ClickHouse for Time-Series

OPEN SOURCE DATABASE CONFERENCE

PERCONA LIVE EUROPE AMSTERDAM

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Altinity

Agenda

What is special about time series

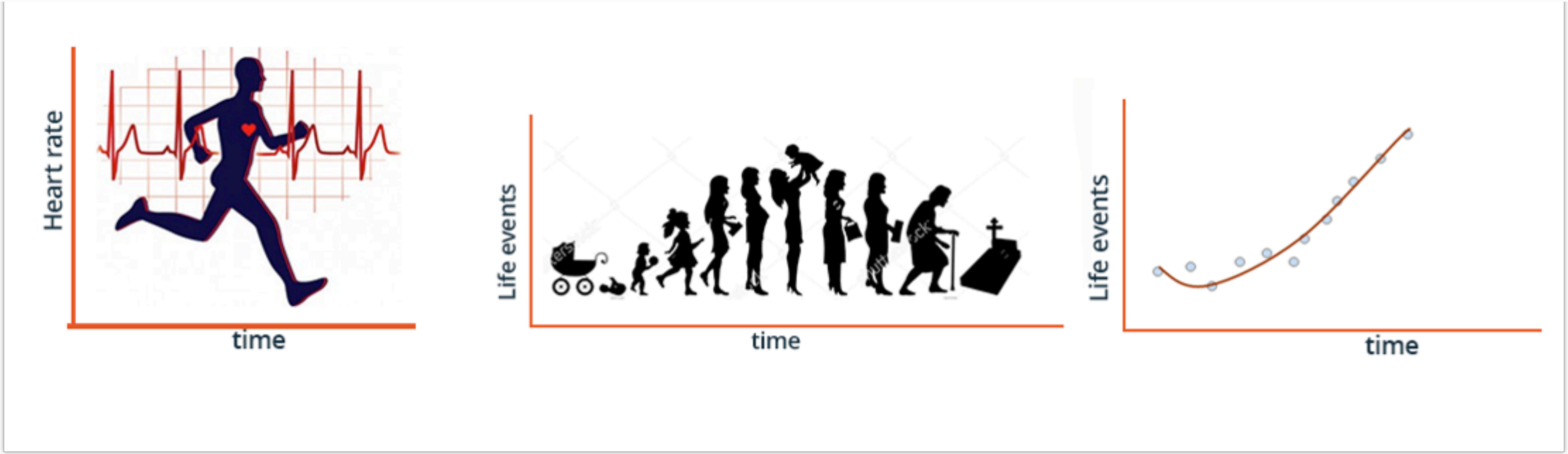
What is ClickHouse

How ClickHouse can be used for time series

Altinity Background

- Premier provider of software and services for ClickHouse
- Incorporated in UK with distributed team in US/Canada/Europe
- Main US/Europe sponsor of ClickHouse community
- Offerings:
  - Enterprise support for ClickHouse and ecosystem projects
  - Software (Kubernetes, cluster manager, tools & utilities)
  - POCs/Training

What is time series?



