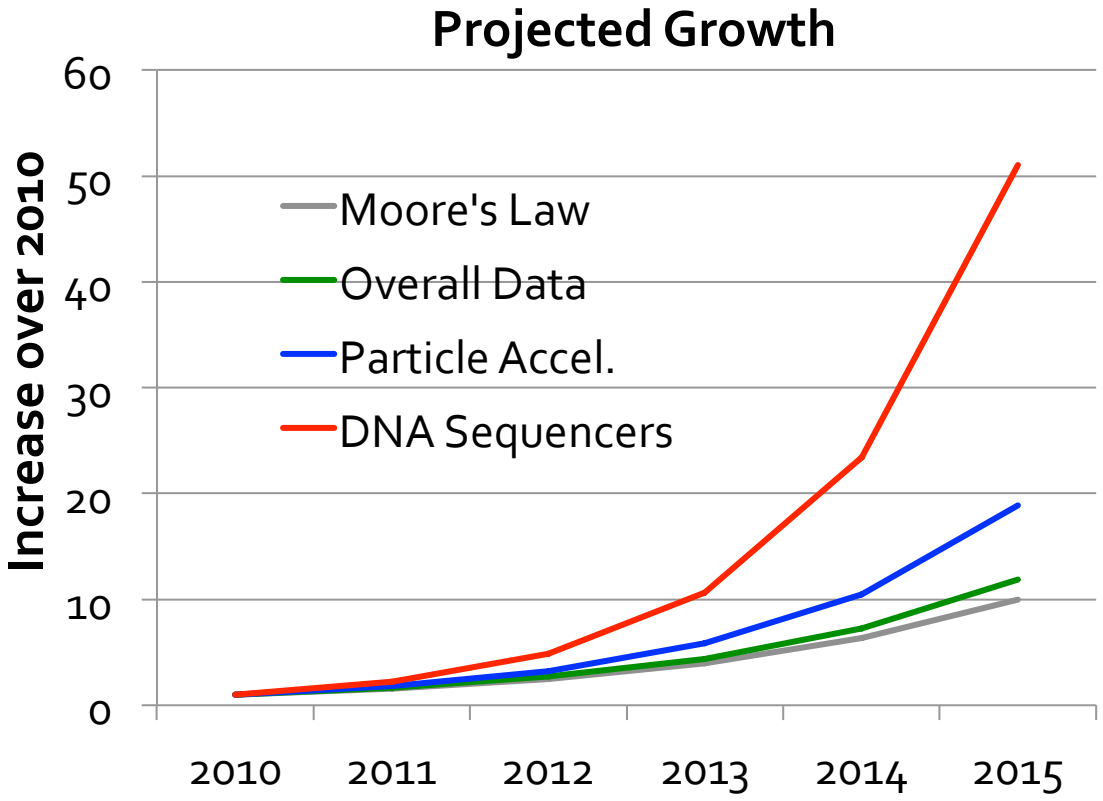
Even if no communication and all data in memory, query may take tens of sec

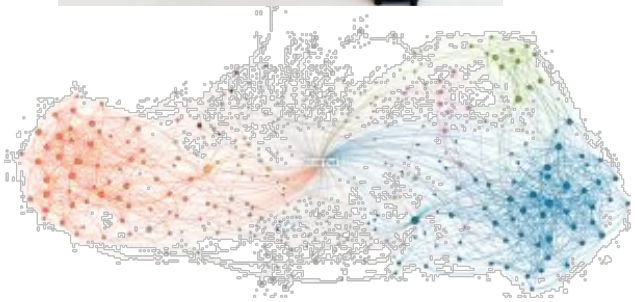
» Just scanning 200-300GB RAM may take 10 sec



Still slow for interactive queries

Why is This a Problem?





Data Grows faster than Moore's Law

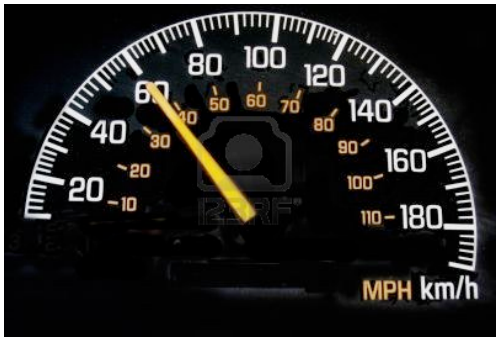
[IDC report, Kathy Yelick, LBNL]

Key Insight

Computations don't always need ***exact*** answers

- Input often ***noisy***: exact computations do ***not*** guarantee exact answers
- ***Error*** often acceptable if ***small*** and ***bounded***

Best scale
± 200g error



Speedometers
± 2.5 % error
(edmunds.com)

OmniPod Insulin Pump
± 0.96 % error
(www.ncbi.nlm.nih.gov/pubmed/22226273)

Approach: Sampling

Compute results on samples instead of full data

» Typically, error depends on sample size (n) ***not*** on original data size, i.e., error $\alpha \ 1/\sqrt{n}$

Can trade between answer's ***latency*** and ***accuracy***

Data rapid increase no longer a "problem":

» Error decreases with Moore's law: halves every **36** months

This Talk

BlinkDB: *approximate query engine for very large data sets using off-line sampling*

BlinkDB Interface

SELECT avg(sessionTime)

FROM Table

WHERE city='San Francisco' AND 'dt=2012-9-2'

WITHIN 1 SECONDS  234.23 ± 15.32

BlinkDB Interface

SELECT avg(sessionTime)

FROM Table

WHERE city='San Francisco' AND 'dt=2012-9-2'

WITHIN 2 SECONDS  ~~234.23 ± 15.32~~

239.46 ± 4.96

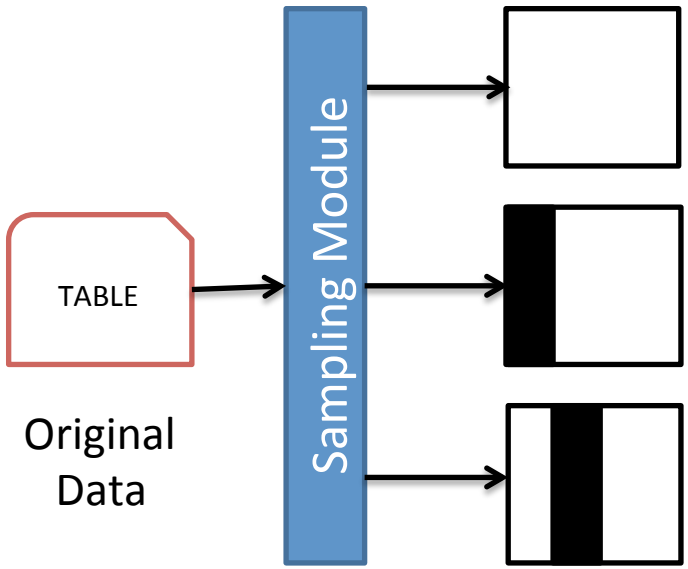
SELECT avg(sessionTime)

FROM Table

WHERE city='San Francisco' AND 'dt=2012-9-2'

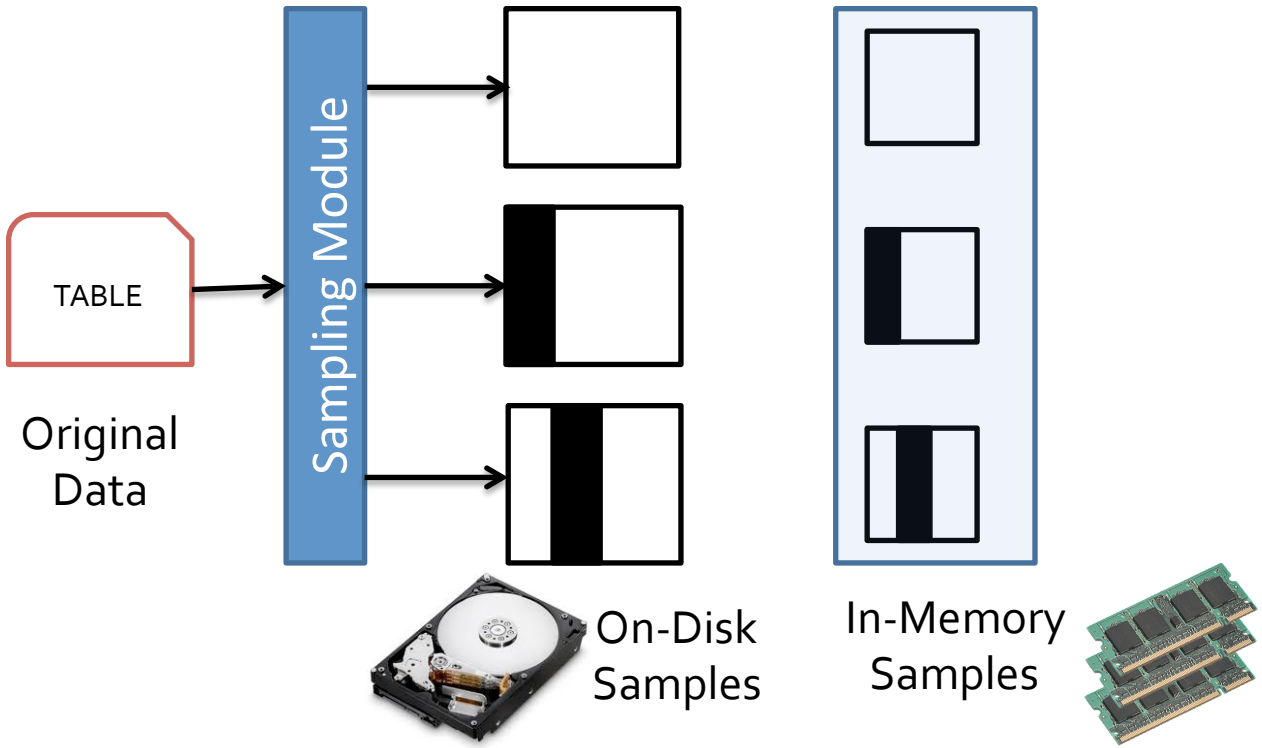
ERROR 0.1 **CONFIDENCE** 95.0%

BlinkDB Overview



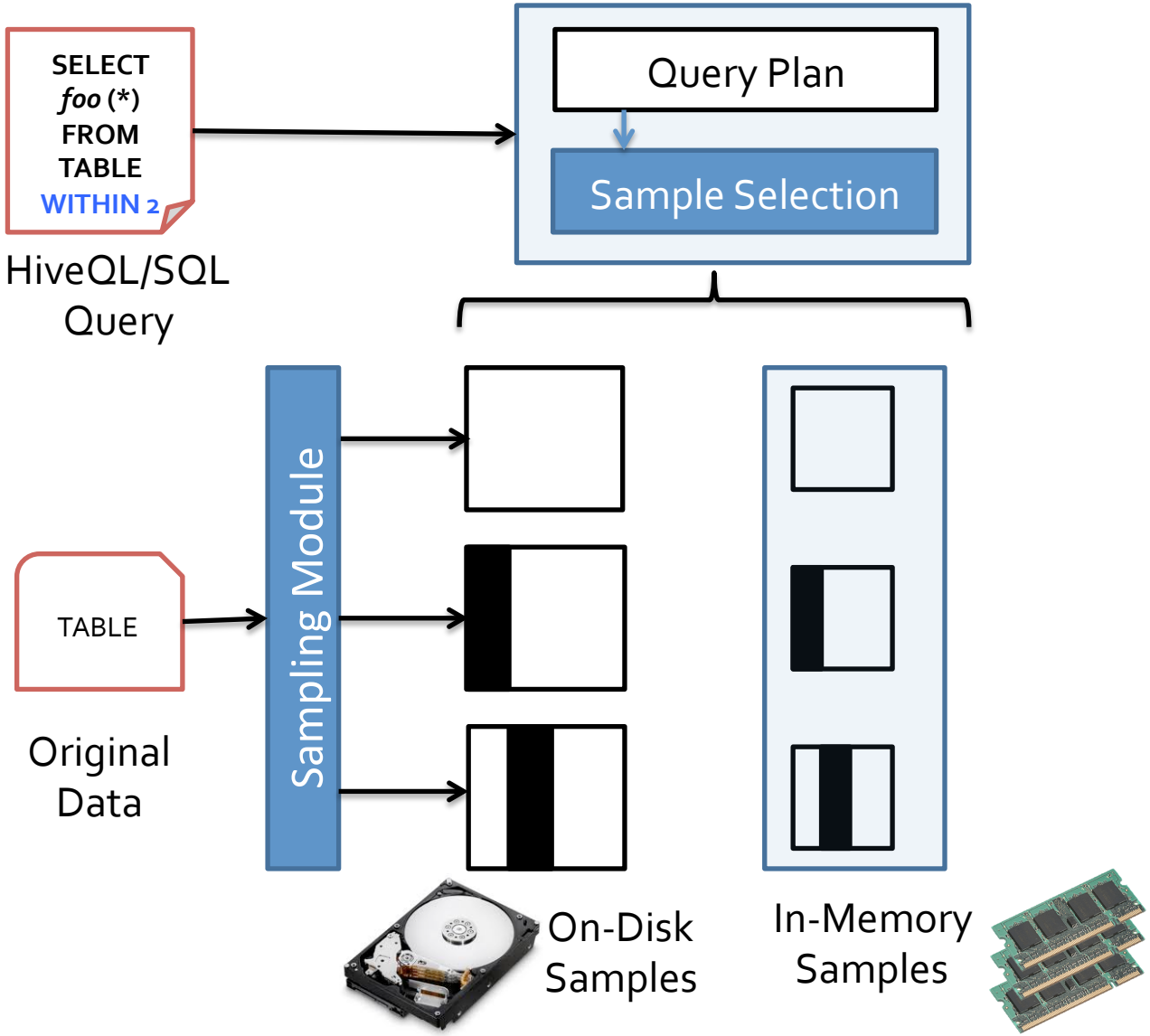
Offline-sampling: Optimal set of samples across different dimensions (*columns or sets of columns*) to support ad-hoc exploratory queries

BlinkDB Overview

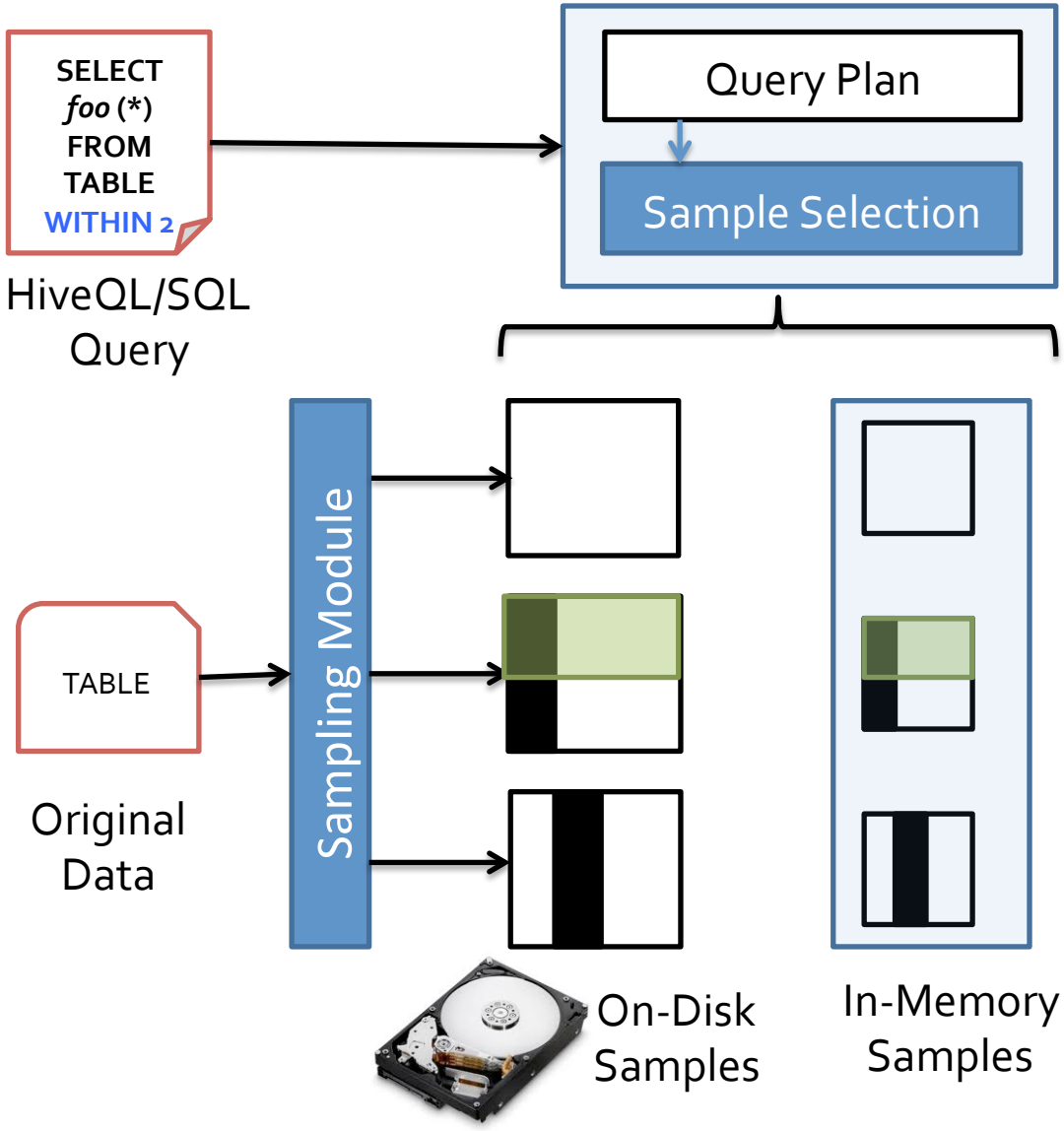


Sample Placement: Samples striped over 100s or 1,000s of machines both on disks and in-memory.

