Database Learning: Toward a Database that Becomes Smarter Over Time

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Today's databases

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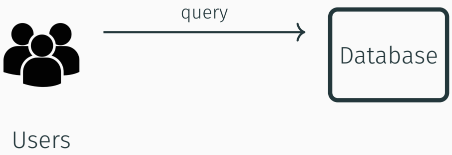

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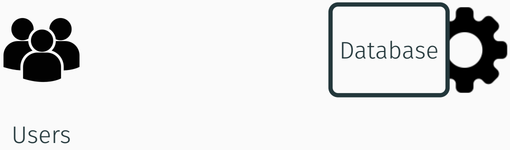

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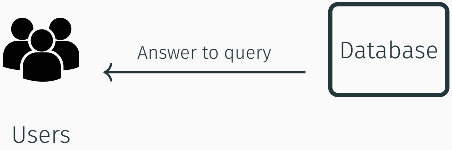

Today's databases

After answering queries,
THE WORK is GONE.

Today’s databases

After answering queries,
THE WORK is GONE.

Our Goal: reuse the work

Our high-level approach

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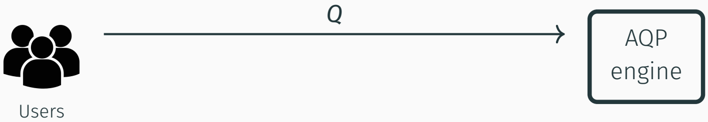

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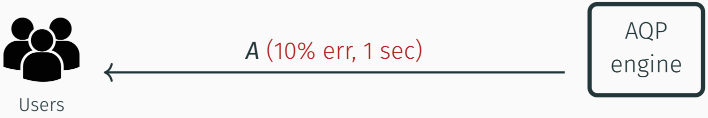

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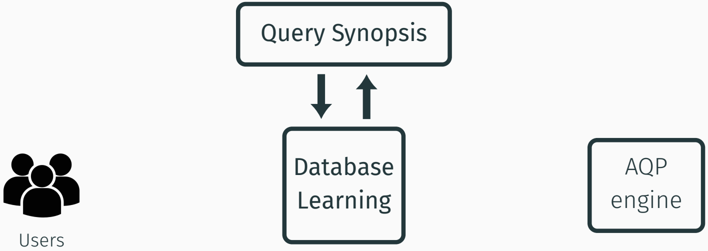

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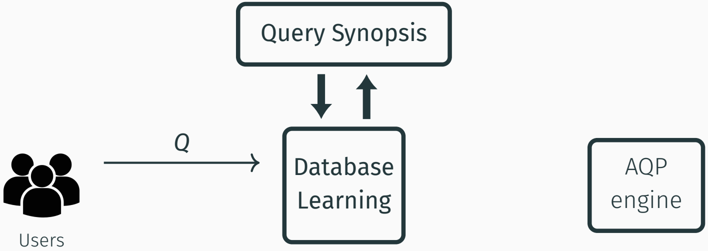

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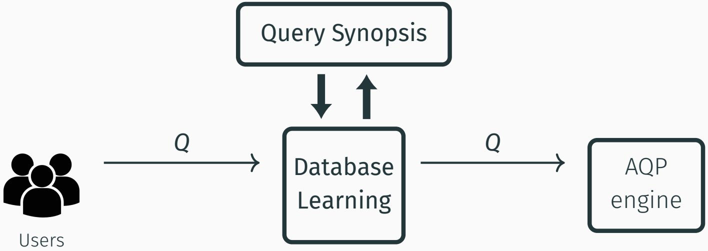

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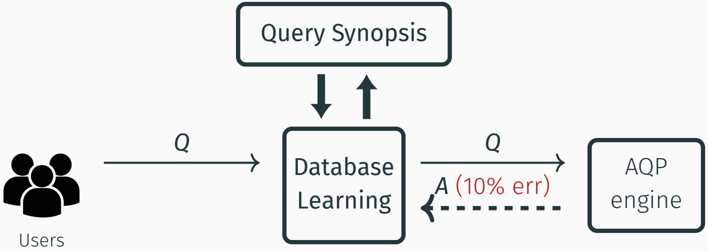

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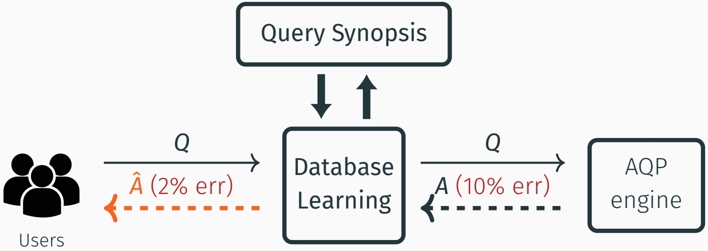

