Altinity

CLICKHOUSE MATERIALIZED VIEWS

A SECRET WEAPON FOR HIGH PERFORMANCE ANALYTICS

Robert Hodges -- Percona Live 2018 Amsterdam

Introduction to Presenter

Robert Hodges - Altinity CEO

30+ years on DBMS plus virtualization and security.

ClickHouse is DBMS #20

www.altinity.com

Leading software and services provider for ClickHouse

Major committer and community sponsor in US and Western Europe

Introduction to ClickHouse

Understands SQL

Runs on bare metal to cloud

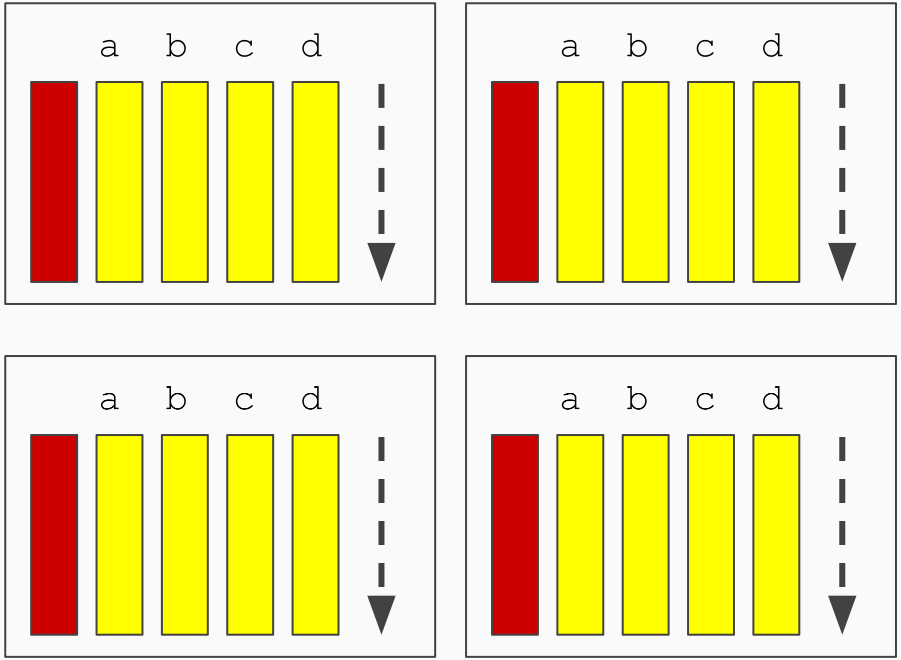
Stores data in columns

Parallel and vectorized execution

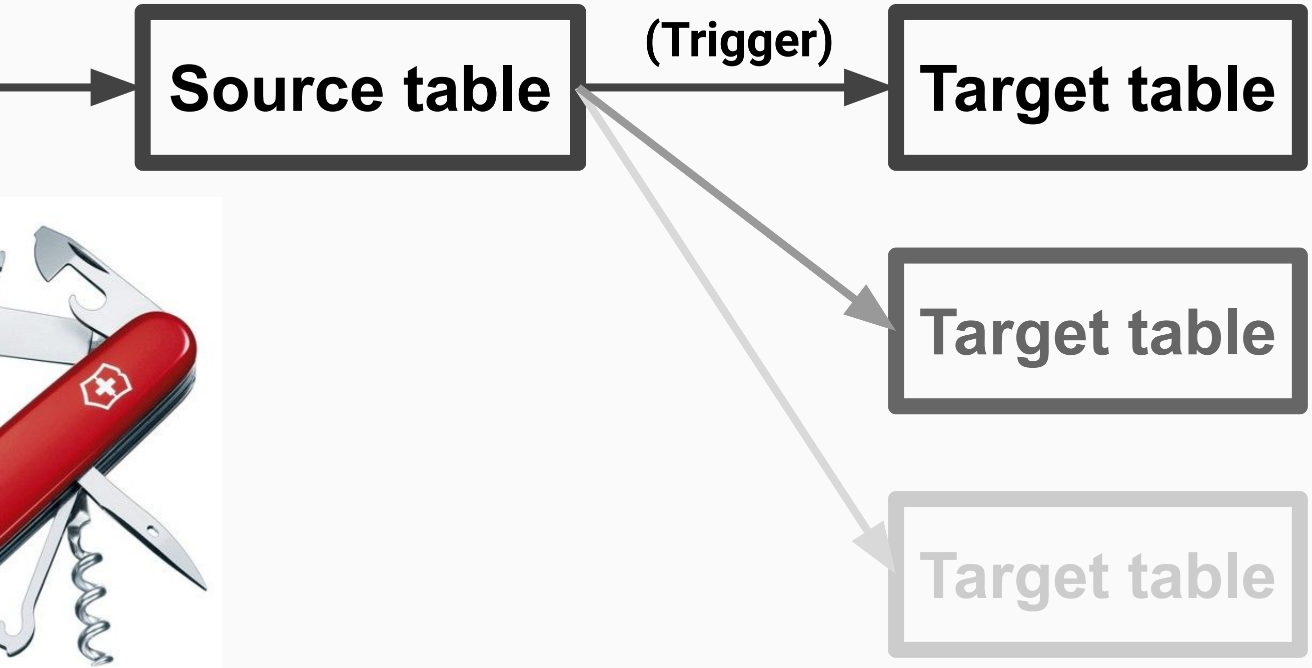
Scales to many petabytes

Is Open source (Apache 2.0)

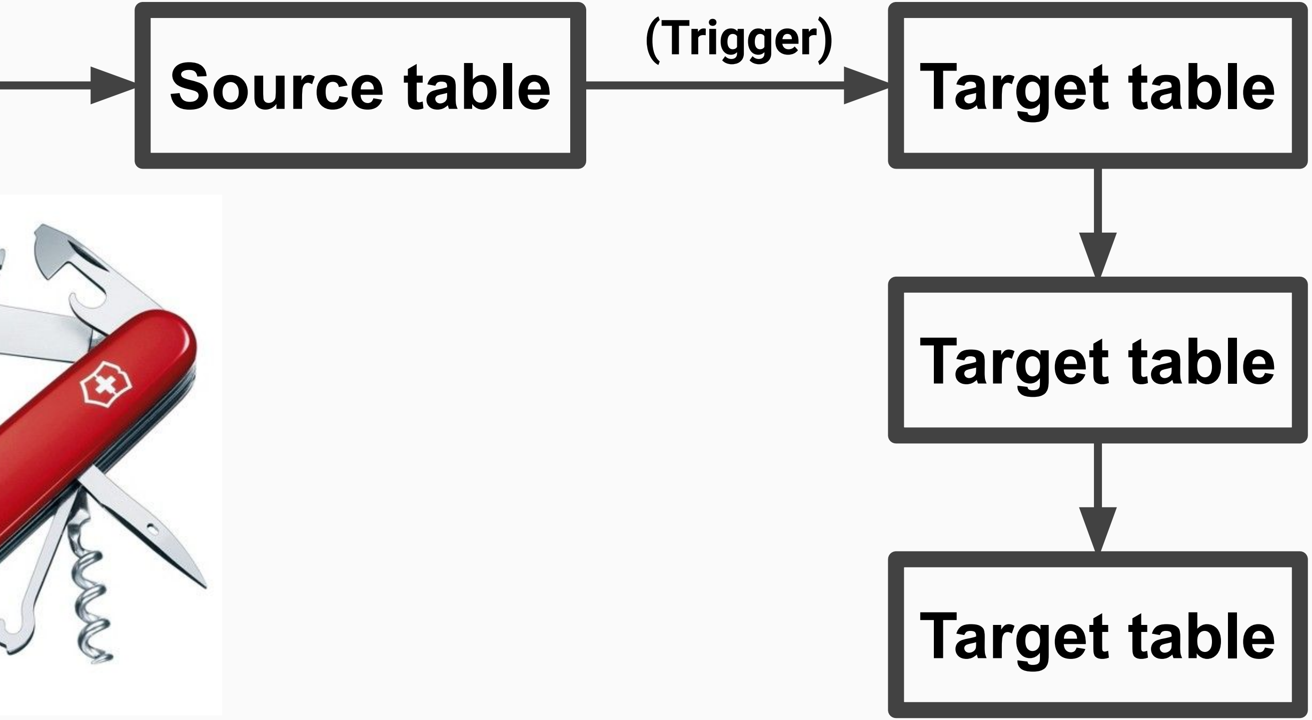
Is WAY fast!