BlinkDB Overview

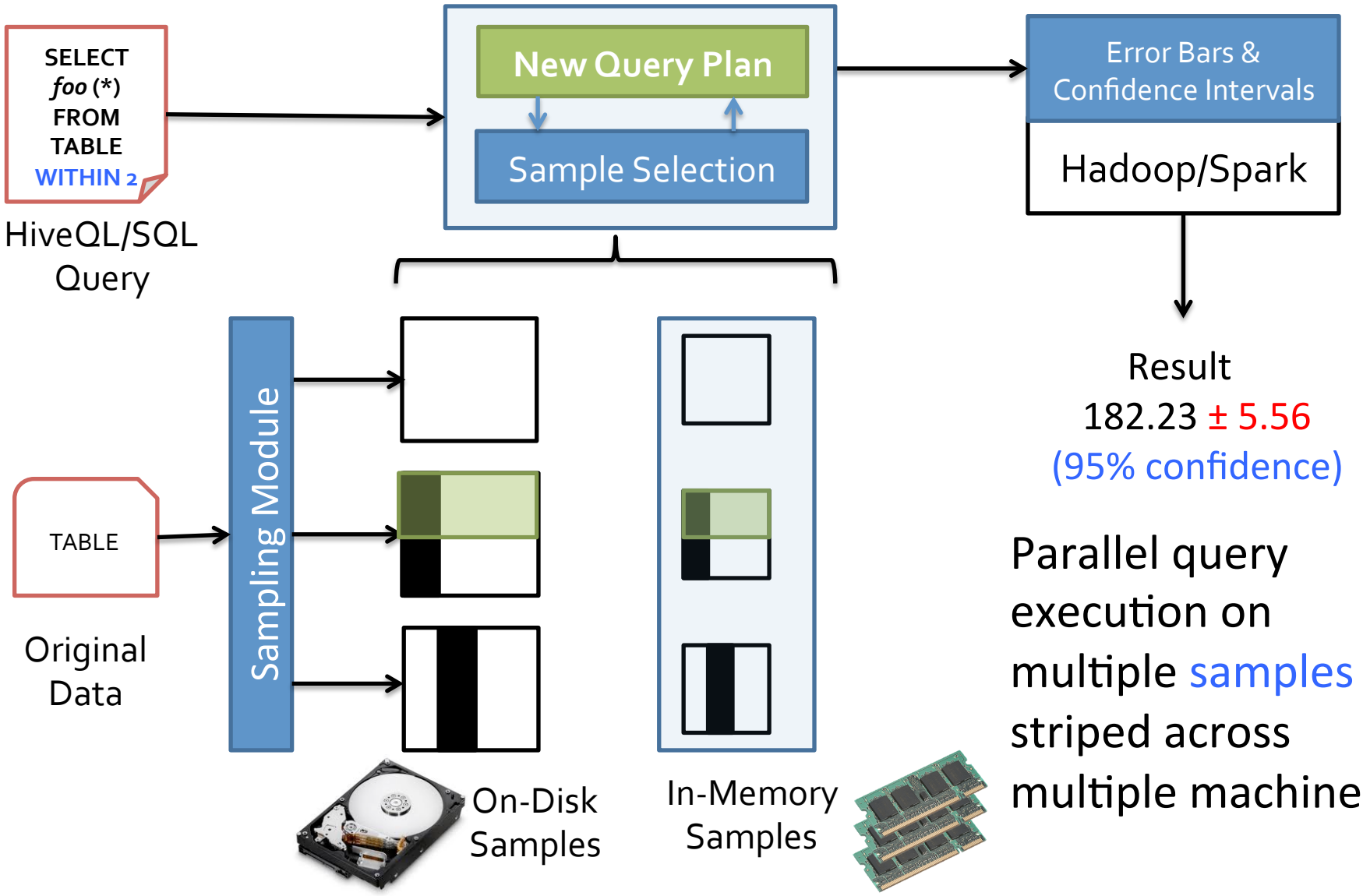


BlinkDB Overview



Online sample selection to pick best sample(s) based on query latency and accuracy requirements

BlinkDB Overview



Challenges

Which set of samples to build given a storage budget?

Which sample to run the query on?

How to accurately estimate the error?

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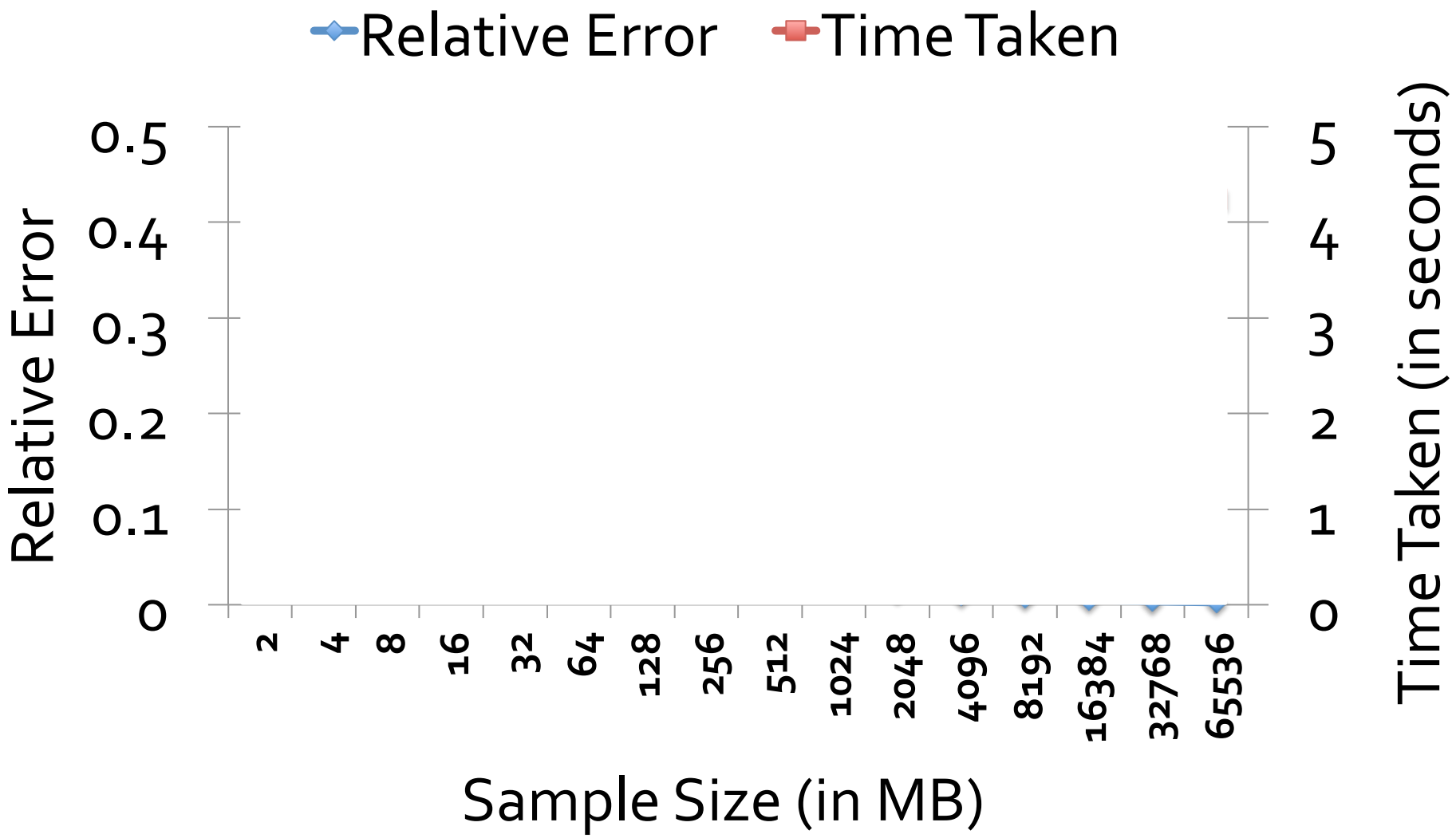
Error Latency Profile (ELP)



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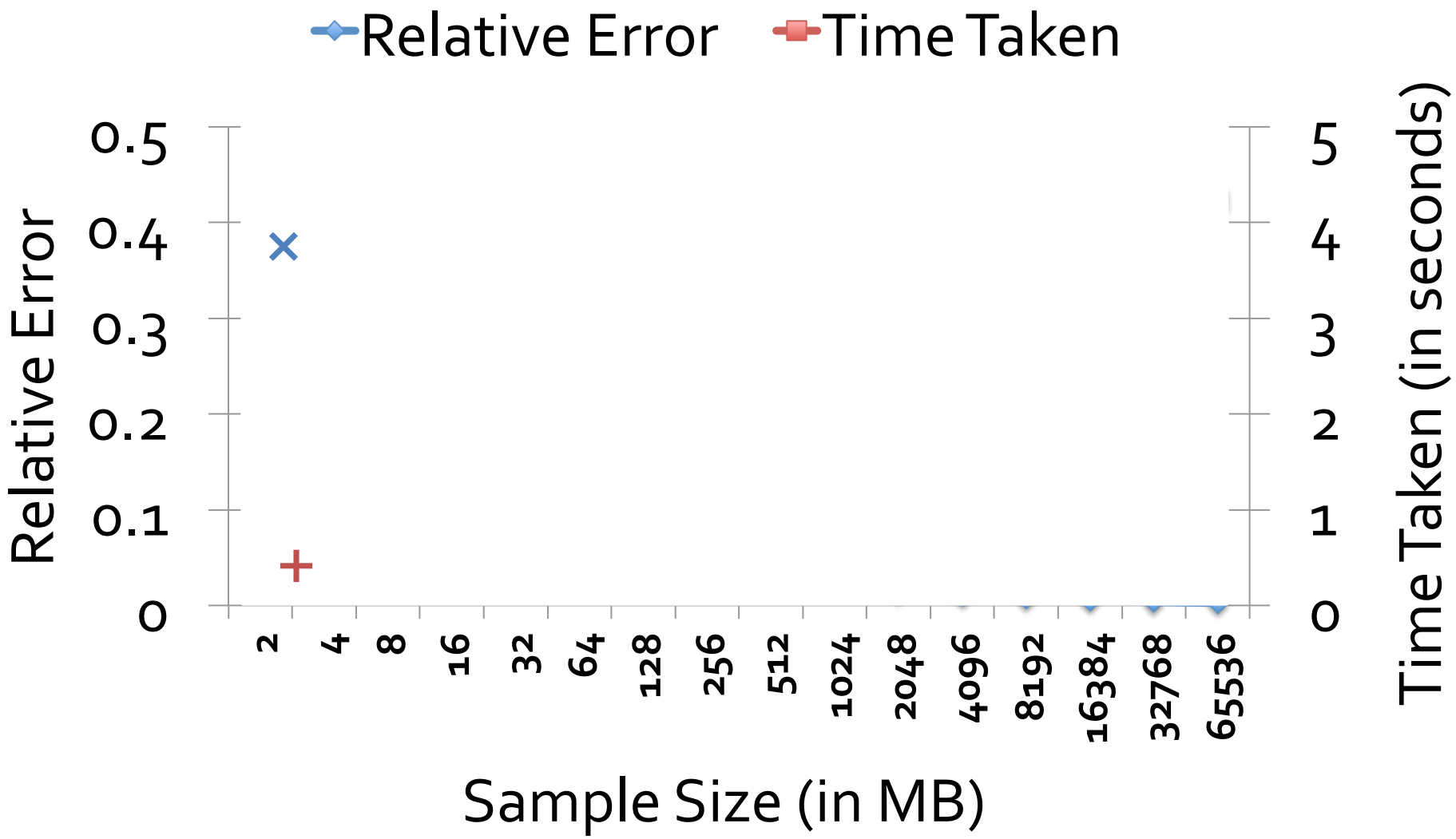

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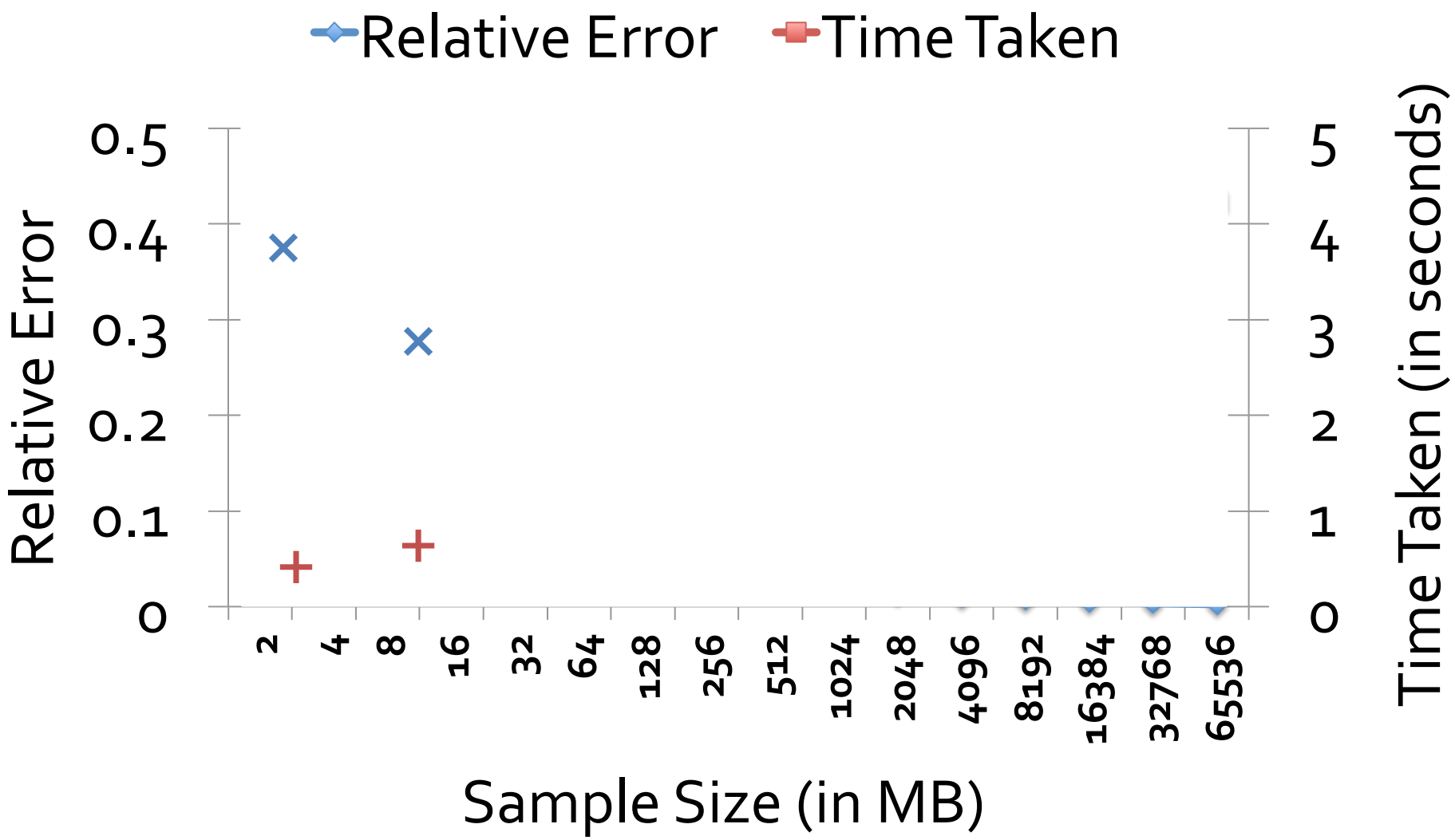

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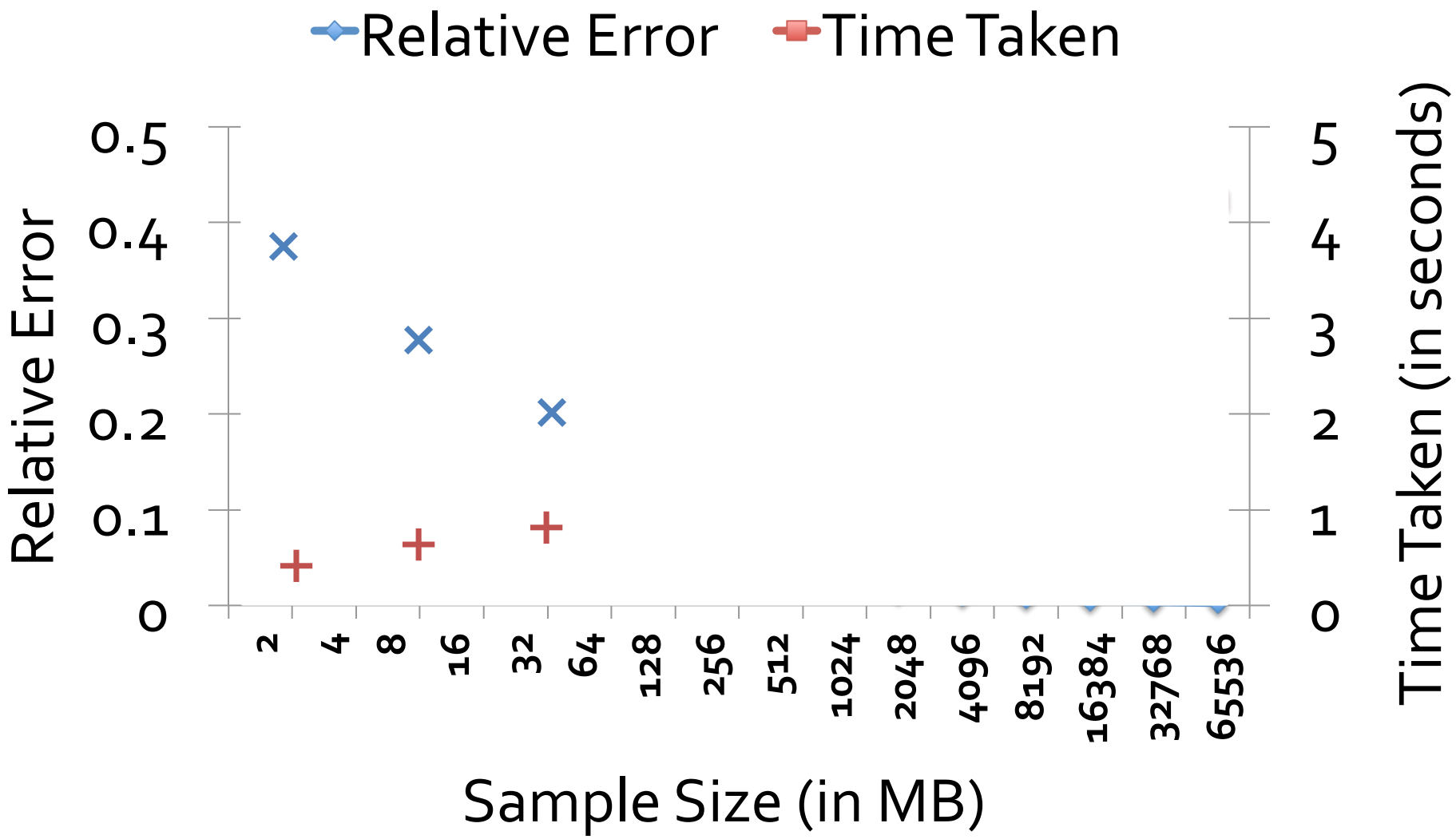