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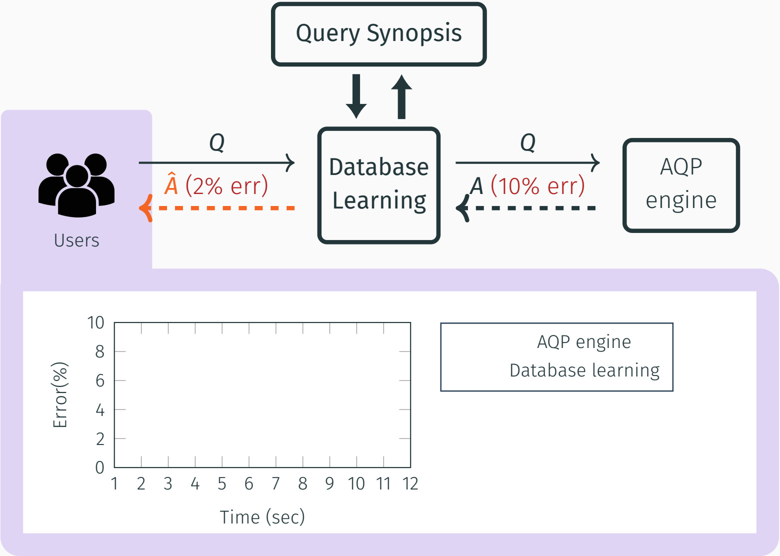

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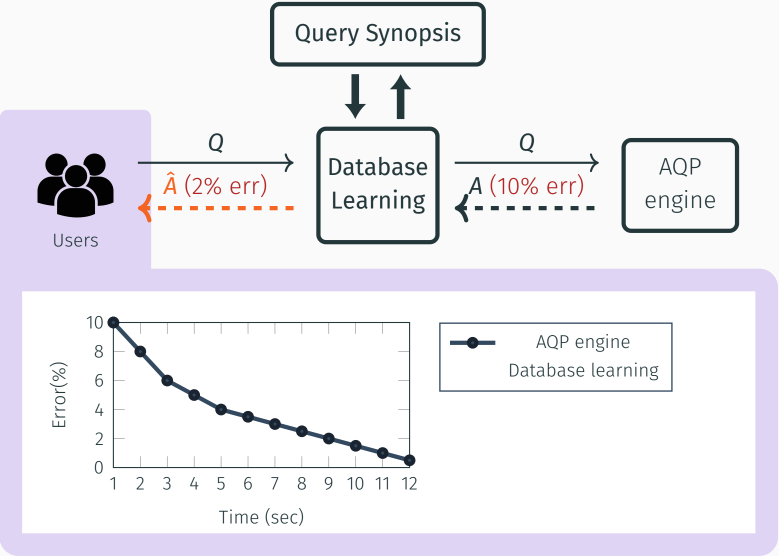

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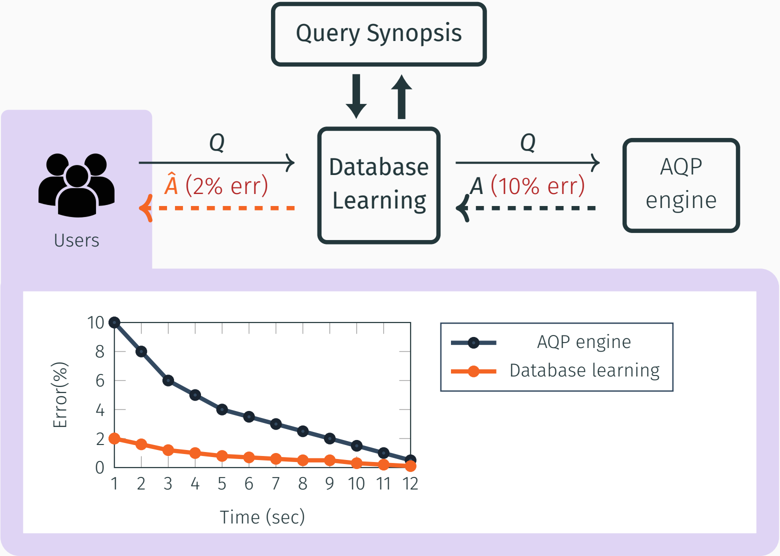
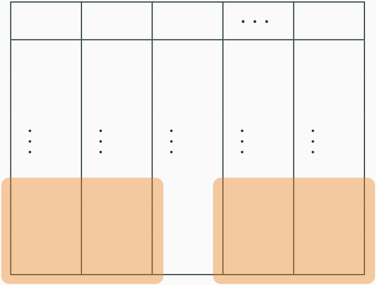


Technical challenges

			…	
⋮	⋮	⋮	⋮	⋮

Technical challenges



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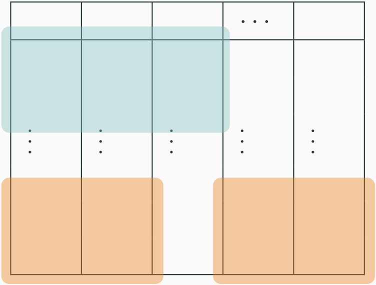