ClickHouse materialized views are <u>triggers</u>



You can even create recursive views



Why might a materialized view be useful?

```
SELECT
   toYear(FlightDate) AS year,
   sum(Cancelled) / count(*) AS cancelled,
   sum(DepDel15) / count(*) AS delayed_15
FROM airline.ontime
GROUP BY year ORDER BY year ASC LIMIT 10

...

10 rows in set. Elapsed: 0.894 sec. Processed 173.82
million rows, 1.74 GB (194.52 million rows/s., 1.95
GB/s.)
```

Can we make it faster?

Let’s precompute and store aggregates!

```
CREATE MATERIALIZED VIEW ontime_daily_cancelled_mv
ENGINE = SummingMergeTree
PARTITION BY tuple() ORDER BY (FlightDate, Carrier)
POPULATE
AS SELECT
   FlightDate, Carrier, count(*) AS flights,
   sum(Cancelled) / count(*) AS cancelled,
   sum(DepDel15) / count(*) AS delayed_15
FROM ontime
GROUP BY FlightDate, Carrier
```

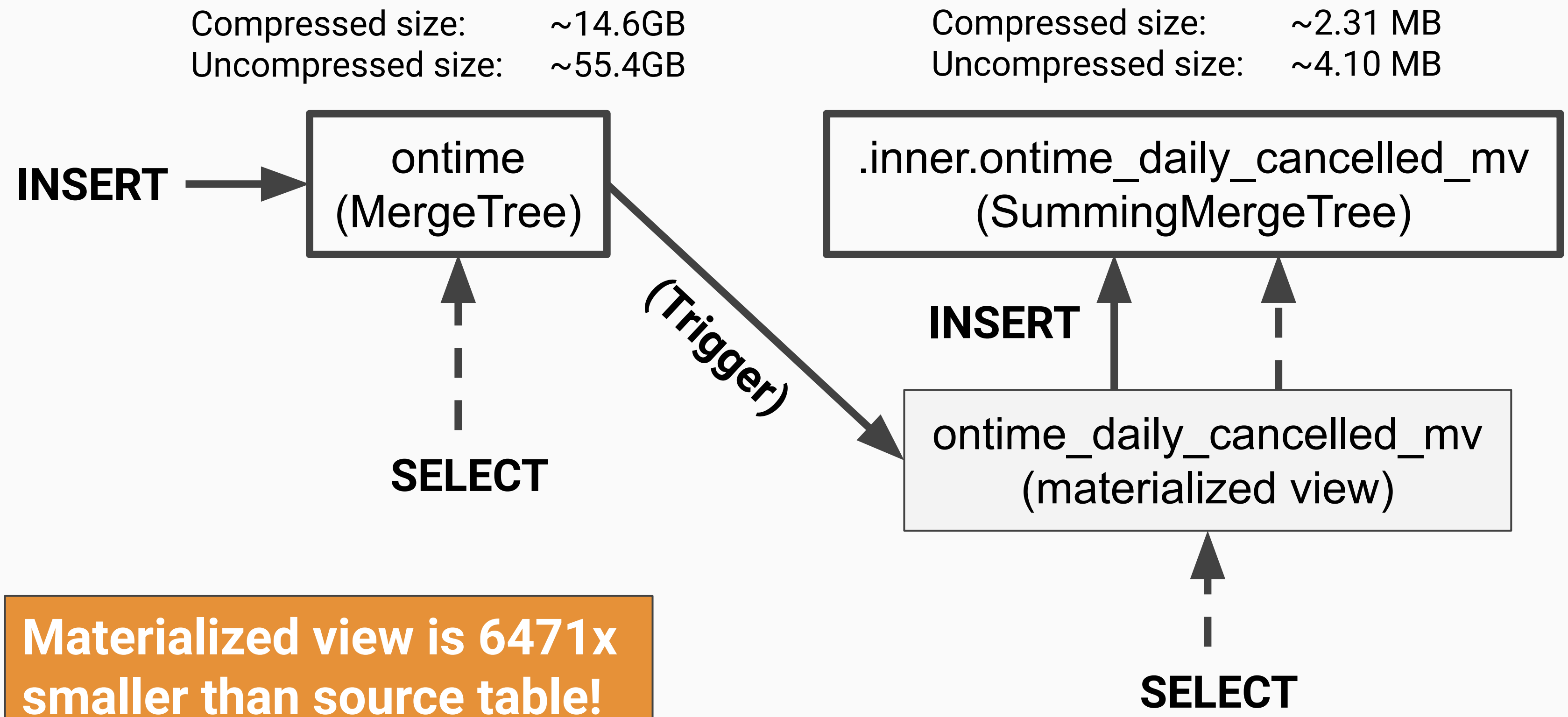
Query performance impact is significant

```
SELECT
   toYear(FlightDate) AS year,
   sum(flights) AS flights,
   sum(cancelled) AS cancelled,
   sum(delayed_15) AS delayed_15
FROM airline.ontime_daily_cancelled_mv
GROUP BY year ORDER BY year ASC LIMIT 10

. . .

10 rows in set. Elapsed: 0.007 sec. Processed 148.16
thousand rows, 3.85 MB (20.37 million rows/s., 529.50
MB/s.)
```