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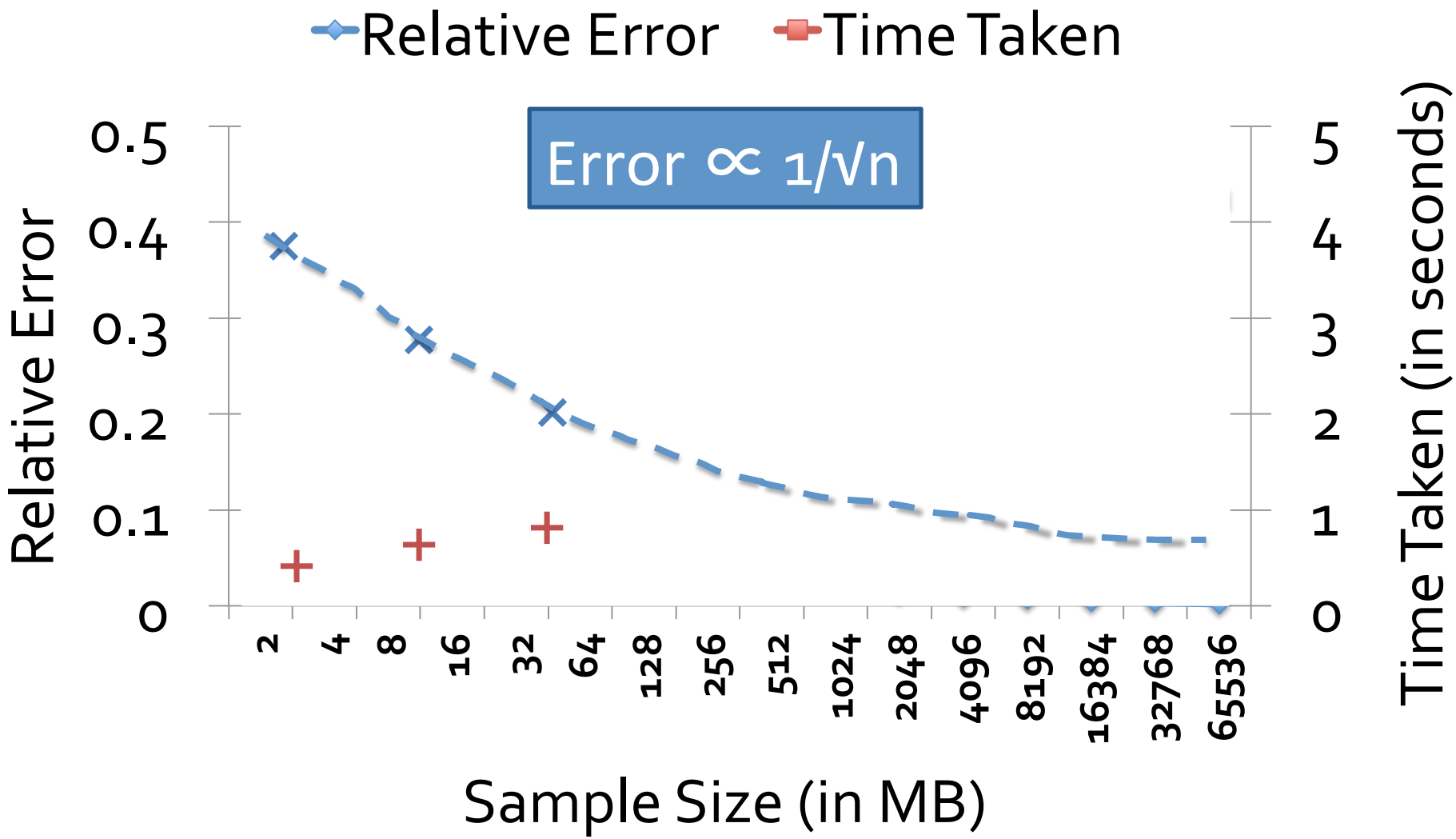

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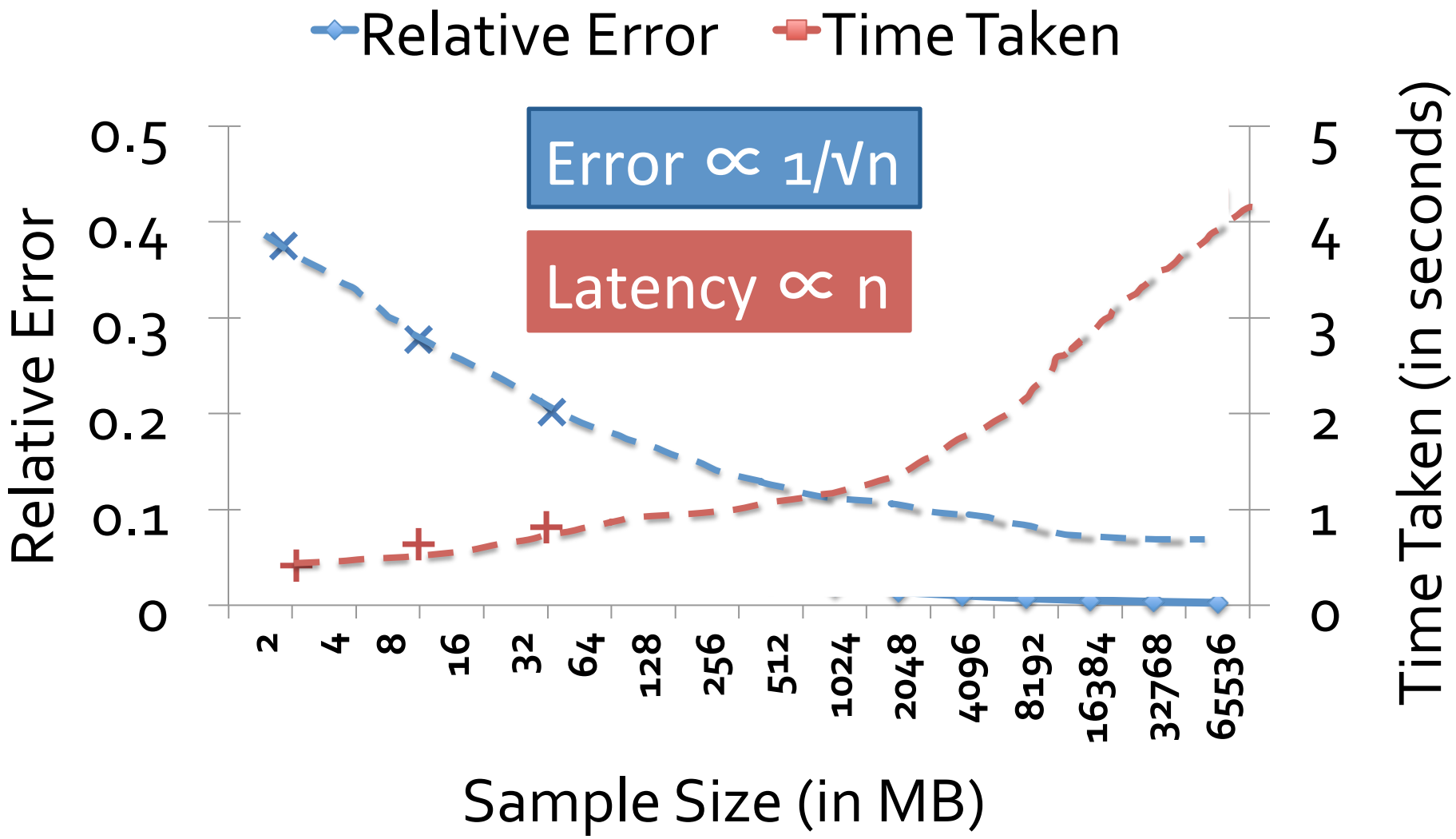
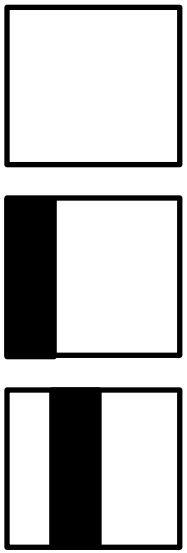
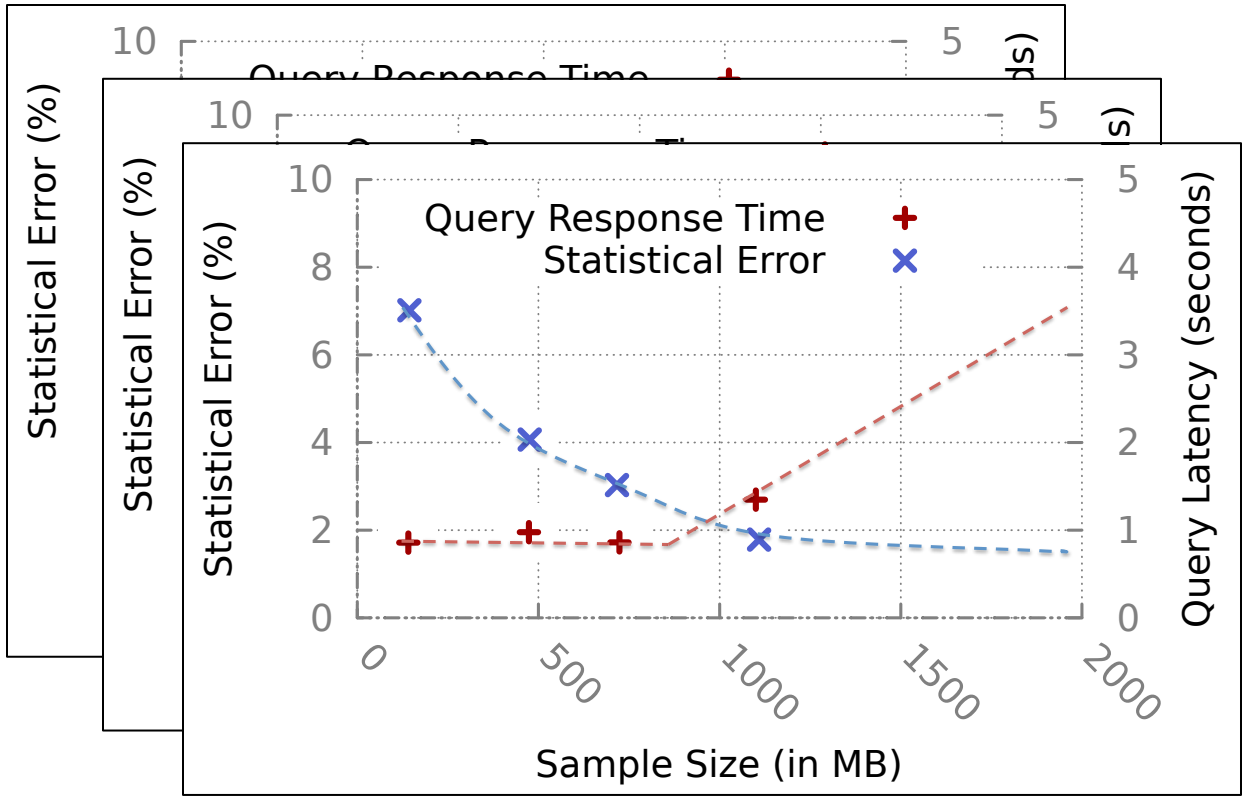