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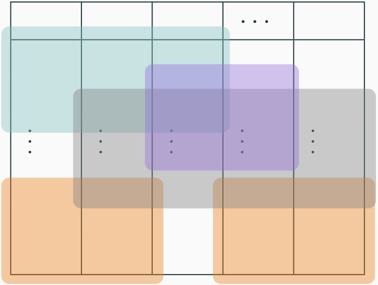
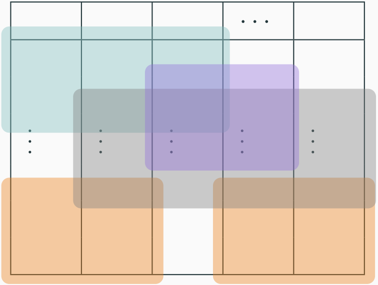


Queries use the data in different columns/rows.

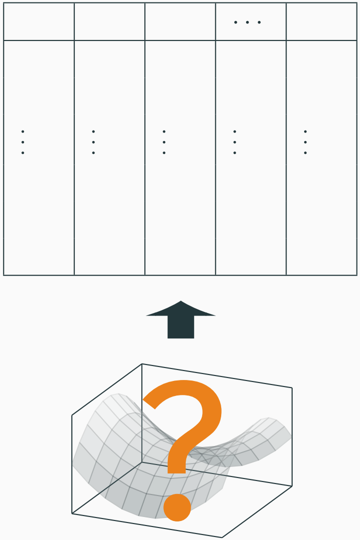
Technical challenges



Queries use the data in different columns/rows.

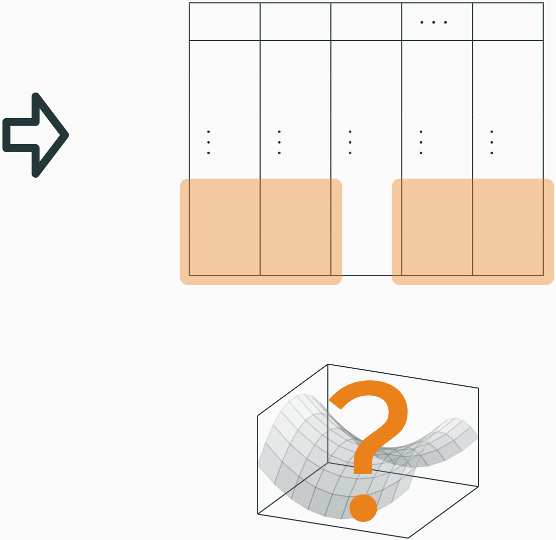
How to leverage those queries for future queries?

Our idea



Our idea

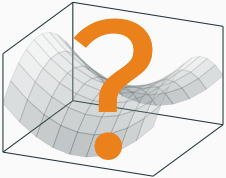
Q1



Our idea

$(Q1, A1)$

			$\cdots$	
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$



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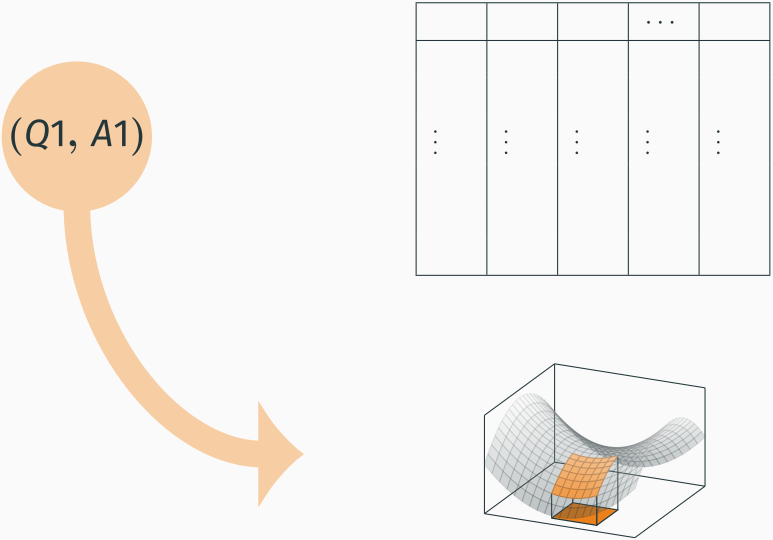
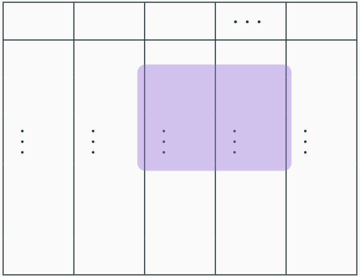
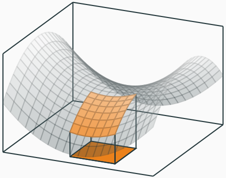