What’s going on under the covers?



Materialized view is 6471x smaller than source table!

A brief study of ClickHouse table structures

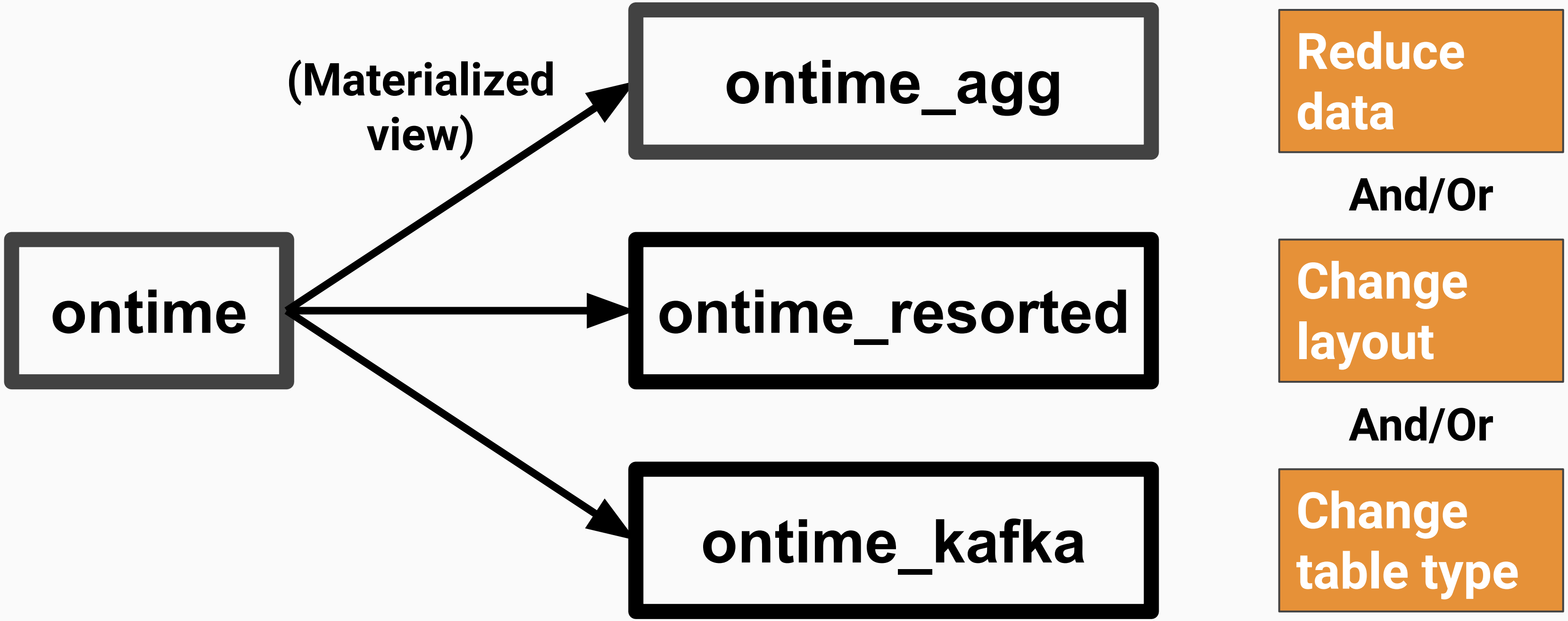
```
CREATE TABLE ontime (
  Year UInt16,
  Quarter UInt8,
  Month UInt8,
  ...
) ENGINE = MergeTree()
PARTITION BY toYYYYMM(FlightDate)
ORDER BY (Carrier, FlightDate)
```