Error Latency Profile (ELP)

```
SELECT
foo (*)
FROM
TABLE
WITHIN 2
```





Error Latency Profile (ELP)

```
SELECT
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```
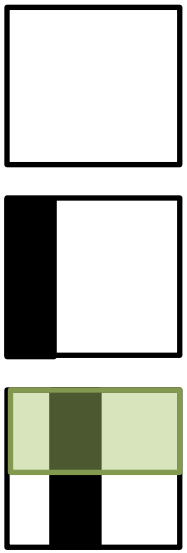
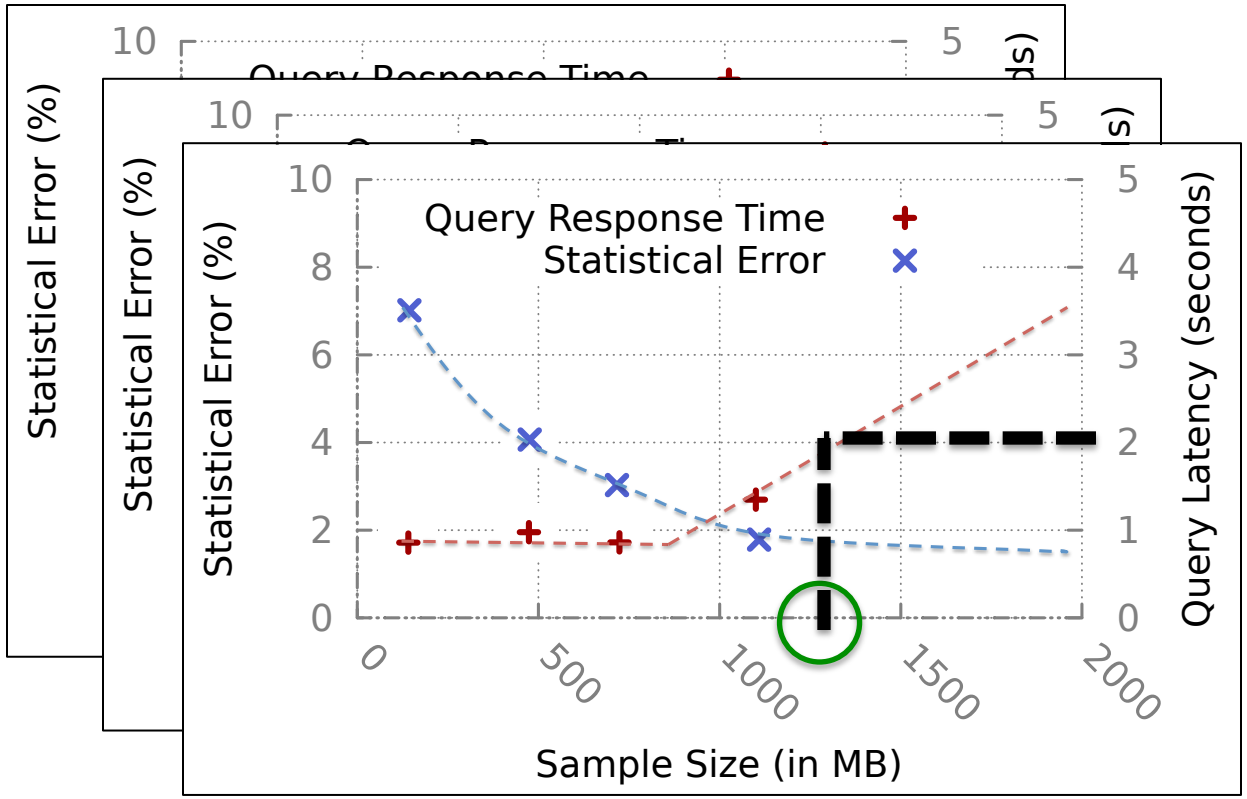

≈ 400 ms





Challenges

Which set of samples to build given a storage budget?

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How to accurately estimate the error?

How to Accurately Estimate Error?

Close formulas for limited number of operators
- » E.g., count, mean, percentiles

What about user defined functions (UDFs)?

Experimental Workload

Conviva: 30-day log of media accesses by Conviva users. Raw data 17 TB, partitioned this data across 100 nodes

Log of 20,000 queries

» 43.6% queries have one or more UDFs

Storage budget: 50% of original data

» 8 stratified samples

Experimental Setting

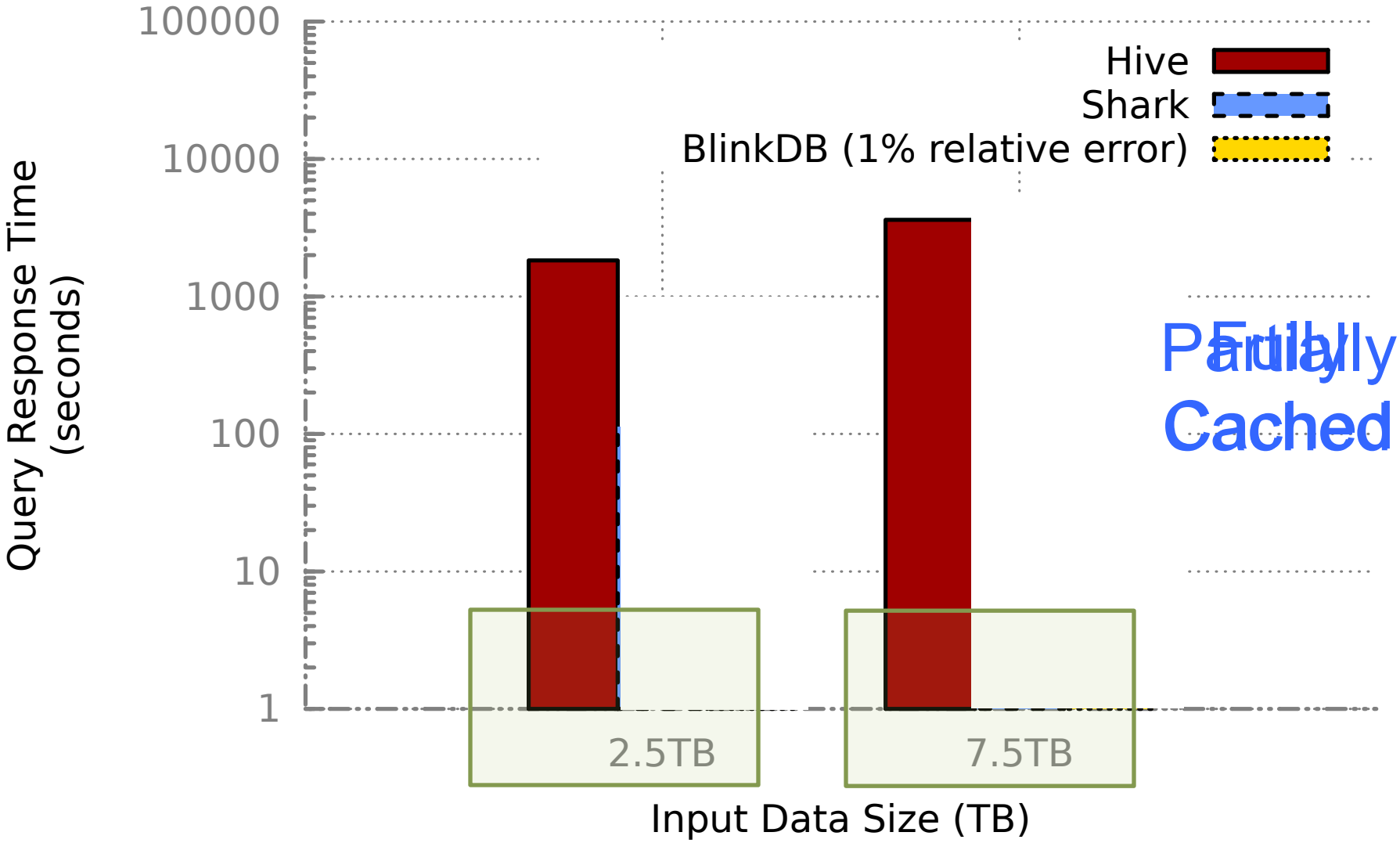
100 node cluster of EC2 extra large instances:

- » 800 cores
- » 6.8TB RAM
- » 75TB disk

Two datasests: 2.5TB, and 7.5TB, respectively

- » Significantly larger when stored in memory

Sampling vs. No Sampling
(close formula)



Sampling vs. No Sampling
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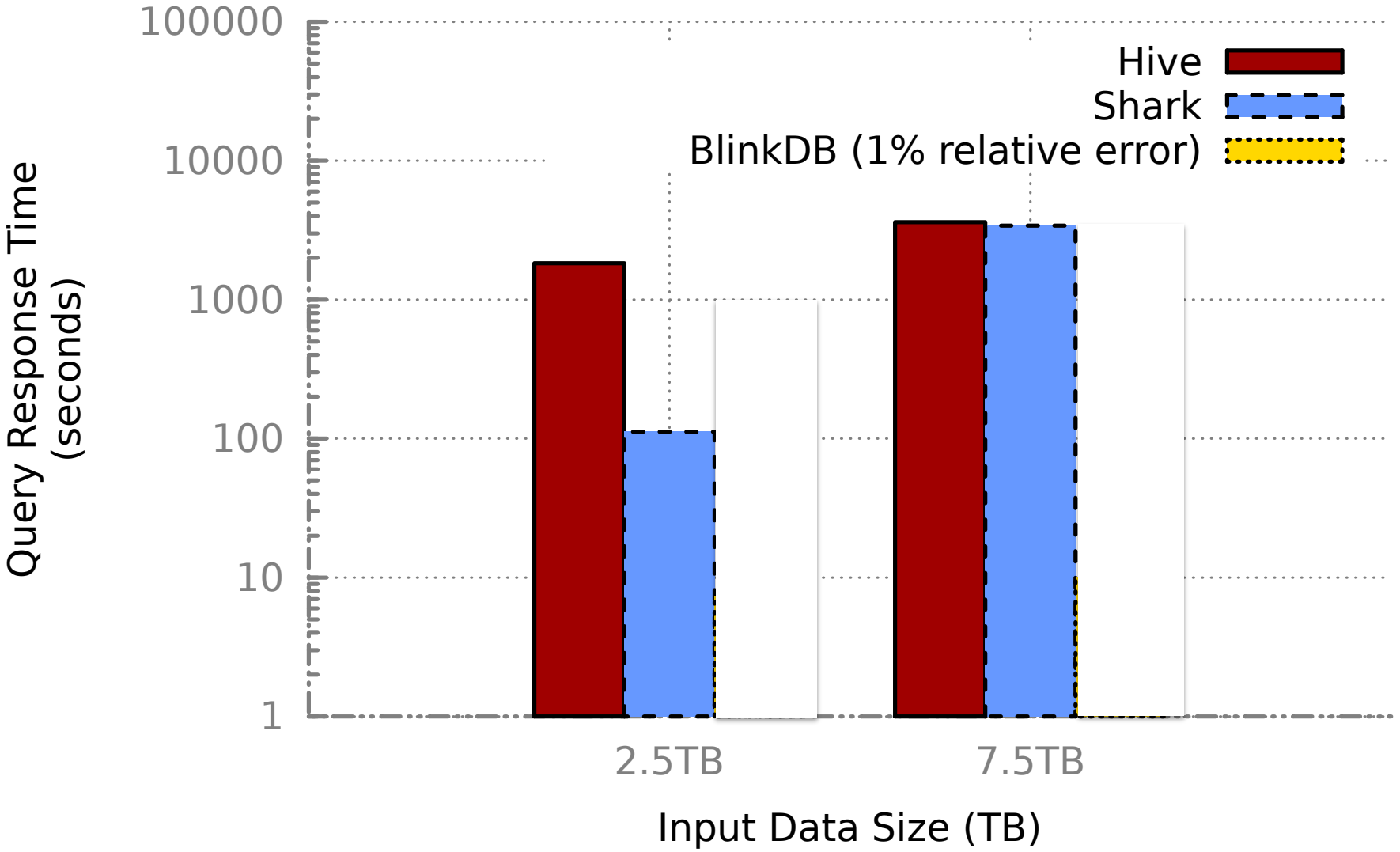

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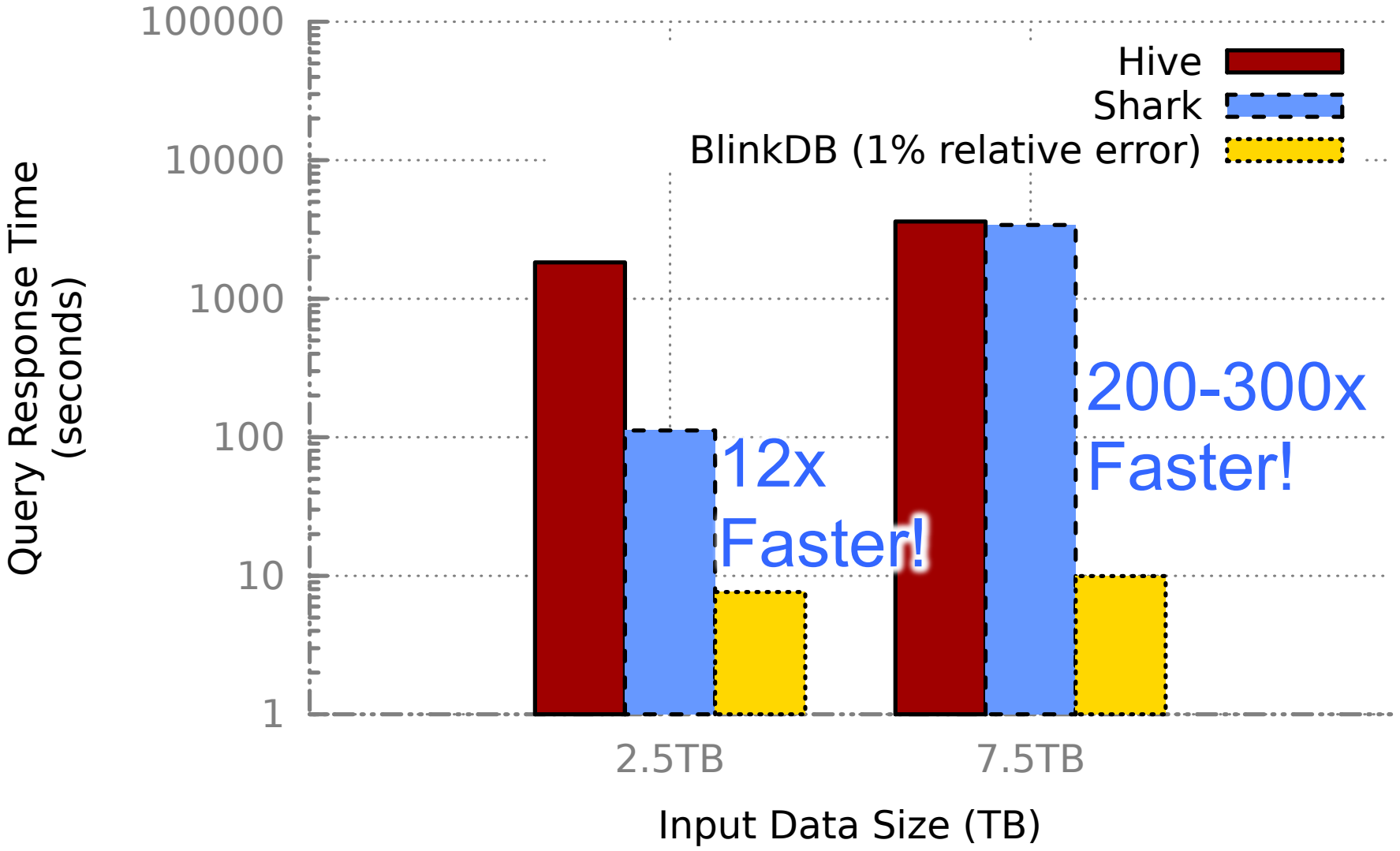


How to Accurately Estimate Error?

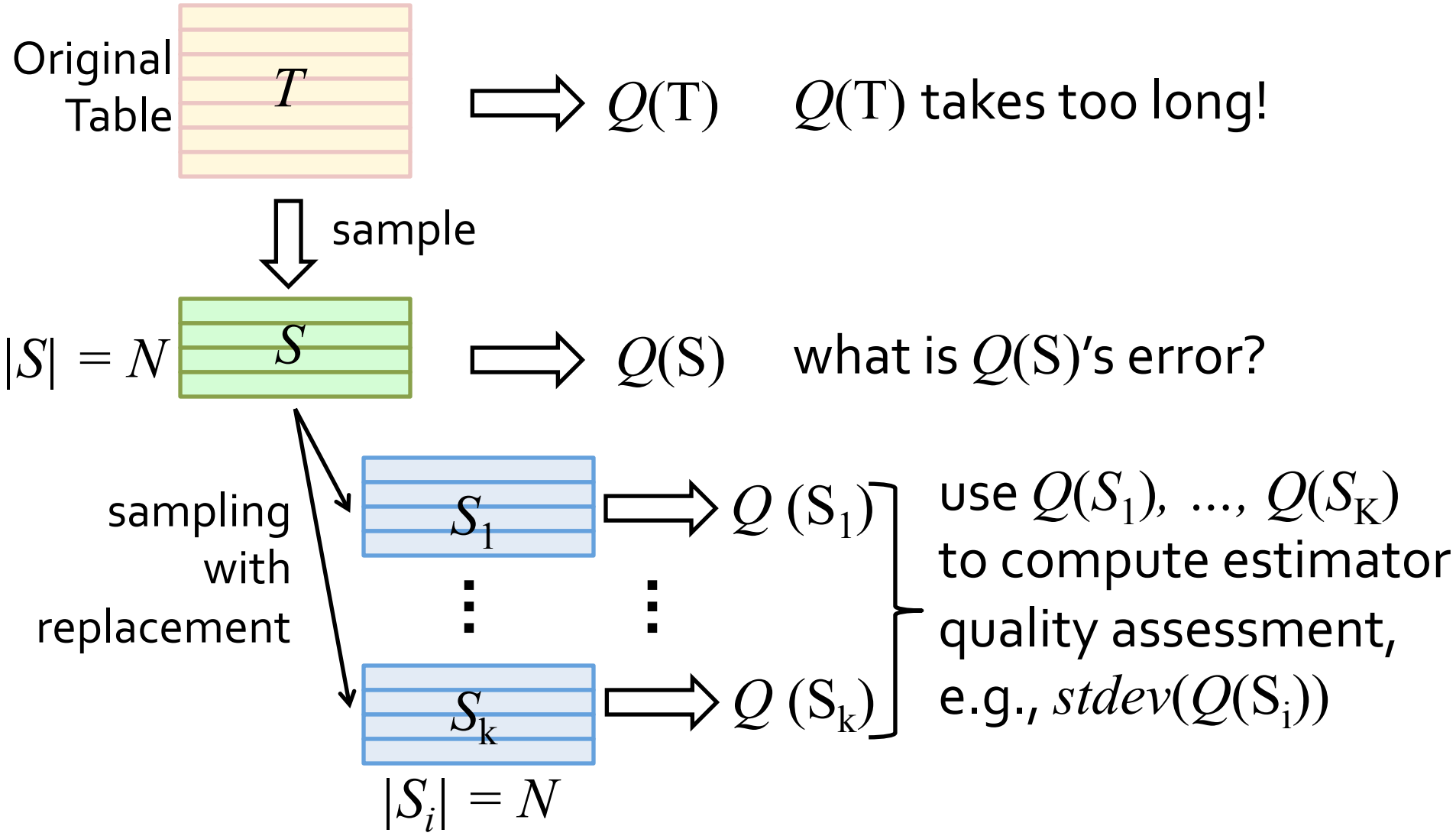
Close formulas for limited number of operators

» E.g., count, mean, percentiles

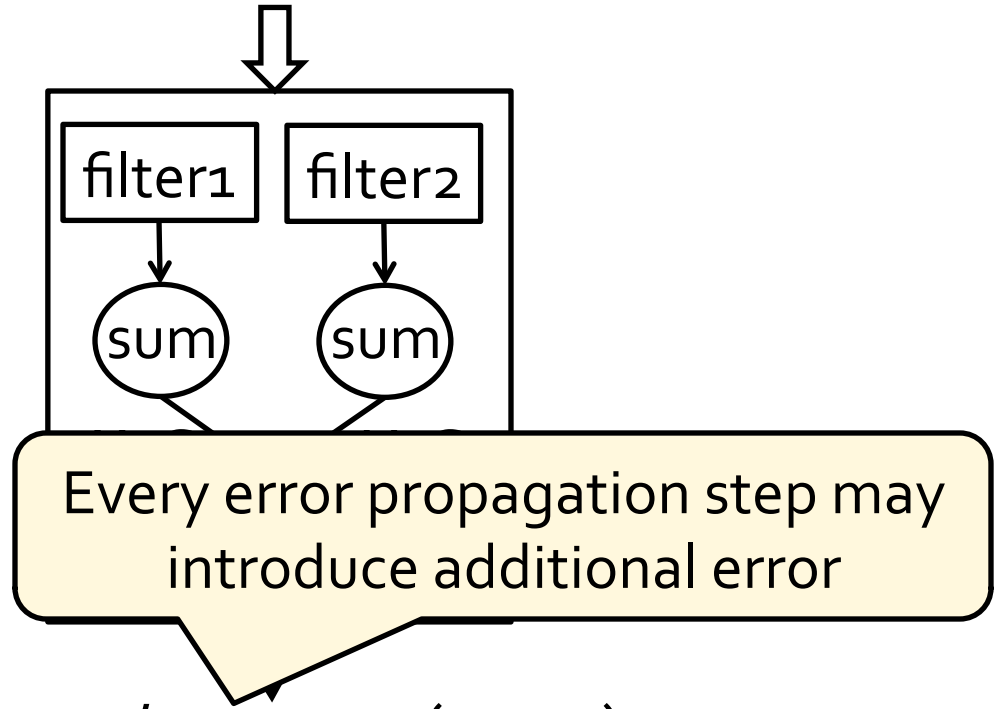
What about user defined functions (UDFs)?

Bootstrap

Quantify accuracy of a query on a sample table



Also Useful for Close Formulas