Our idea

Q2

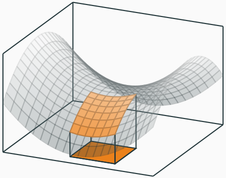




Our idea

$(Q2, A2)$

			$\cdots$	
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$



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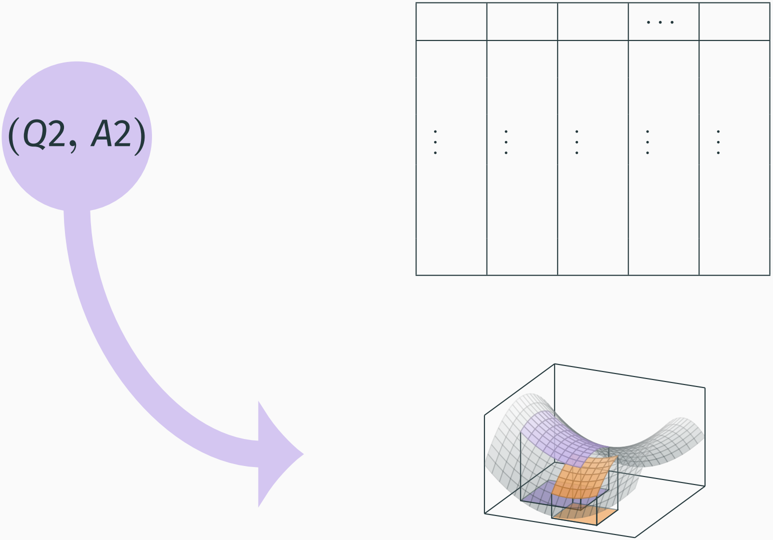

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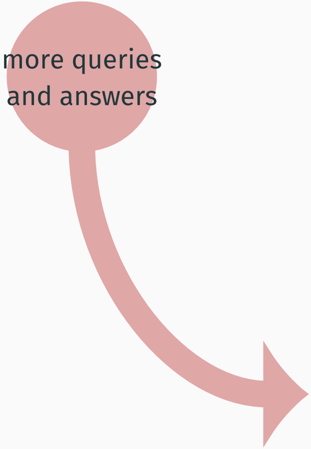
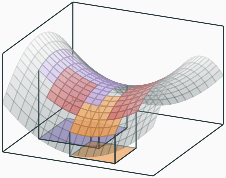
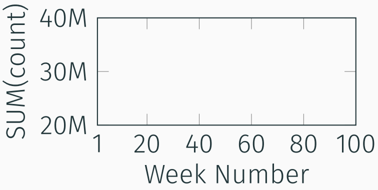


			$\cdots$	
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$



Concrete example



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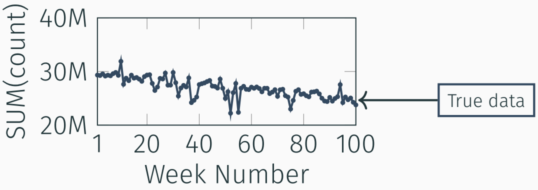

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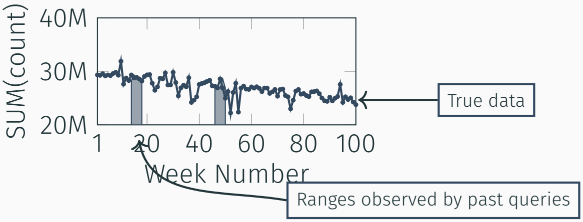

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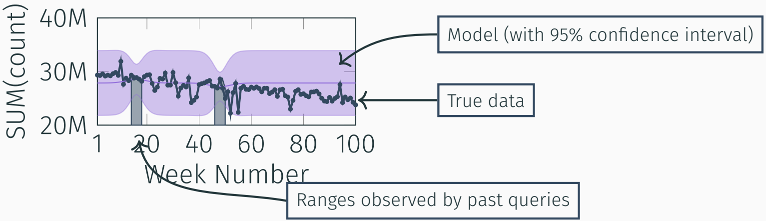
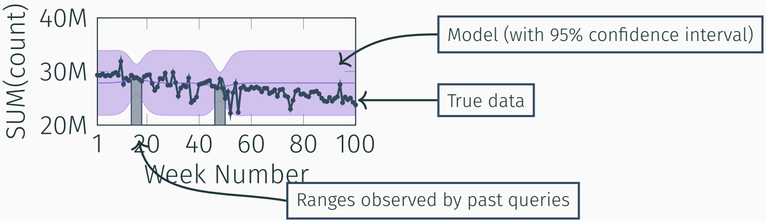
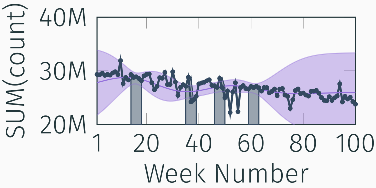