Table engine type

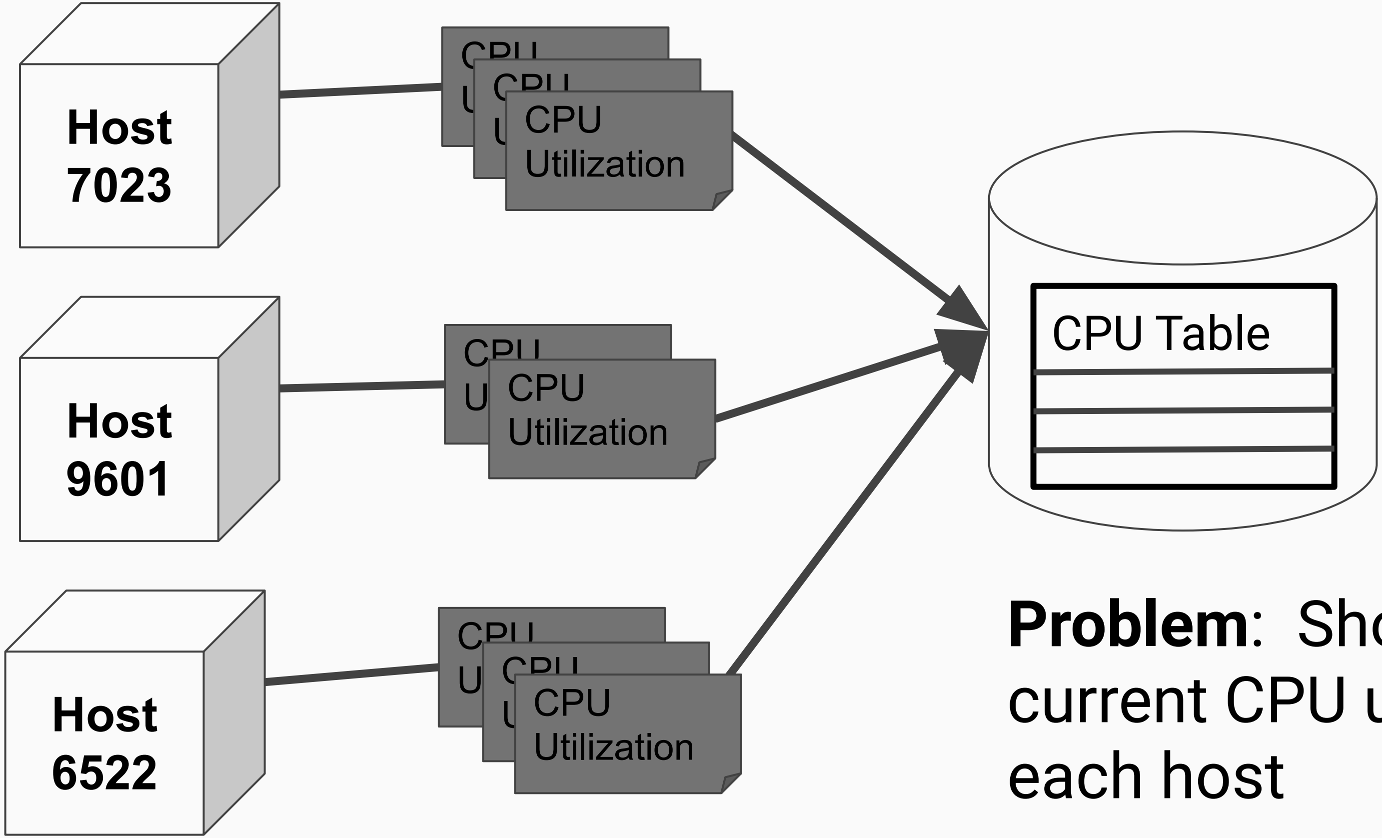
How to break data into parts

How to index and sort data in each part

Possible ways to transform tables



Exercise: the famous ‘last point problem’