$r = x/y,\ \varepsilon = epr(\varepsilon_1, \varepsilon_2)$

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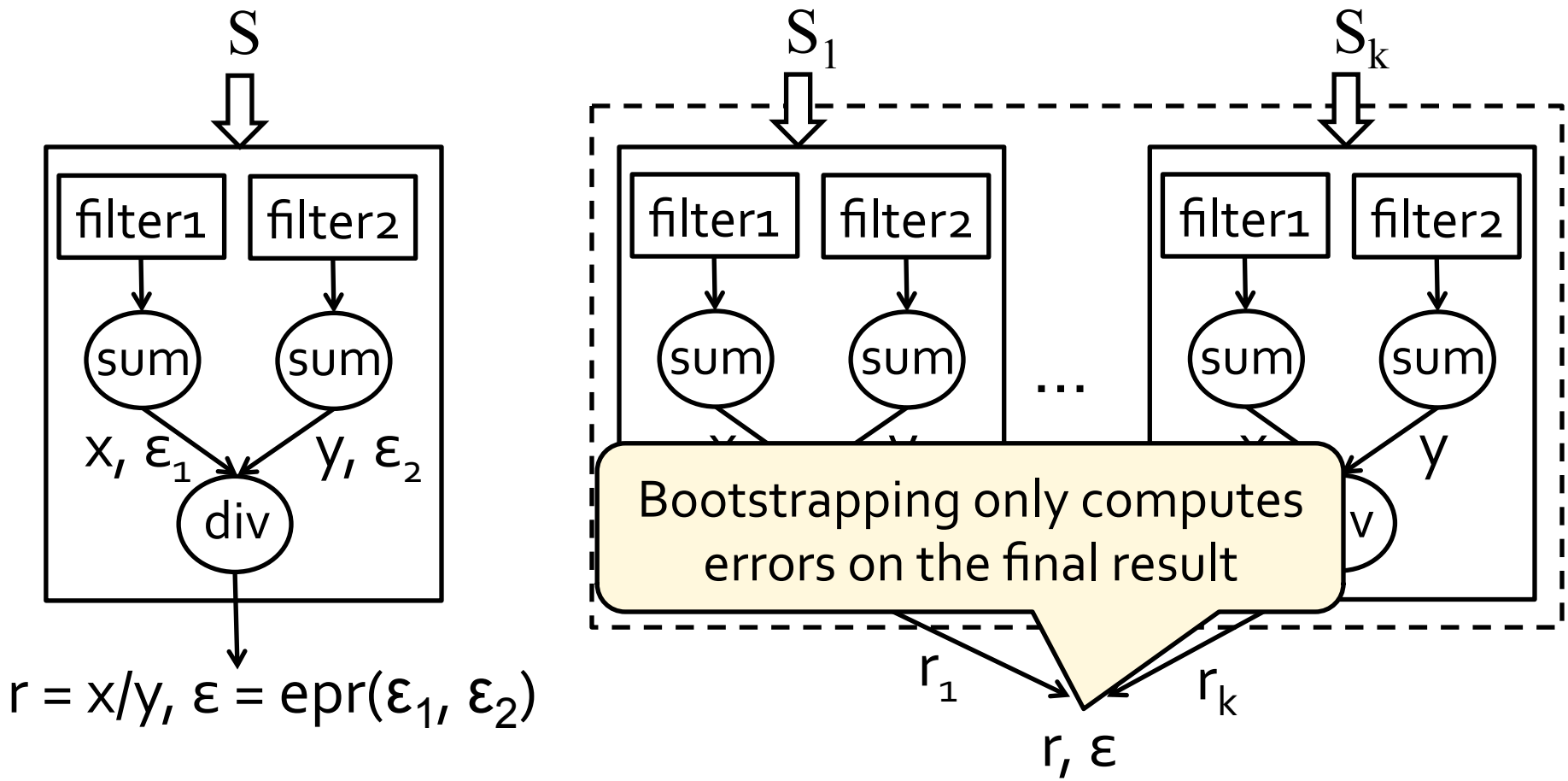

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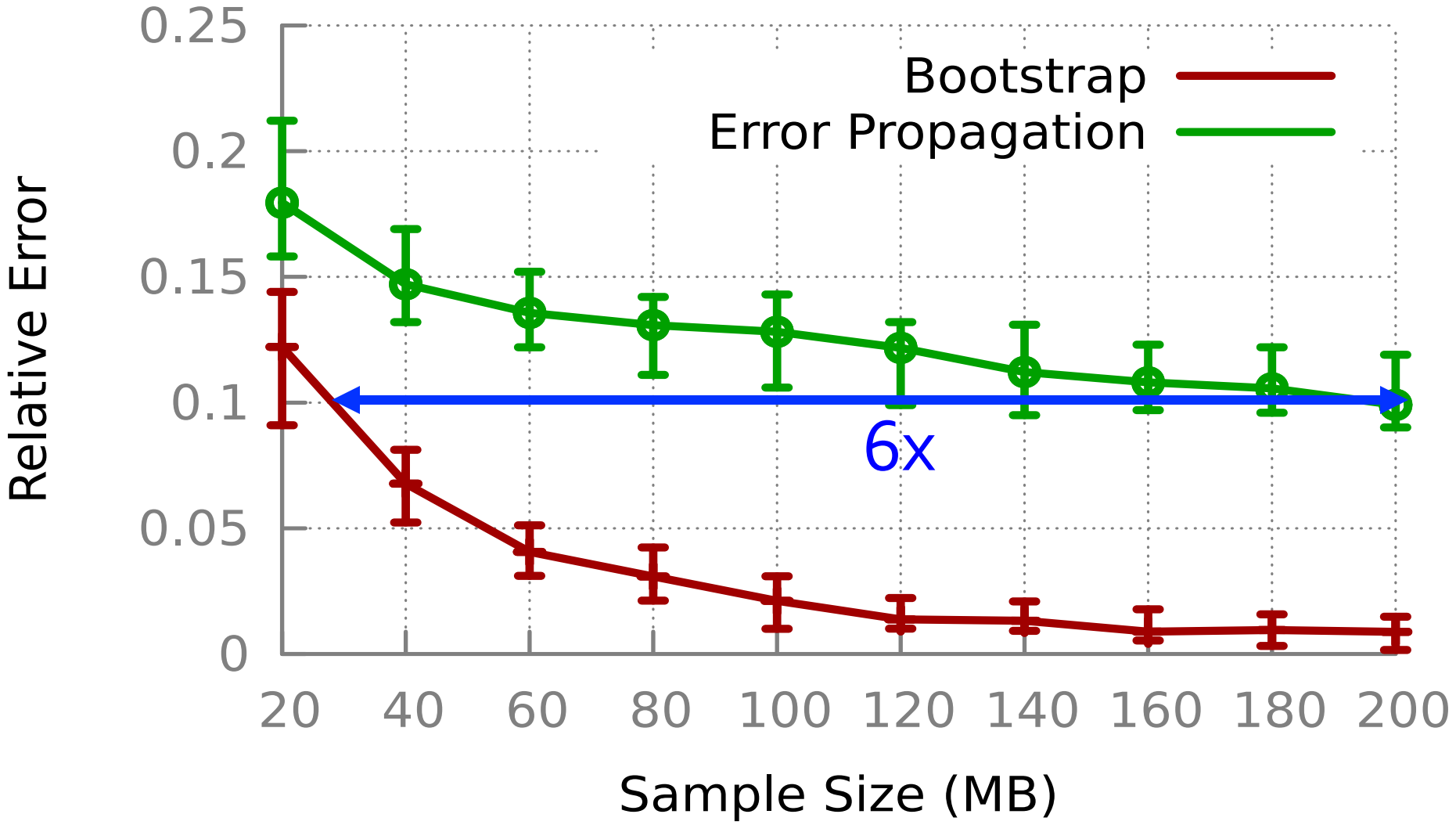


Bootstrap Challenges

How do you know the bootstrap is working?

» Depends on distribution, computation, sample size

Overhead

How Do You Know Bootstrap is Working?

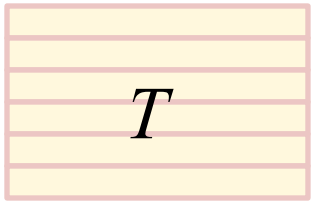
Assumption: $f()$ is Hadamard differentiable

- How do you know an UDF is Hadamard differentiable?
- Only **asymptotic** consistency
- Sufficient, not necessary condition

Developed data-driven diagnostic for Bootstrap

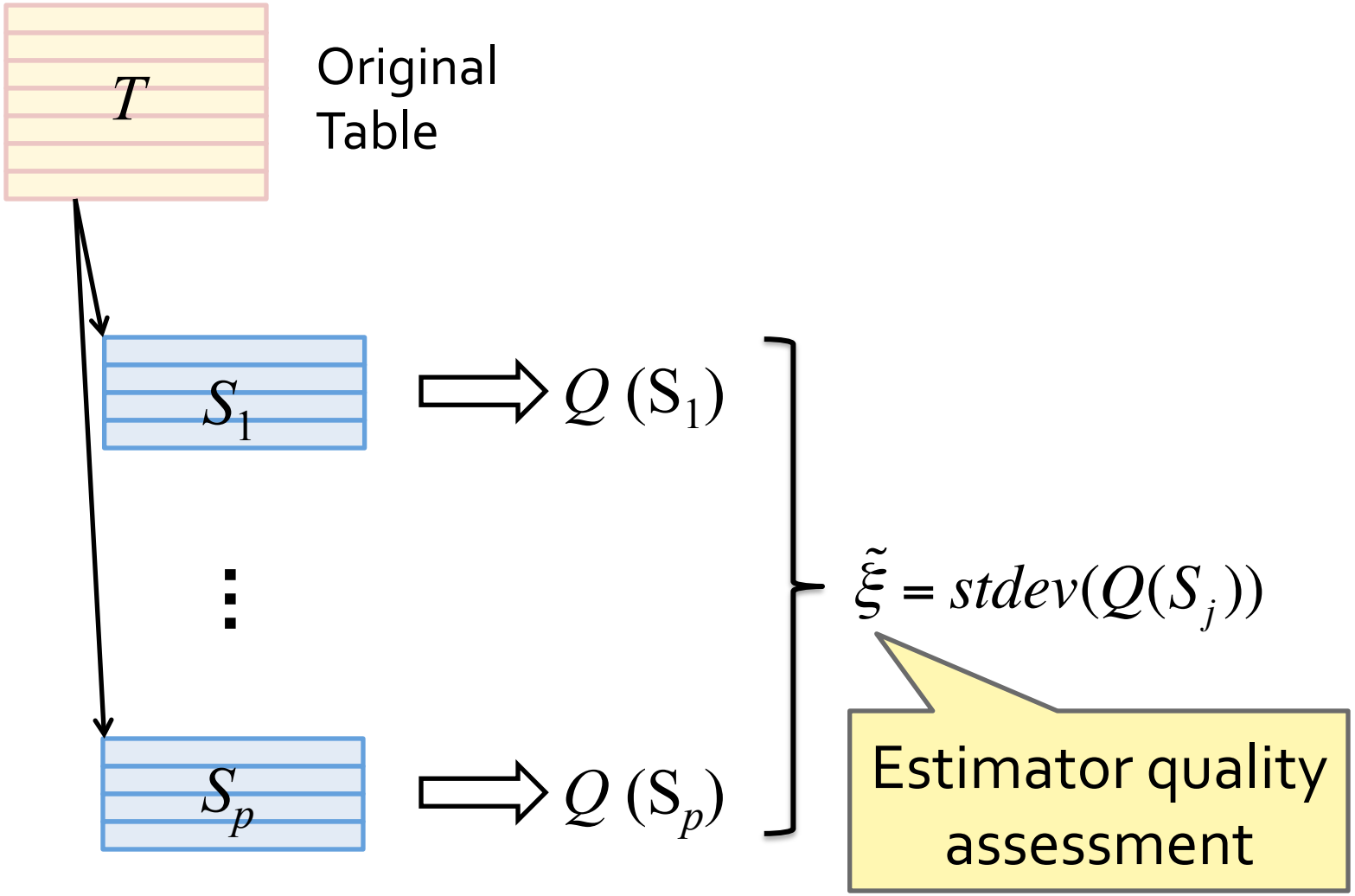
- Compare bootstrapping with **ground truth** for small samples
- Check whether error improves as sample size increases

Ground Truth (Approximation)

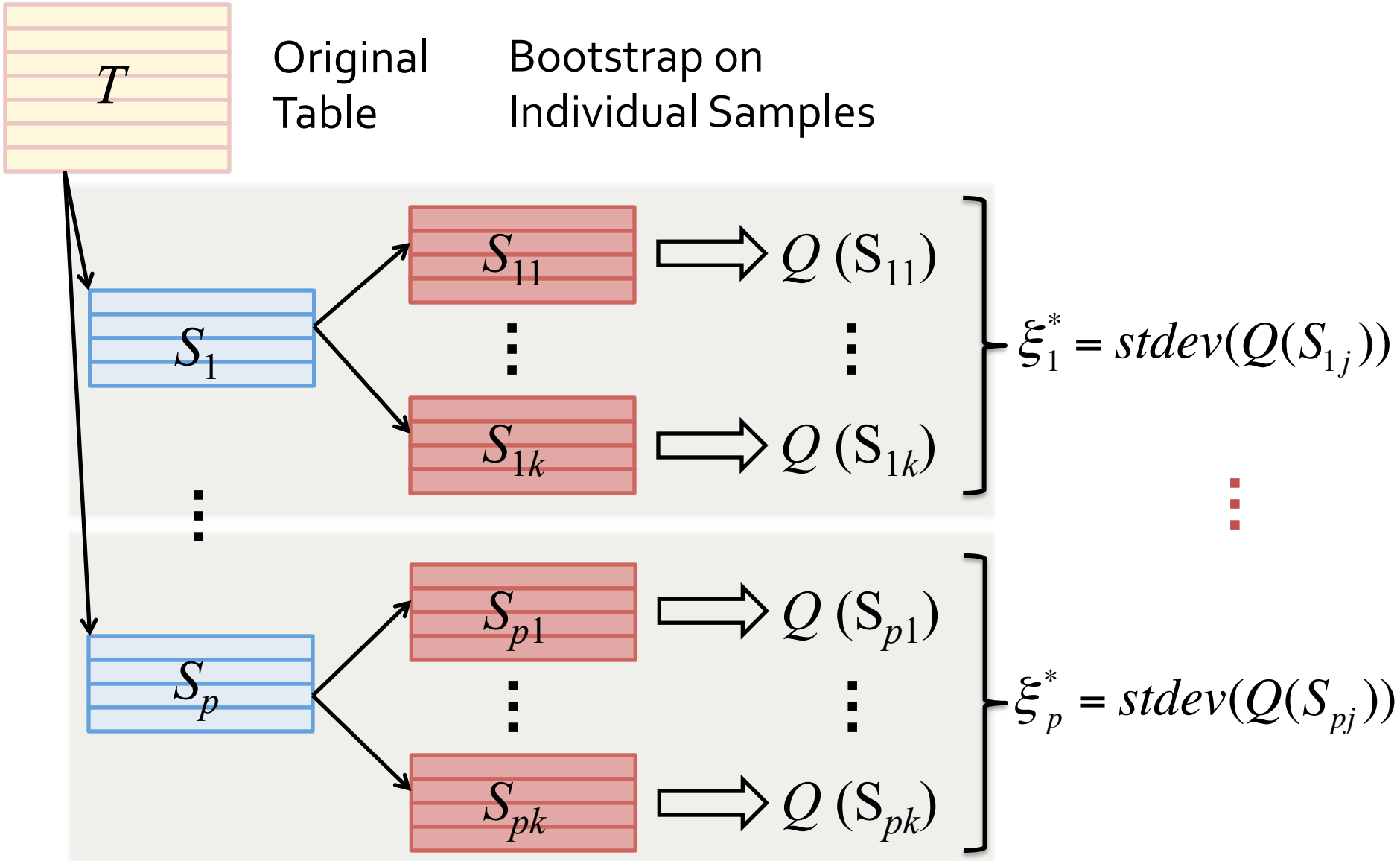


Original
Table

Ground Truth (Approximation)



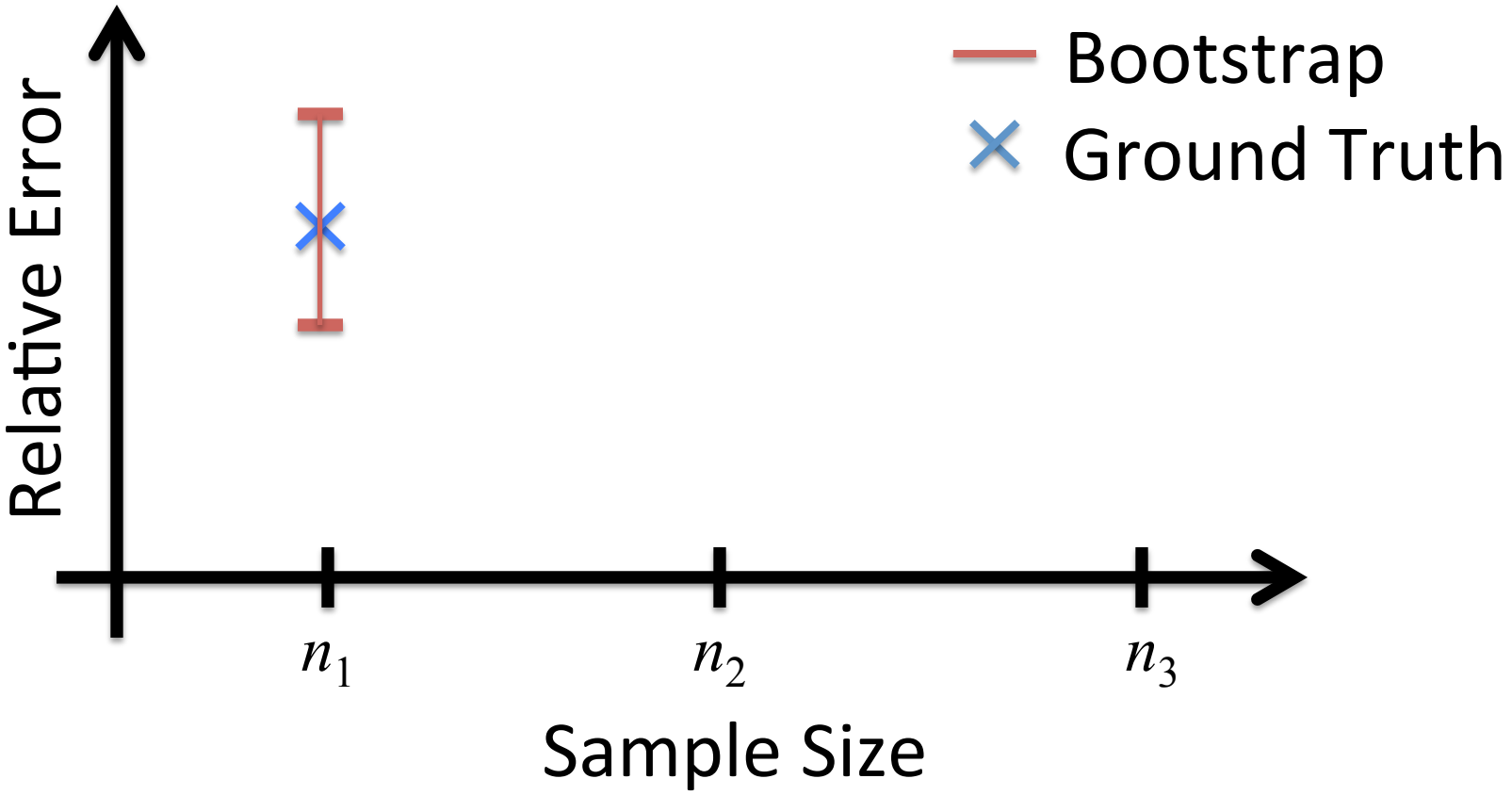
Ground Truth and Bootstrap



Ground Truth vs. Bootstrap

$$\tilde{\xi}_i = mean(\xi_{ij})$$

$$\xi^*_{i1} = stdev(Q(S_{i1j})) \quad \cdots \quad \xi^*_{ip} = stdev(Q(S_{ipj}))$$



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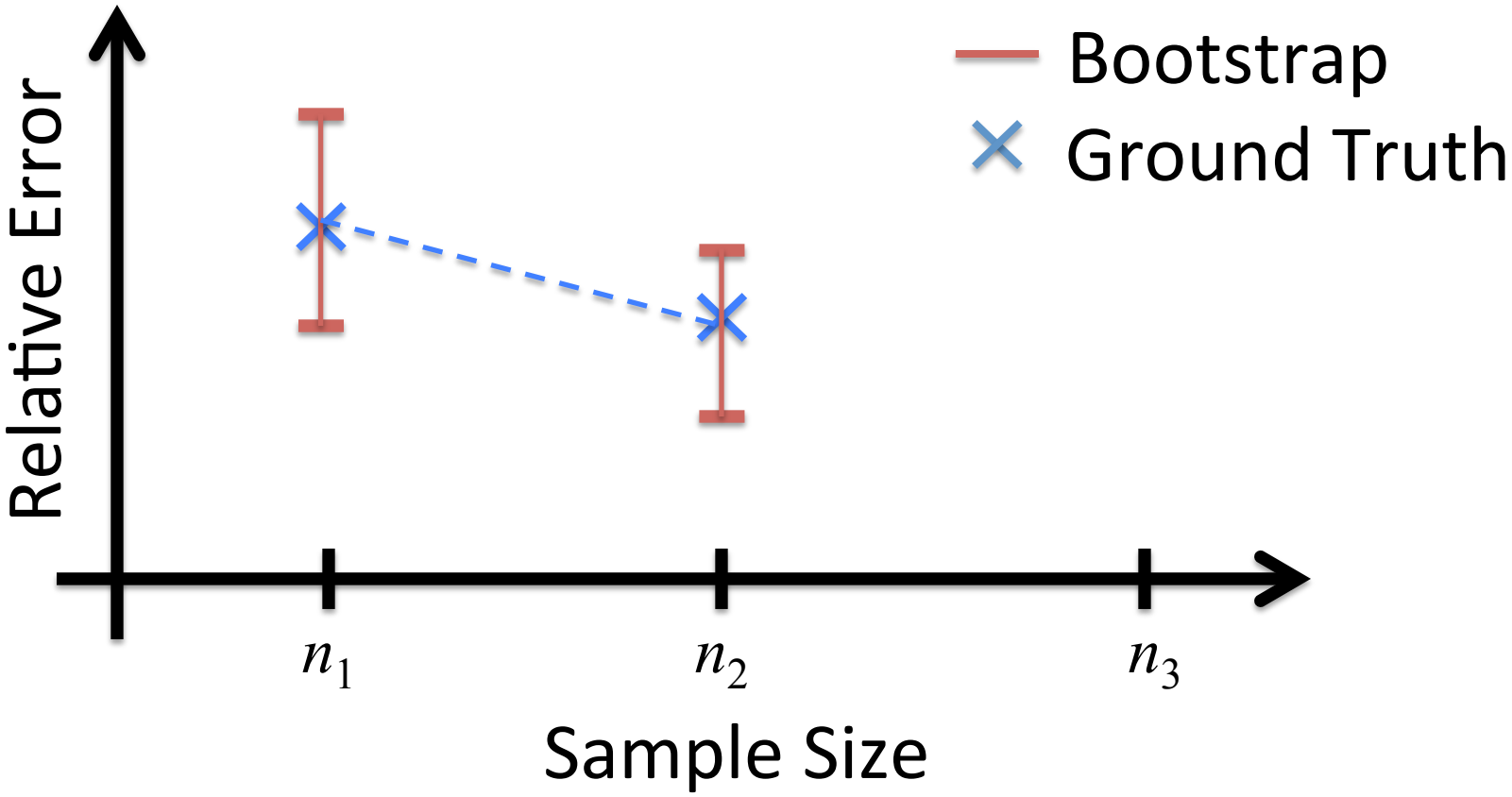

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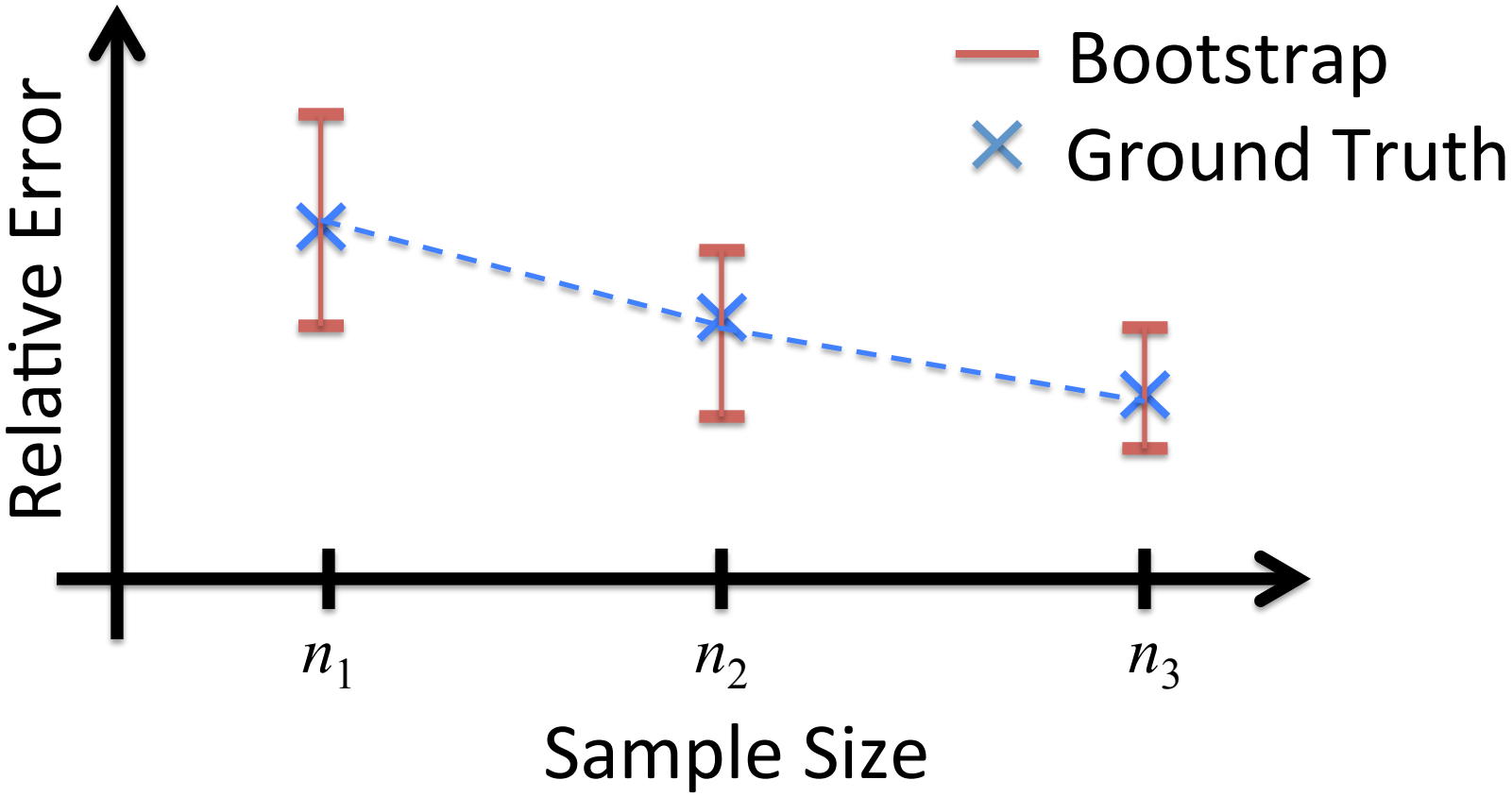


Bootstrap Diagnosis

Expectation test:

» Bootstrap results should not deviate "too much" from ground truth, on average

Standard deviation test:

» Bootstrap results should not vary "too much"

Confidence interval test:

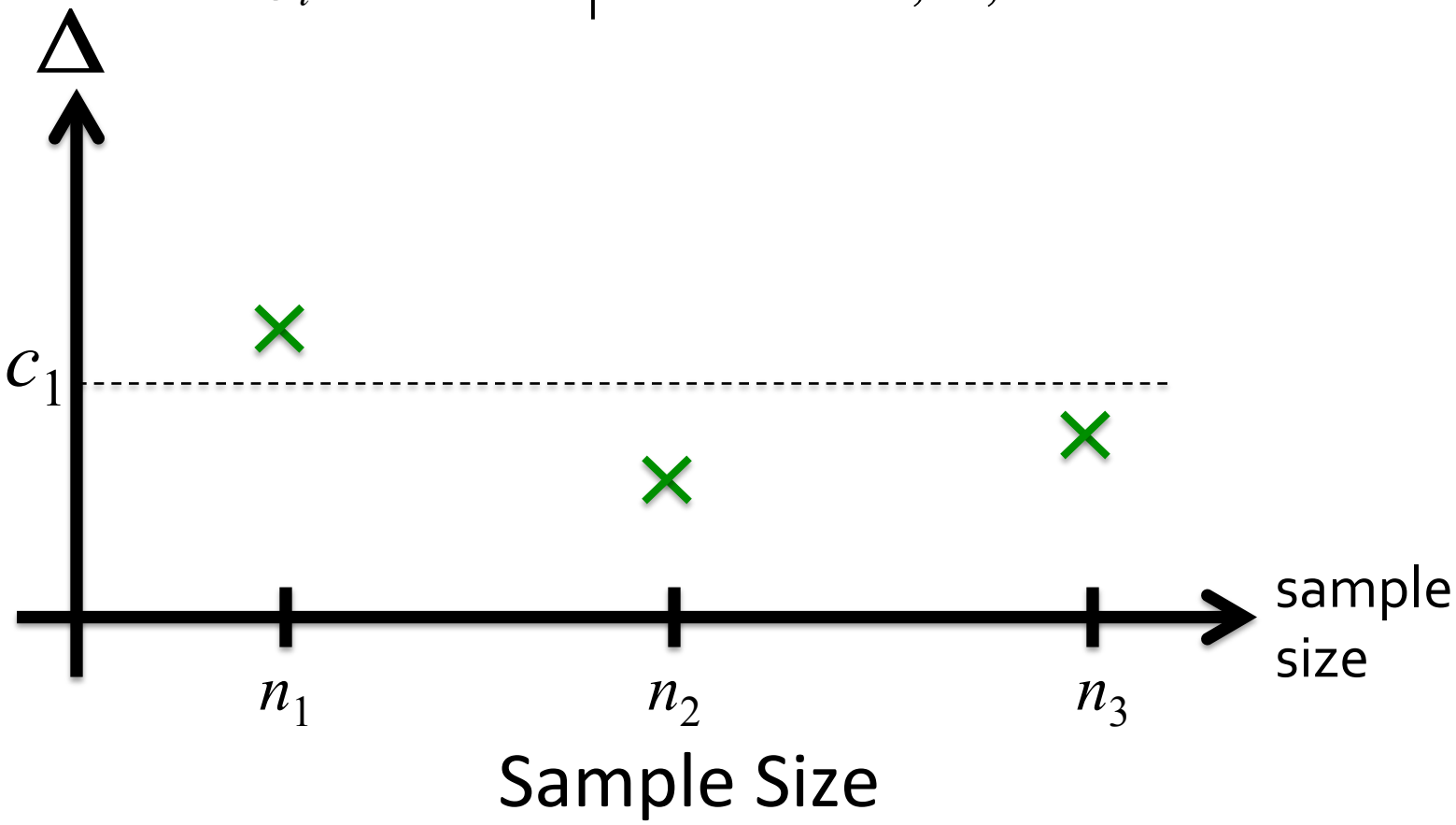
» Most (e.g., 95%) of bootstrap results should be "close" to ground truth