SUM(count)
40M
30M
20M
1
20
40
60
80
100
Week Number
Model (with 95% confidence interval)
True data
Ranges observed by past queries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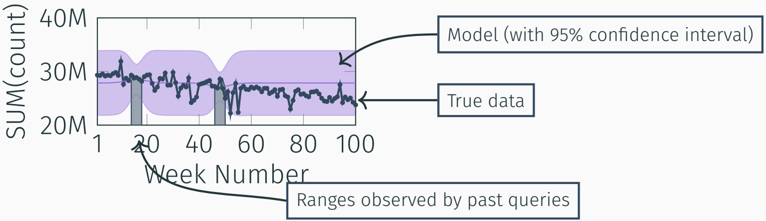
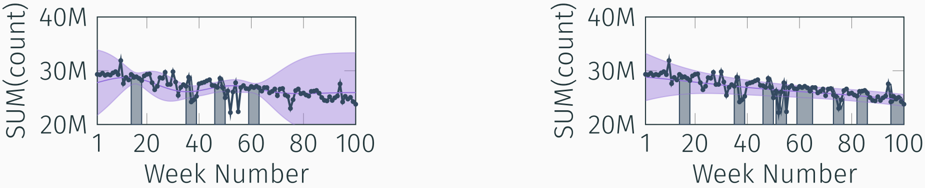
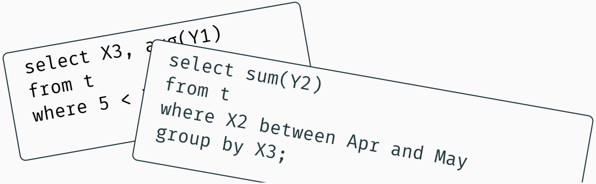
Concrete example



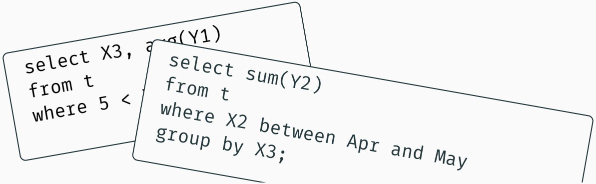


Design goals



1. Support a wide class of SQL queries

Design goals



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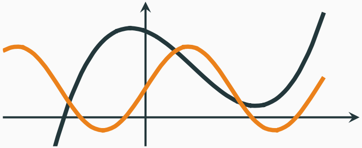
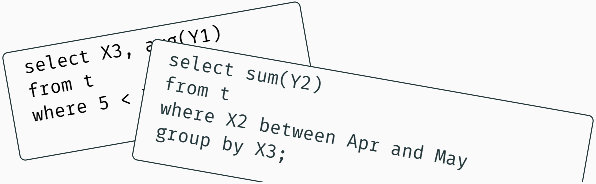


2. No Assumptions about Data

Design goals



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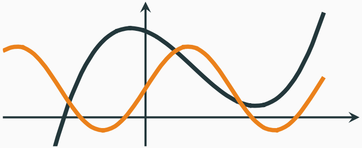

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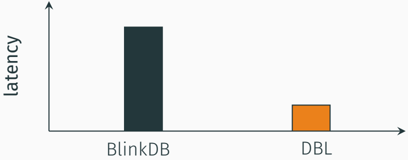

3. Lightweight

Our Approach

Problem statement

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Given past queries $(q_1, \ldots, q_n)$, a new query (q_{n+1}), and their approximate answers,

Find the most likely answer to the new query (q_{n+1}) and its estimated error.

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Our result:

Under a *certain model assumption*,

our answer's error bound $\leq$ original answer's error bound

(in practice, much more accurate)

if the error bounds provide the same probabilistic guarantees.

Overview of our technique

```sql
select avg(Y2)
from t
where 6 < X1 < 8;
```

Overview of our technique

```
select sum(Y2)
from t
where 5 < X1 < 8;
```

Overview of our technique

```
select sum(Y2)
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① →

Random variables
(our uncertainty on answers)

$\theta_1, \quad \theta_2, \quad \theta_3$

Overview of our technique

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select sum(Y2)
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```

1

Random variables
(our uncertainty on answers)

$\boldsymbol{\theta}_1, \quad \boldsymbol{\theta}_2, \quad \boldsymbol{\theta}_3$

2

$Pr(\theta_1, \; \theta_2, \; \theta_3)$

Probability distribution

Overview of our technique