Problem: Show the current CPU utilization for each host

ClickHouse can solve this using a subquery

```
SELECT t.hostname, tags_id, 100 - usage_idle usage
FROM (
    SELECT tags_id, usage_idle
    FROM cpu
    WHERE (tags_id, created_at) IN
      (SELECT tags_id, max(created_at)
       FROM cpu GROUP BY tags_id)
) AS c
INNER JOIN tags AS t ON c.tags_id = t.id
ORDER BY
    usage DESC,
    t.hostname ASC
LIMIT 10
```

TABLE SCAN!

USE INDEX

OPTIMIZED JOIN COST

SQL queries work but are inefficient

OUTPUT:

hostname	tags_id	usage
host_1002	9003	100
host_1116	9117	100
host_1141	9142	100
host_1163	9164	100
host_1210	9211	100
host_1216	9217	100
host_1234	9235	100
host_1308	9309	100
host_1419	9420	100
host_1491	9492	100

Using direct query on table:

10 rows in set. **Elapsed: 0.566 sec.** Processed 32.87 million rows, 263.13 MB (53.19 million rows/s., 425.81 MB/s.)

Can we bring last point performance closer to real-time?

Create target table for aggregate data

```
CREATE TABLE cpu_last_point_idle_agg (
  created_date AggregateFunction(argMax, Date, DateTime),
  max_created_at AggregateFunction(max, DateTime),
  time AggregateFunction(argMax, String, DateTime),
  tags_id UInt32,
  usage_idle AggregateFunction(argMax, Float64, DateTime)
)
ENGINE = AggregatingMergeTree()
PARTITION BY tuple()
ORDER BY tags_id
```

Minimal data

Different table type

Different storage layout

argMaxState links columns with aggregates

MV table

```
CREATE MATERIALIZED VIEW cpu_last_point_idle_mv
TO cpu_last_point_idle_agg
AS SELECT
    argMaxState(created_date, created_at) AS created_date,
    maxState(created_at) AS max_created_at,
    argMaxState(time, created_at) AS time,
    tags_id,
    argMaxState(usage_idle, created_at) AS usage_idle
FROM cpu
GROUP BY tags_id
```

Derive data

Digression: How aggregation works

Source value → `created_at`

Partial aggregate → `maxState(created_at)`

Merged aggregate → `maxMerge(max_created_at)`

Selecting rows that match max value

Source values

(Same row)

`created_at` ------------------> `usage_idle`

(Pick usage_idle value from any row with matching created_at)

Partial aggregates

`maxState(created_at)` ----> `argMaxState(usage_idle, created_at)`

(Pick usage_idle from aggregate with matching created_at)

Merged aggregates

`avgMerge(created_at)` ----> `avgMaxMerge(usage_idle)`

Let’s hide the merge details with a view

```
CREATE VIEW cpu_last_point_idle_v AS
SELECT
   argMaxMerge(created_date) AS created_date,
   maxMerge(max_created_at) AS created_at,
   argMaxMerge(time) AS time,
   tags_id,
   argMaxMerge(usage_idle) AS usage_idle
FROM cpu_last_point_idle_mv
GROUP BY tags_id
```

...Select again from the covering view

```
SELECT t.hostname, tags_id, 100 - usage_idle usage
FROM cpu_last_point_idle_v AS b
INNER JOIN tags AS t ON b.tags_id = t.id
ORDER BY usage DESC, t.hostname ASC
LIMIT 10

...

10 rows in set. Elapsed: 0.005 sec. Processed 14.00
thousand rows, 391.65 KB (2.97 million rows/s., 82.97
MB/s.)
```

Last point view is 113 times faster

Common uses for materialized views

- Precompute aggregates
- Fetch last point data
- Transform table on-disk indexing and sorting
  - Like a Vertica projection
- Keep aggregates after raw input is dropped
- Create data cleaning pipelines
- Read from Kafka queues

Thank you!

We’re hiring!

Presenter:
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ClickHouse:
https://github.com/ClickHouse/ClickHouse

Altinity:
https://www.altinity.com

...to reduce the amount of data we read