Expectation Test

$$\Delta_i \leftarrow \left| \frac{mean(\xi^*_{i1},\ldots,\xi^*_{ip}) - \tilde{\xi}_i}{\tilde{\xi}_i} \right|$$

$$(\Delta_{i+1} < \Delta_i) \vee (\Delta_{i+1} \leq c_1)$$

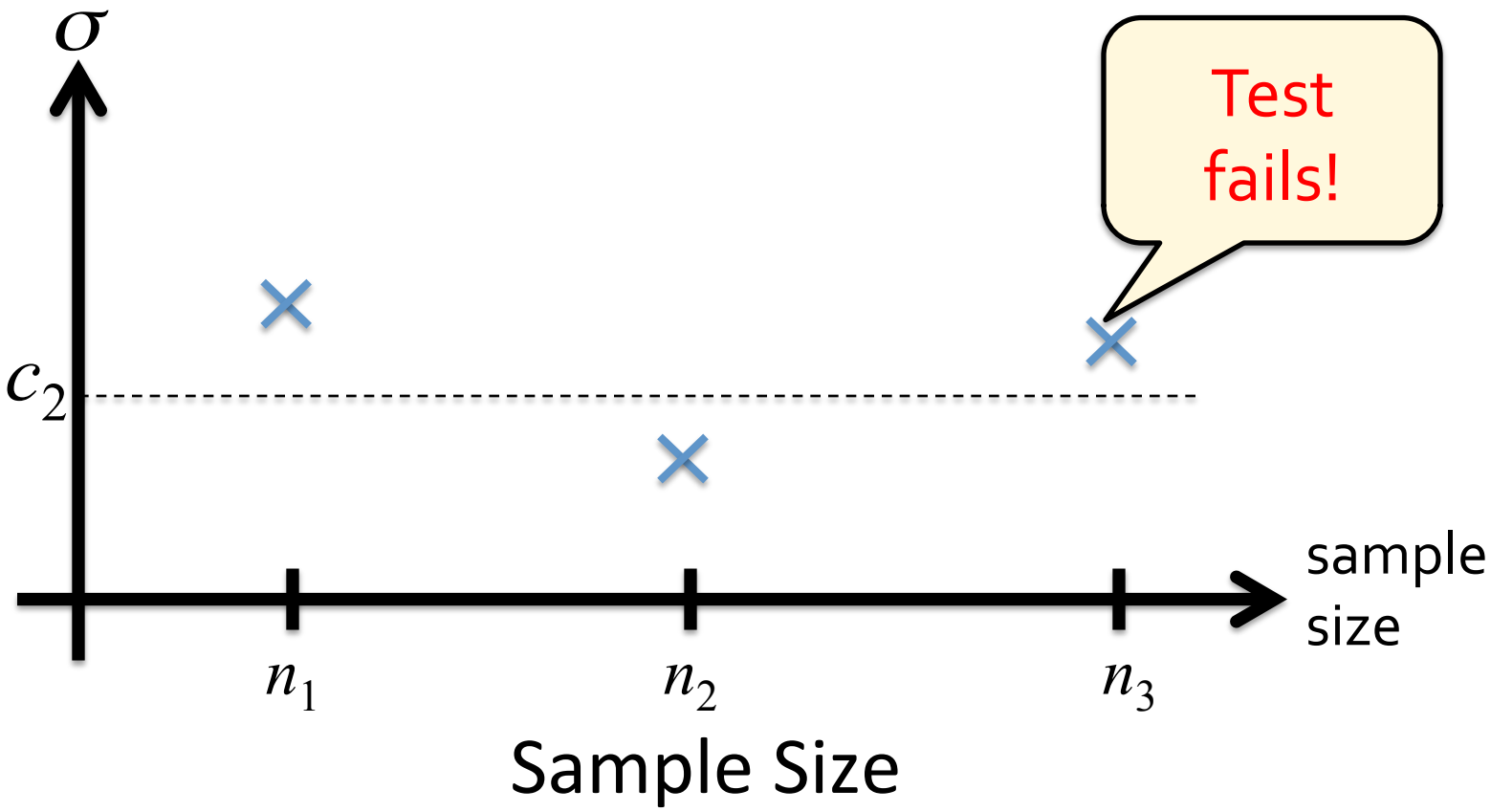
$$\forall i = 1,\ldots,s$$



Standard Deviation Test

$$\sigma_i \leftarrow \left| \frac{stddev(\xi^*_{i1},\ldots,\xi^*_{ip})}{\tilde{\xi}_i} \right|$$

$$(\sigma_{i+1} < \sigma_i) \vee (\sigma_{i+1} \leq c_2),$$
$$\forall i = 1,\ldots,s$$



Confidence Interval Test

$$\frac{\#\left\{ j \in 1,\ldots,p : \left| \frac{\xi_{ij}^{*} - \tilde{\xi}_i}{\tilde{\xi}_i} \right| \leq c_3 \right\}}{p} \geq \alpha$$

Fraction α of bootstrap results have rel. error of at most c_3 from **ground truth** (e.g., $\alpha = 0.95,\ c_3 = 0.5$)

How Well Does it Work in Practice?

Evaluated on **268** real-world Conviva Queries of which **113** had custom User-Defined Functions

Diagnostic predicted that **207 (77%)** queries can be approximated

- » False Positives: 3 (conditional UDFs)
- » False Negatives: 18

Bootstrap Challenges

How do you know the bootstrap is working?

» Depends on distribution, computation, sample size

Overhead

Very, Very Preliminary Results

Setting:

- » 25 EC2 instances with 4 slots and 15GB RAM
- » Input: 365mil rows, 204GB on disk, > 600GB in memory (deserialized format)
- » Workload: query computing 95-th percentile

Overheads:

- » Bootstrap to estimate result's error
- » Bootstrap diagnosis

Query Resp. Time & Overhead

Operation	Computation complexity	I/O complexity
Full data	$C(N)$	$O(N)$

N – data size

Query Resp. Time & Overhead

Operation	Computation complexity	I/O complexity
Full data	$C(N)$	$O(N)$
Sample	$C(n)$	$O(n)$