```
select sum(Y2)
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① →

Random variables
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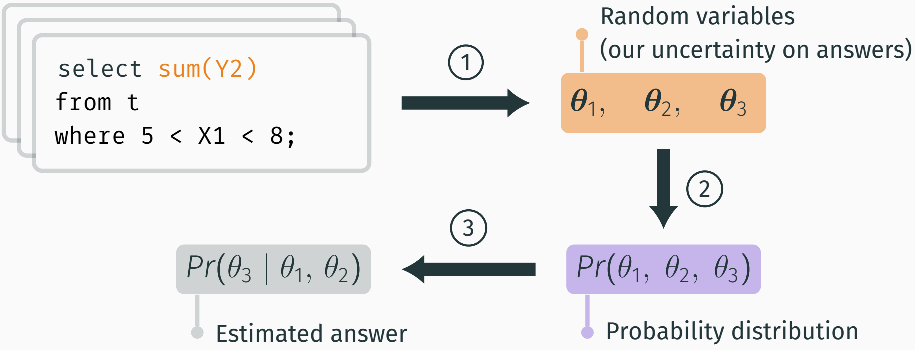
↓ ②

$Pr(\theta_1, \ \theta_2, \ \theta_3)$

Probability distribution

Two aggregations involve common values
$\rightarrow$ correlation between answers

Overview of our technique



Two aggregations involve common values

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How to define random variables

```
select sum(Y2)
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- Aggregate function

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- Selection predicates

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We define a random variable θ
for every combination of:

- Aggregate function
- Selection predicates

```
select X3, avg(Y1), sum(Y2)
from t
where 5 < X1 < 8
  and X2 between Apr and May
group by X3;
```

What if your query is complex?

How to define random variables

```
select sum(Y2)
from t
where 5 < X1 < 8;
```

We define a random variable θ
for every combination of:

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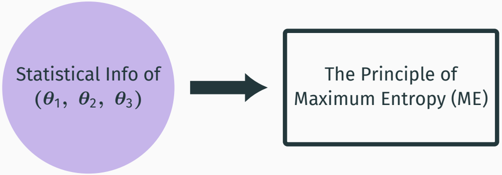
What if your query is complex?

How to determine the probability distribution

The Principle of
Maximum Entropy (ME)

How to determine the probability distribution



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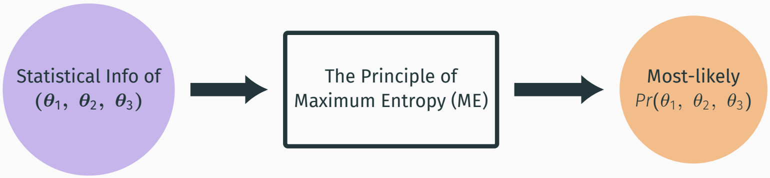
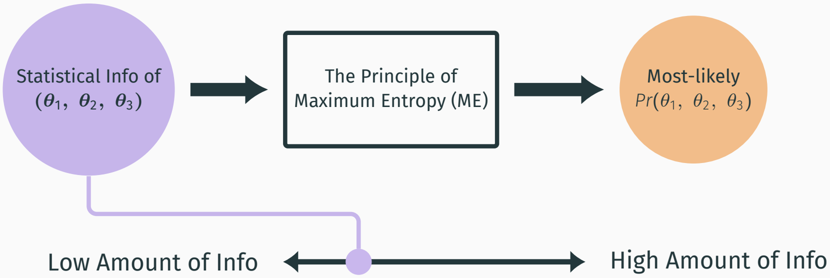


How to determine the probability distribution

Statistical Info of $(\theta_1, \theta_2, \theta_3)$ $\rightarrow$ The Principle of Maximum Entropy (ME) $\rightarrow$ Most-likely $Pr(\theta_1, \theta_2, \theta_3)$

Low Amount of Info $\longleftrightarrow$ High Amount of Info

How to determine the probability distribution



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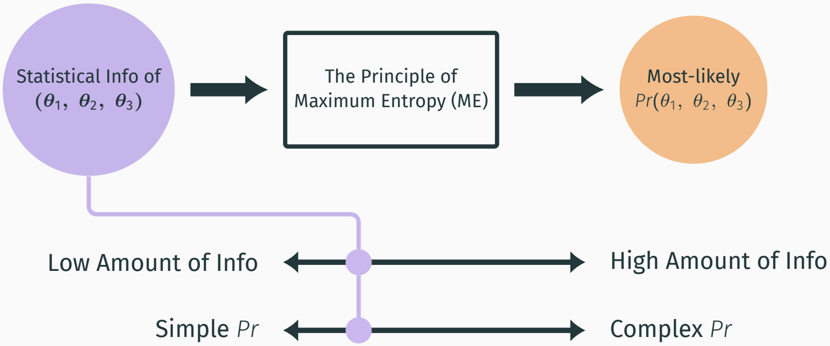

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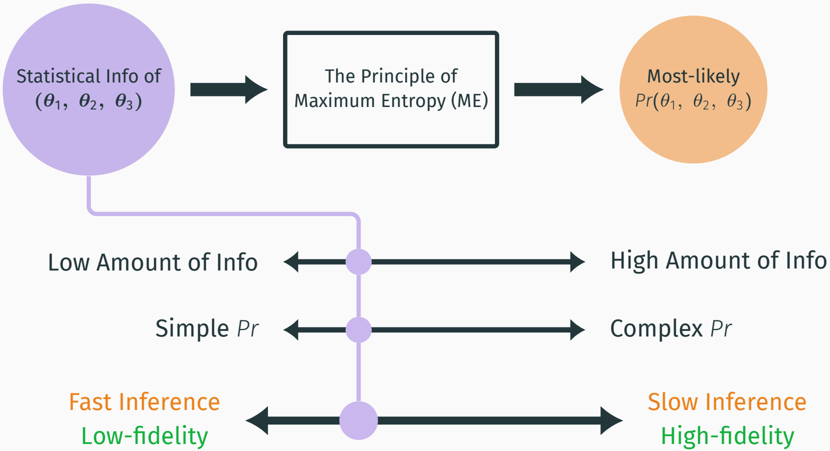

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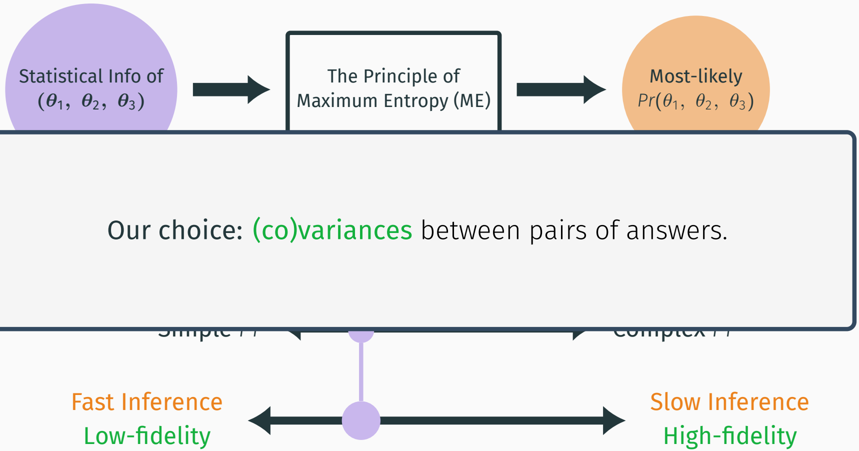


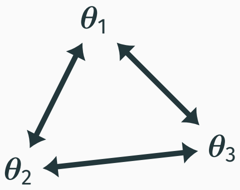
Our choice: (co)variances between pairs of answers.

Most-likely probability distribution

θ_1

θ_2 θ_3

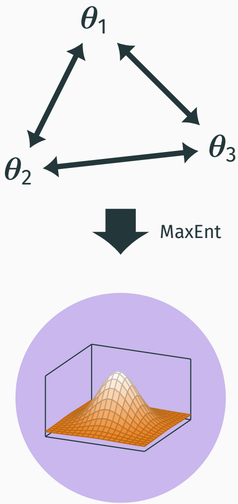
Most-likely probability distribution



Statistical Information:

Mean, variances, covariances

Most-likely probability distribution

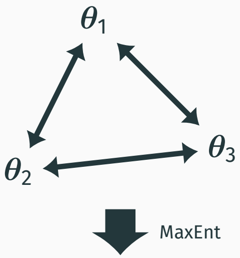


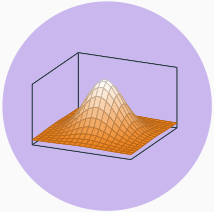
Statistical Information:

Mean, variances, covariances

Multivariate normal distribution

Most-likely probability distribution





Statistical Information:

Mean, variances, covariances

Multivariate normal distribution

Fast inference using a closed form

Benefits of database learning

Database learning vs. indexing

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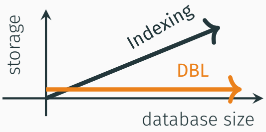
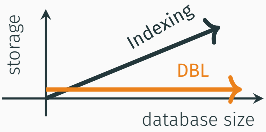
Database learning vs. indexing



1. Little storage overhead

Benefits of database learning

Database learning vs. indexing



1. Little storage overhead

Database learning vs. materialized view

Benefits of database learning

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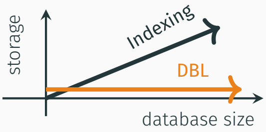

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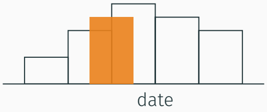
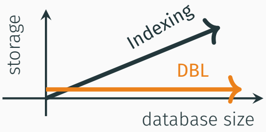


2. Without alignment

Benefits of database learning