N – data size
n – sample size

Query Resp. Time & Overhead

Operation	Computation complexity	I/O complexity
Full data	$C(N)$	$O(N)$
Sample	$C(n)$	$O(n)$
Bootstrap	$k \times C(n)$	$k \times O(n)$

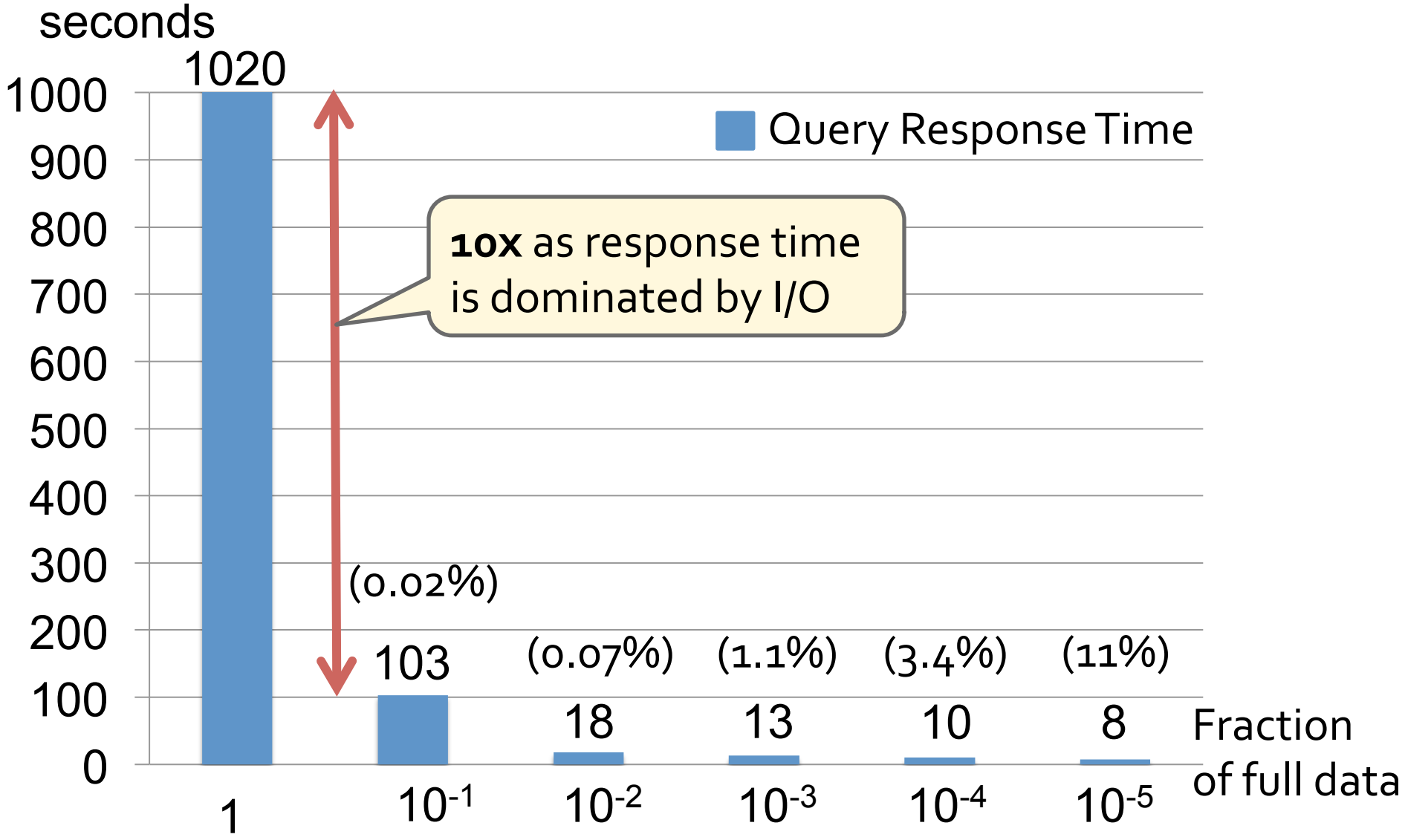
N – data size
n – sample size
k – # of samples used by bootstrap

Query Resp. Time & Overhead

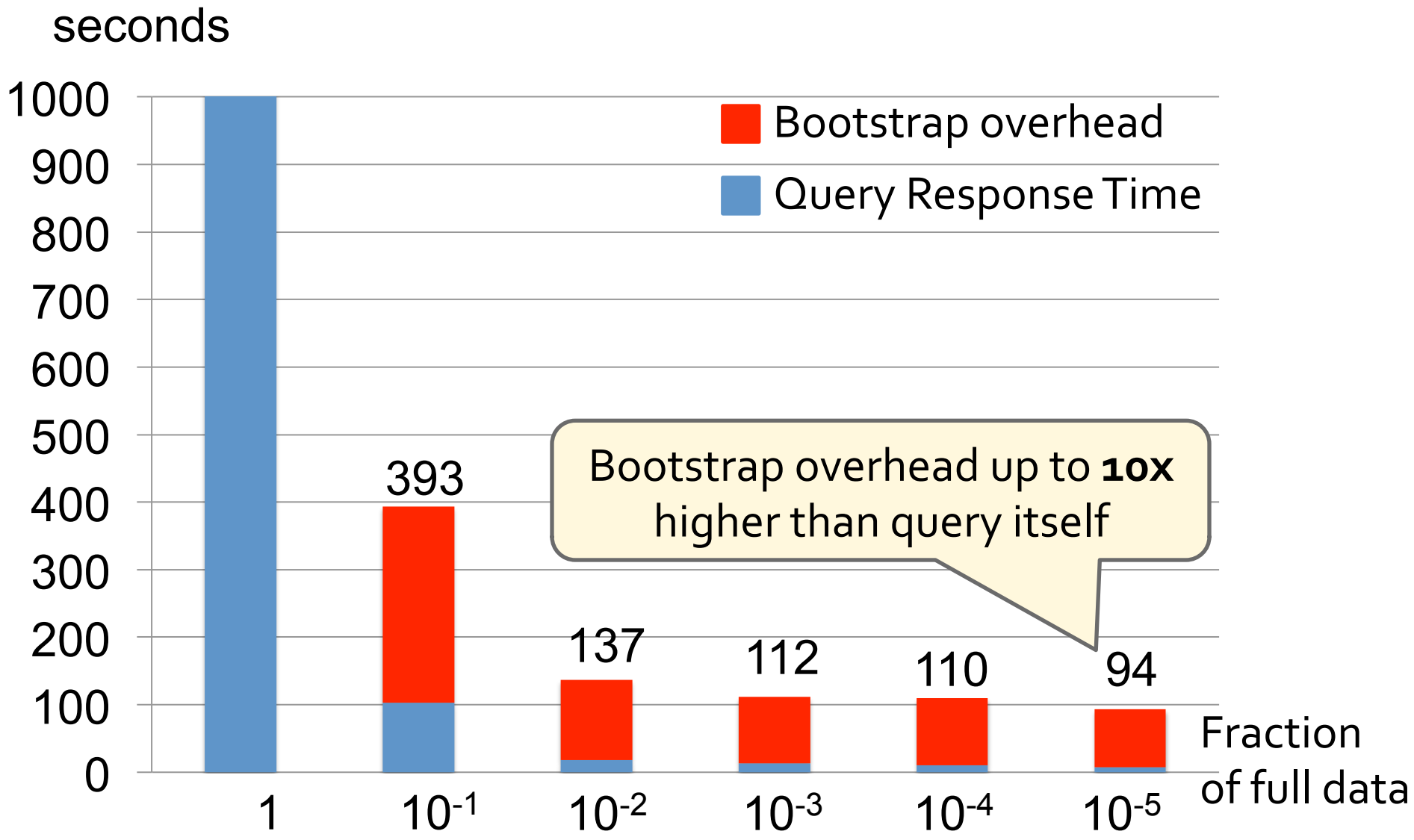
Operation	Computation complexity	I/O complexity
Full data	$C(N)$	$O(N)$
Sample	$C(n)$	$O(n)$
Bootstrap	$k \times C(n)$	$k \times O(n)$
Diagnosis	$p \times k \times \sum_{i=1}^{s} C(n_i)$	$p \times k \times \sum_{i=1}^{s} O(n_i)$

N – data size
n – sample size
n_i – sample size for iteration i of diagnostic
k – # of samples used by bootstrap
p – # of samples used by ground truth
s – # of iteration used by diagnostic

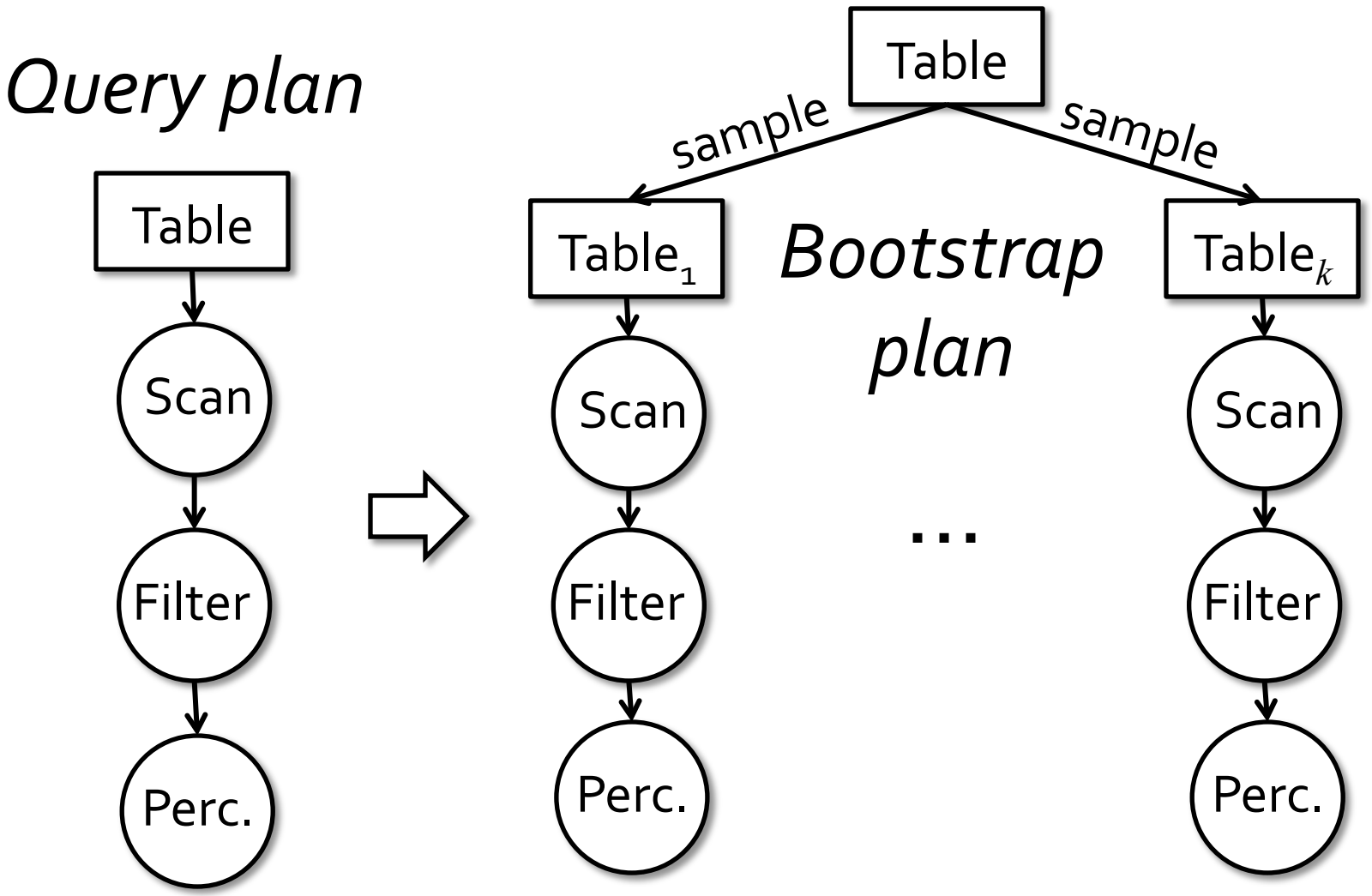
Query Response Time



Query Resp. Time + Bootstrap

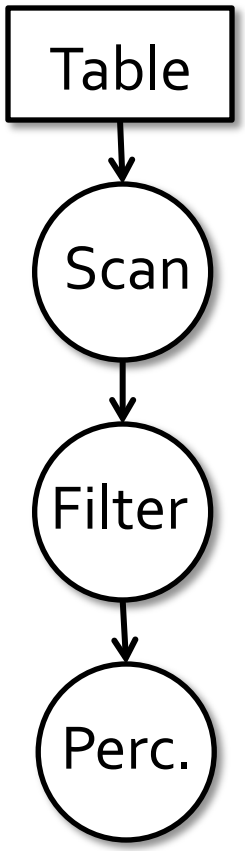


Bootstrap Query Plan



Detailed Query Plan

Query plan

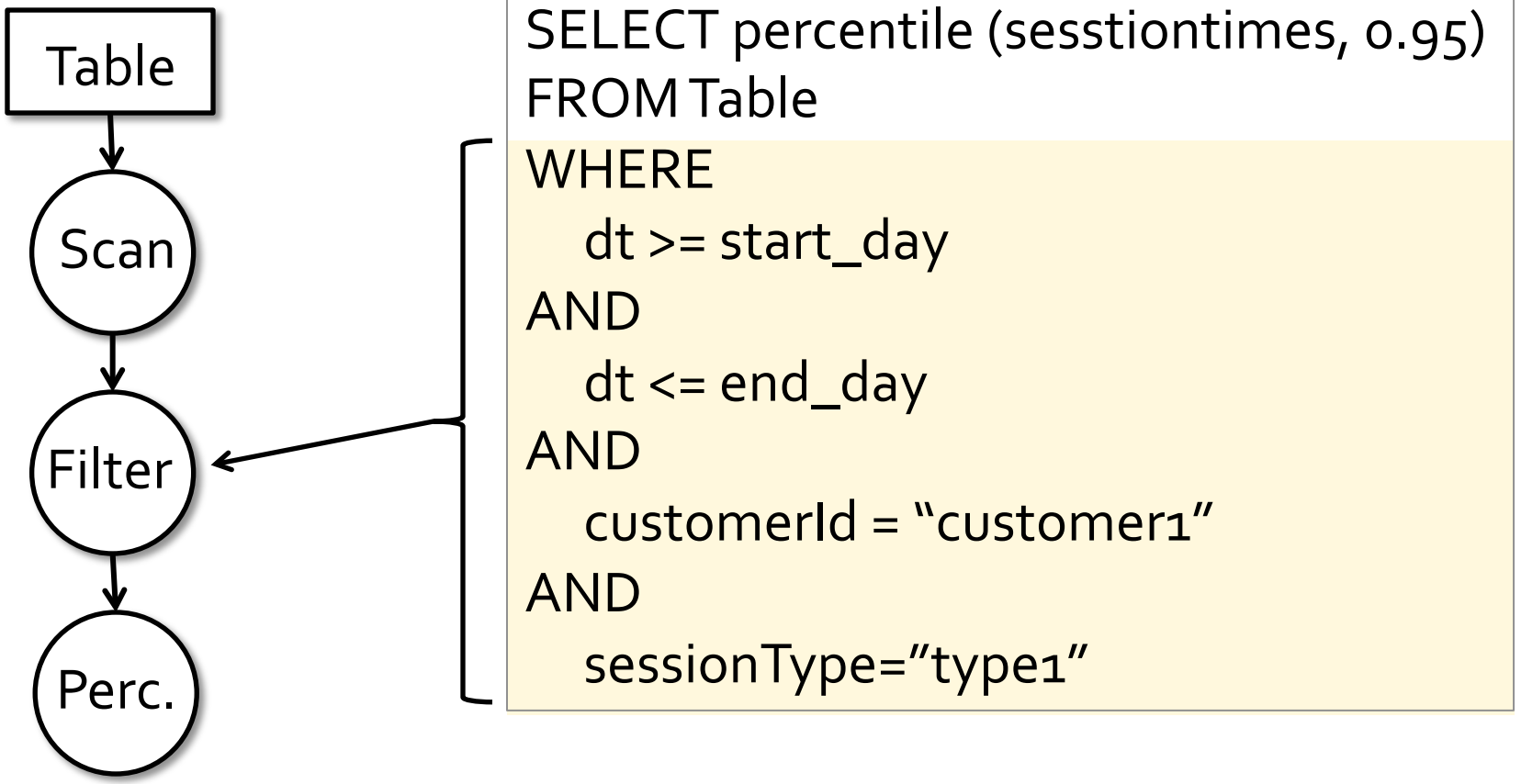


Query

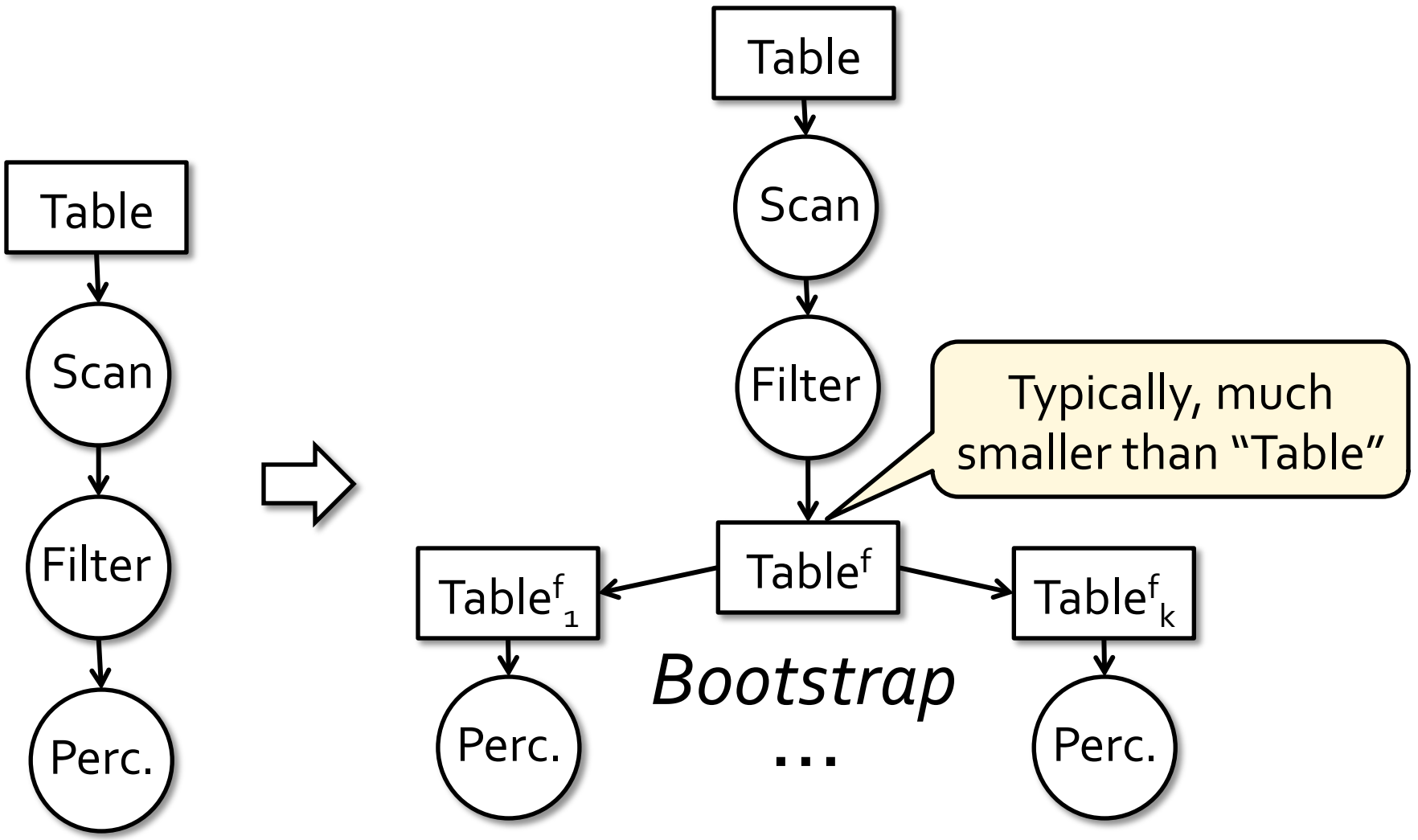
```
SELECT percentile (sesstiontimes, 0.95)
FROM Table
WHERE
    dt >= start_day
AND
    dt <= end_day
AND
    customerId = "customer1"
AND
    sessionType="type1"
```

Detailed Query Plan

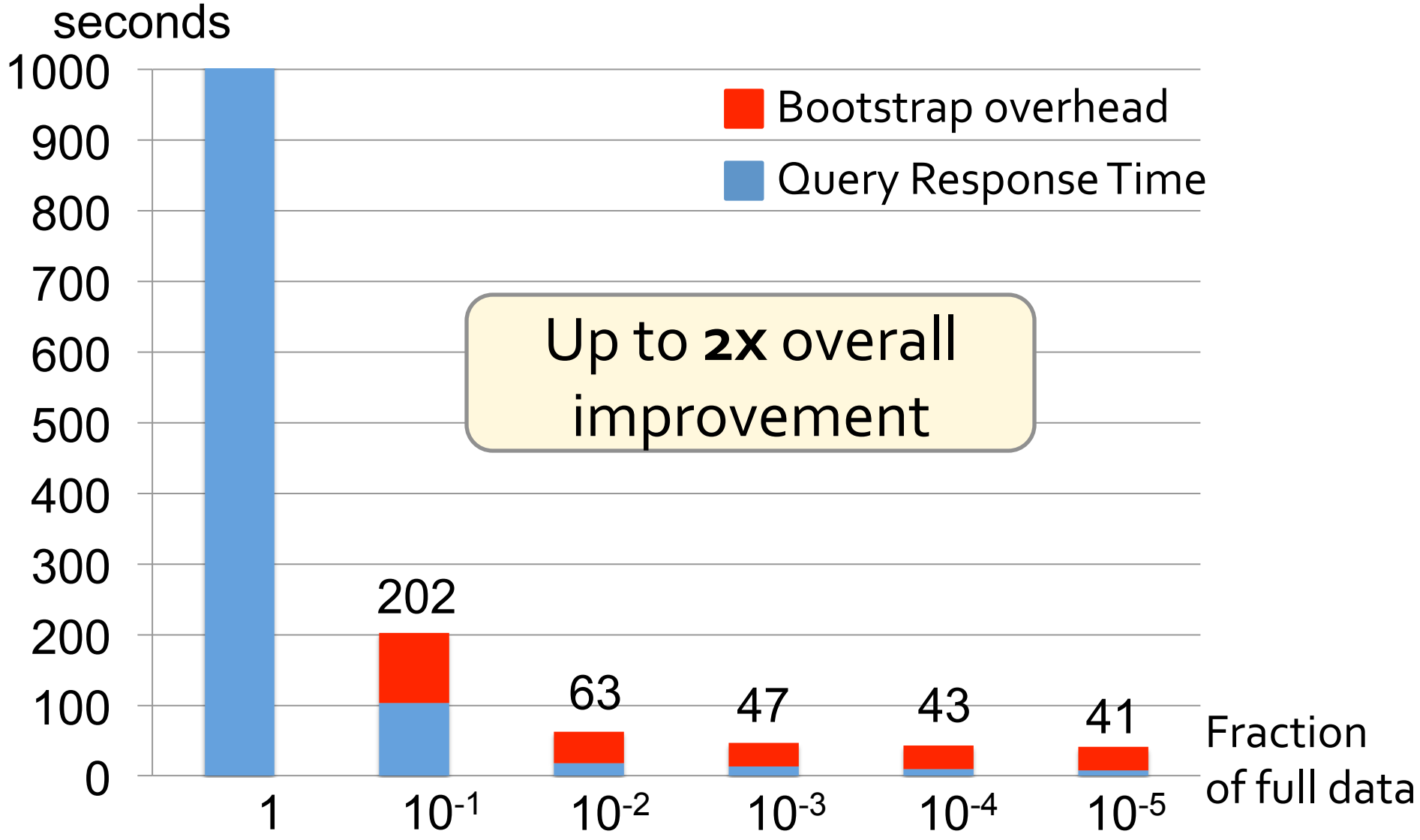
Typically, filters remove ***many*** rows from input table



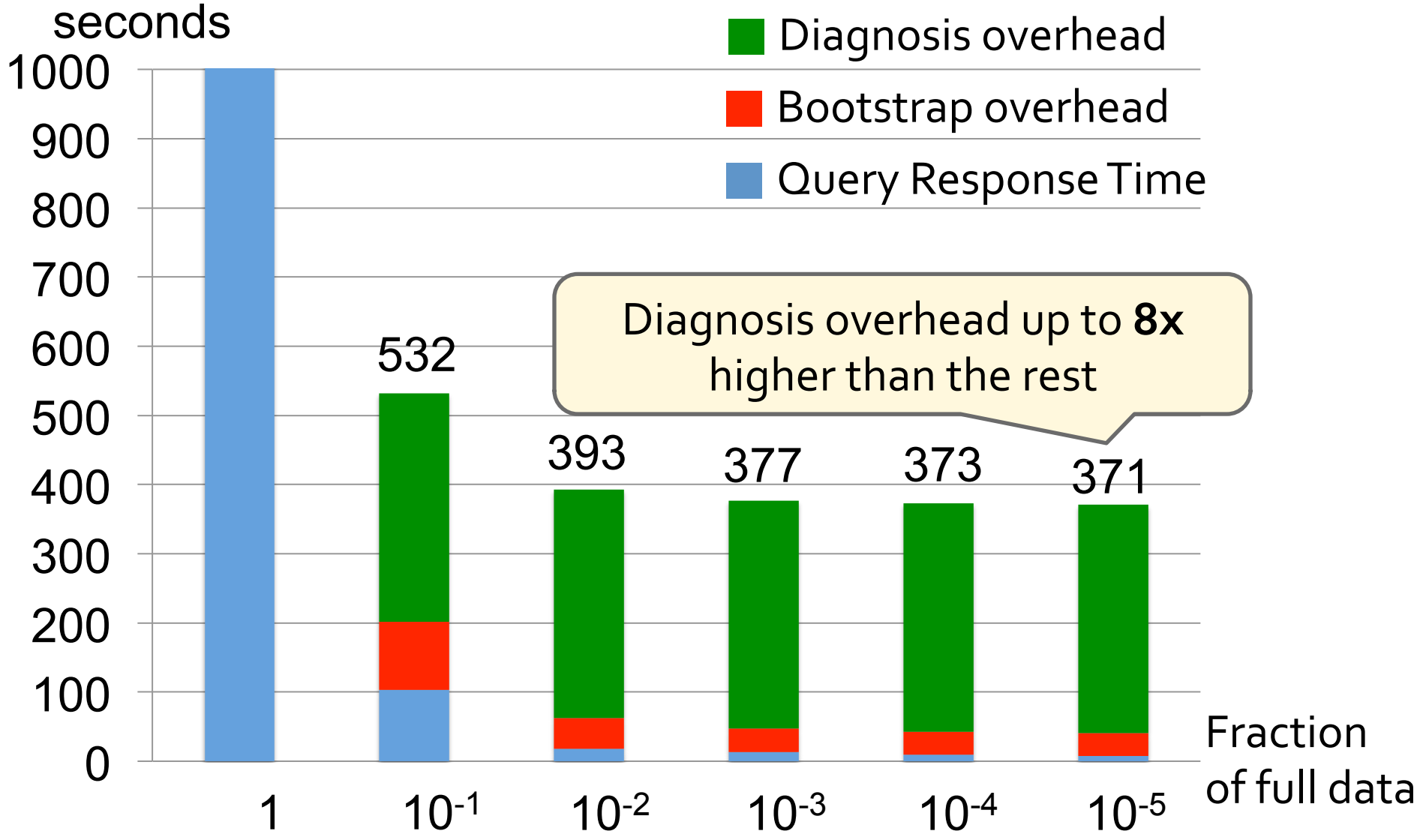
Filter Pushdown Optimization



Query + Bootstrap
(with Filter Pushdown)



Query + Bootstrap + Diagnosis
(with Filter Pushdown)



Overhead

Operation	Comp. complexity	Comm. complexity	# of tasks
Full data	$C(N)$	$O(N)$	$O(d)$
Sample	$C(n)$	$O(n)$	$O(d)$
Bootstrap	$k \times C(n)$	$k \times O(n)$	