Database learning vs. indexing



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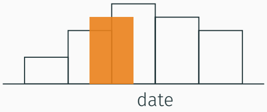

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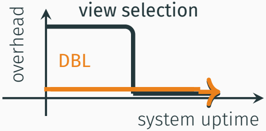

3. No upfront overhead

Experiment

Experiment setup

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   - NoLearn: Approximate query processing engine (The longer runtime, the more accurate answer)
   - Verdict: Our database learning system (on top of NoLearn)

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   - `Customer1`: 536GB data and query log from a customer
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3. Environment:
   - 5 Amazon EC2 workers (`m4.2xlarge`) + 1 master
   - SSD-backed HDFS for Spark's data loading

Our experimental claims

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3. VERDICT works with small memory and computational overhead

Generality of VERDICT

Dataset	# Analyzed	# Supported	Percentage
`Customer1`	3,342	2,463	73.7%
`TPC-H`	21	14	66.7%

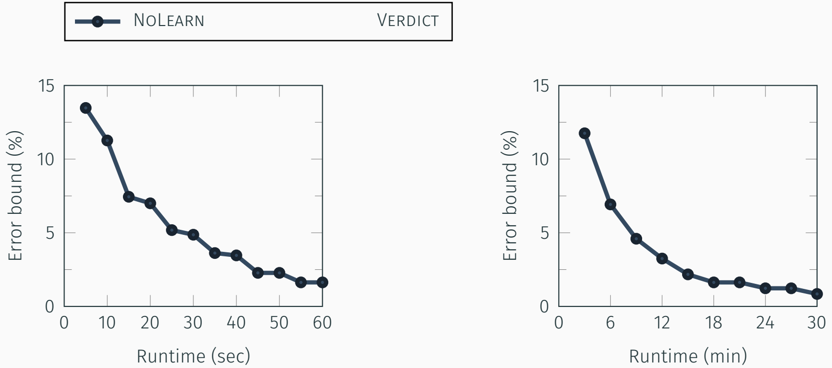
Unsupported queries:

1. Nested queries (that cannot be flattened)
2. Textual filters: `city like '%arbor%'`

Runtime-error trade-off

Results on the `TPC-H` dataset (the paper has the `Customer1` results)

Number of past queries fixed to 50



(a) Data in Memory

(b) Data on SSD

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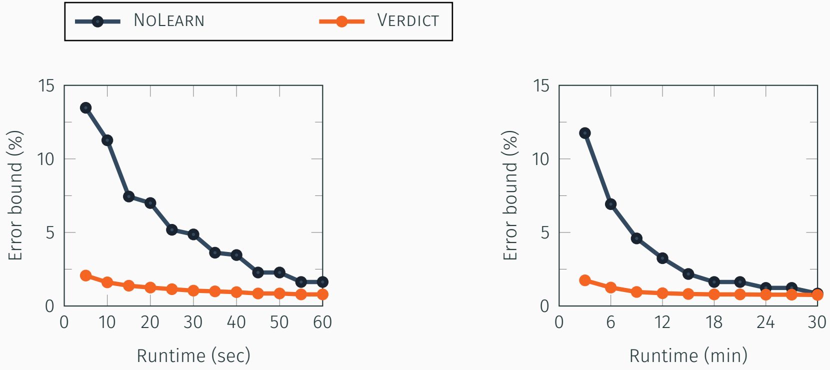

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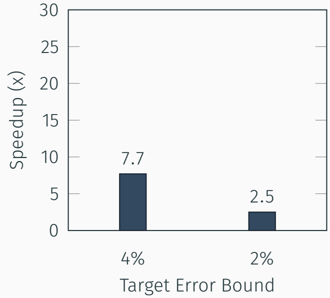
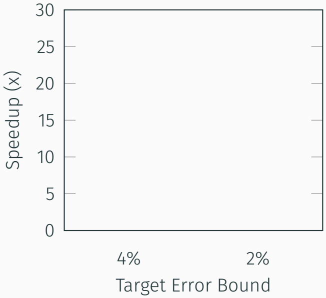
Speedup

The results on the `Customer1` dataset (the paper has the `TPC-H` results)



(a) Data in memory



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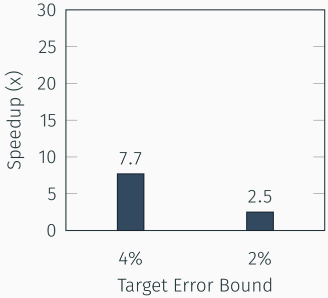

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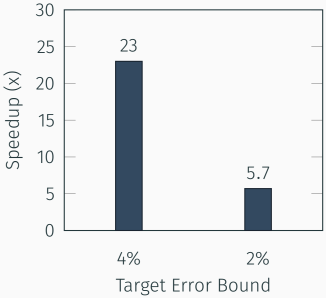

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Memory and computational overhead

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    - 23.2 KB per query for the `Customer1` dataset
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1. Memory overhead:
   - Queries and their answer, some matrices and their inverses
   - 23.2 KB per query for the `Customer1` dataset
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2. Computational overhead:

	Latency for memory	Latency for SSD
NoLearn	2.083 sec	52.50 sec
Verdict	2.093 sec	52.51 sec
Overhead	0.010 sec (0.48%)	0.010 sec (0.02%)

Thank You!