Diagnosis	$p \times k \times \sum_{i=1}^{s} C(n_i)$	$p \times k \times \sum_{i=1}^{s} O(n_i)$	$s \times p \times k \times O(d)$

Can generate millions of tasks

N – data size
n – sample size
n_i – sample size for iteration i of diagnostic

k – # of samples used by bootstrap
p – # of samples used by ground truth
s – # of iteration used by diagnostic
d – degree of parallelism

Diagnosis Optimization

Problem: too many tasks to launch & schedule

- » Fixed overhead dominates

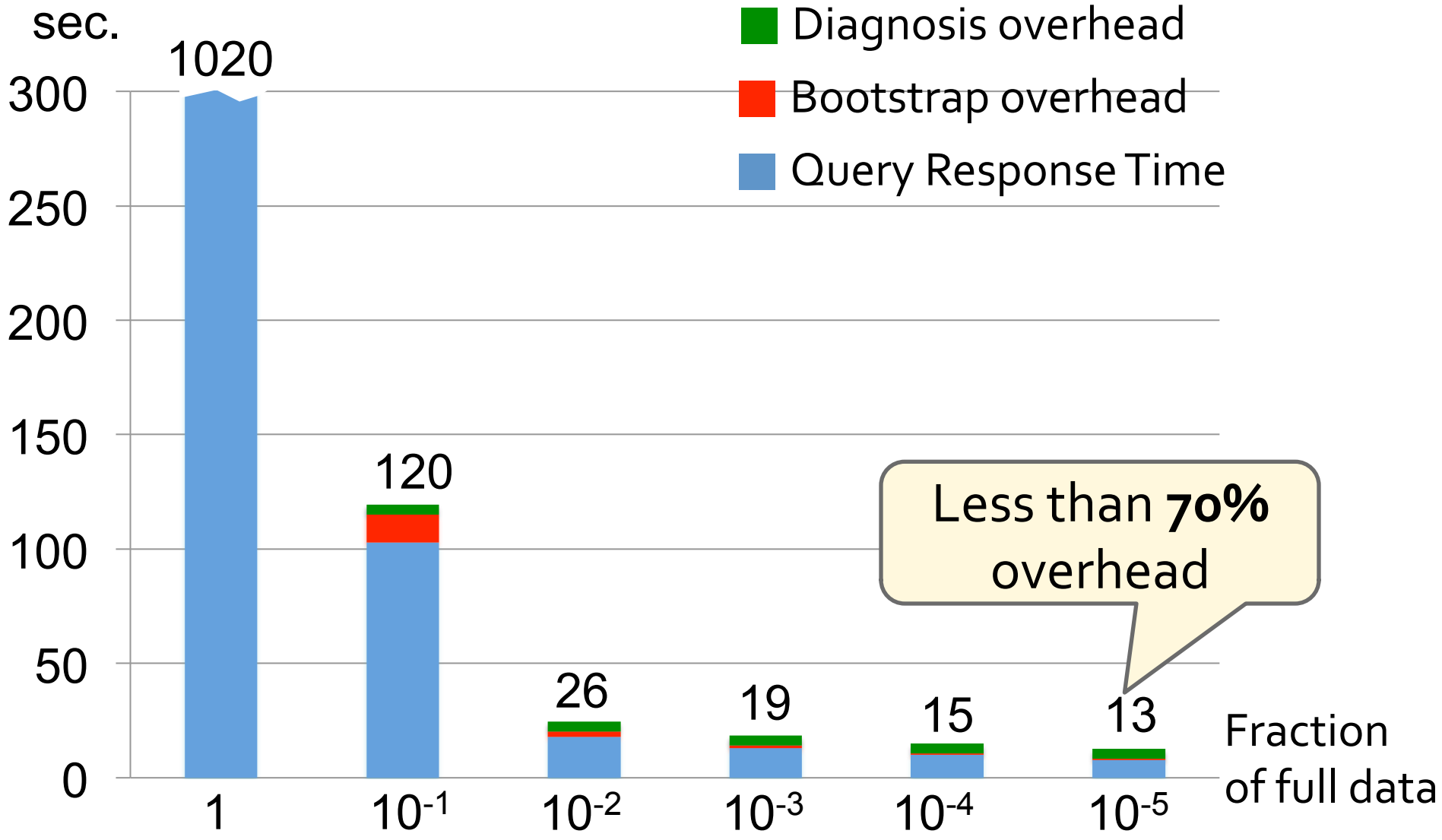
Solution: task consolidation

- » Consolidate the computation into d tasks, where d is the number of slots in the system
- » Caveat: currently a hack; not part of BlinkDB codebase

Result:

- » Reduce diagnosis from 330s to 4.5s
- » Reduce bootstrap overhead by up to 10X

Query + Bootstrap + Diagnosis
(with Filter Pushdown and Task Consolidation)



Summary

*Computing error bounds for approximate queries on massive data sets: a **hard**, **important**, and **exciting** problem*

At the intersection between:

- » ML: error computation
- » Databases: query plan optimization, sample creation and selection
- » Systems: improved parallelism, scheduling

Preliminary results encouraging

Future Work

Improve bootstrap diagnostic:

- » Provable properties for specific settings

Improve coverage for error estimation

- » E.g., use static analysis to decompose programs in multiple Hadamard differentiable components

Improve Bootstrap scalability with Bag of Little Bootstraps [Kleiner et al. 2012]:

- » No need to distribute query computation even for huge samples (e.g., 100 billion records @ 1KB per record)

Scheduling concurrent parallel, dependent jobs …