Time ordered events representing the process change over time

Monitoring
Finance
Internet of Things

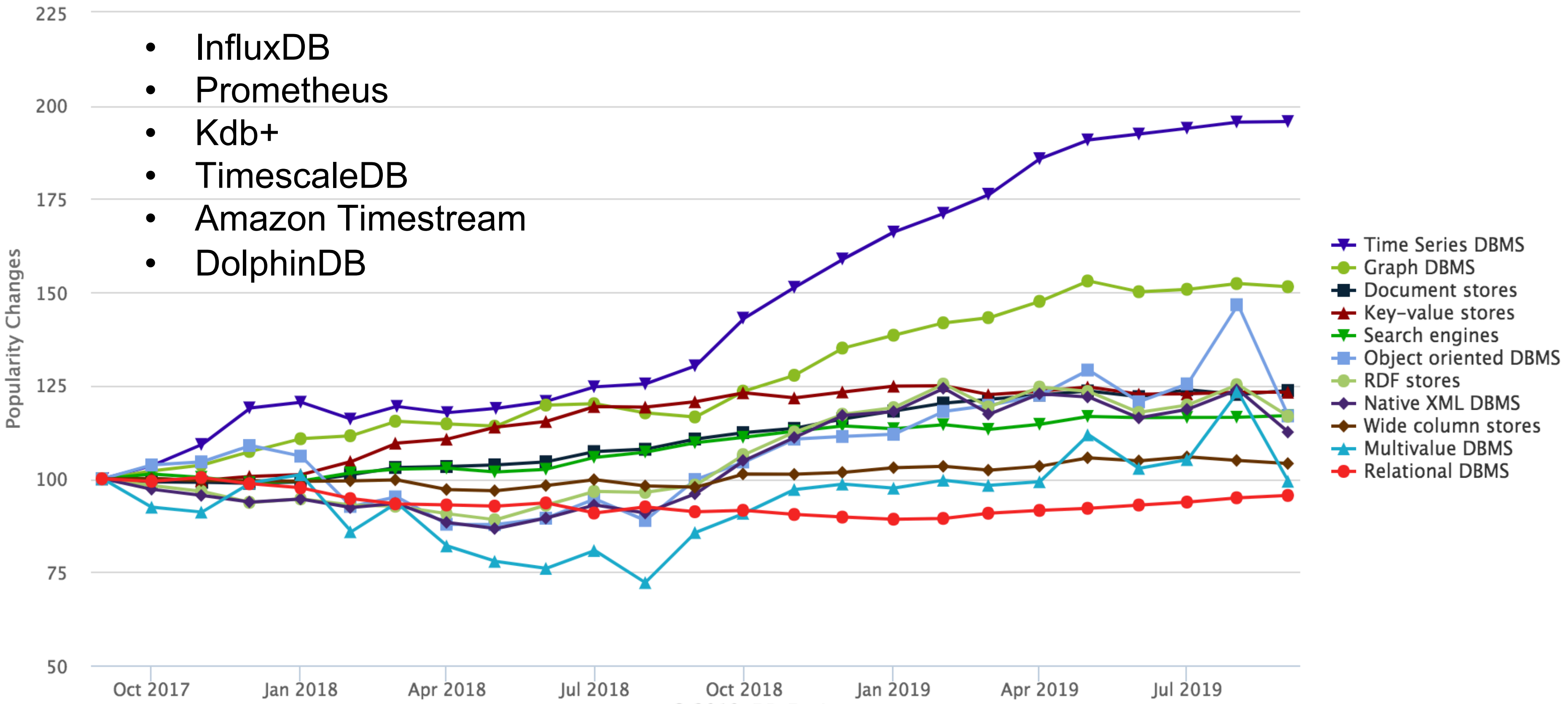
What is time series analytics?

Measure the *change*:

- How something has been changed comparing to the past
- What changes are going on right now
- Predict changes in the future

Dedicated time series DBMSs grow!

- InfluxDB
- Prometheus
- Kdb+
- TimescaleDB
- Amazon Timestream
- DolphinDB



© 2019, DB-Engines.com

What is special about time series DBMS?

- Optimized for very fast INSERT
- Efficient data storage, retention
- Aggregates, downsampling
- Fast queries

Looks like ClickHouse!

ClickHouse Overview

ClickHouse is a powerful data warehouse that handles many use cases

Understands SQL

Runs on bare metal to cloud

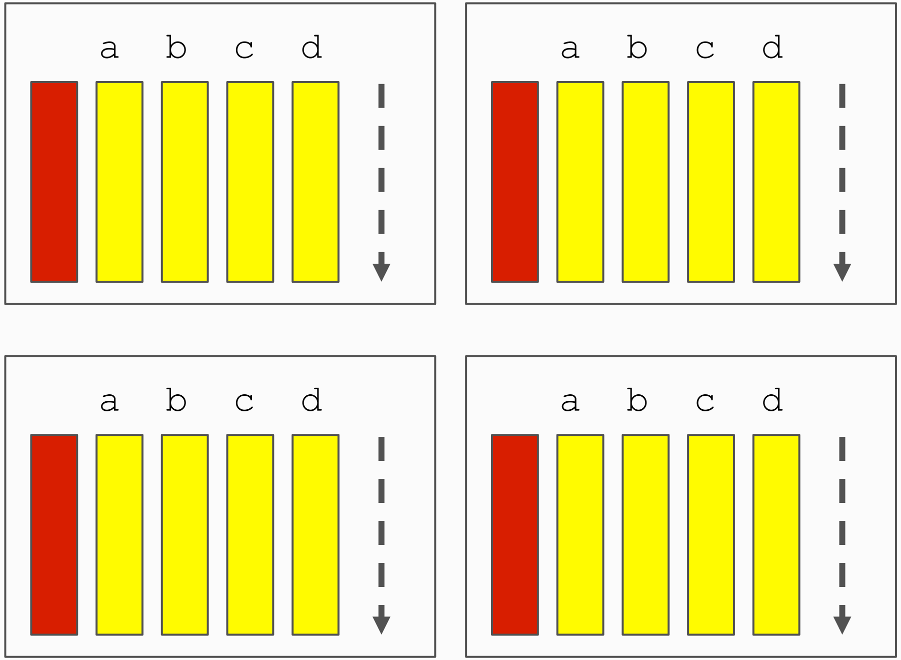
Stores data in columns

Parallel and vectorized execution

Scales to many petabytes

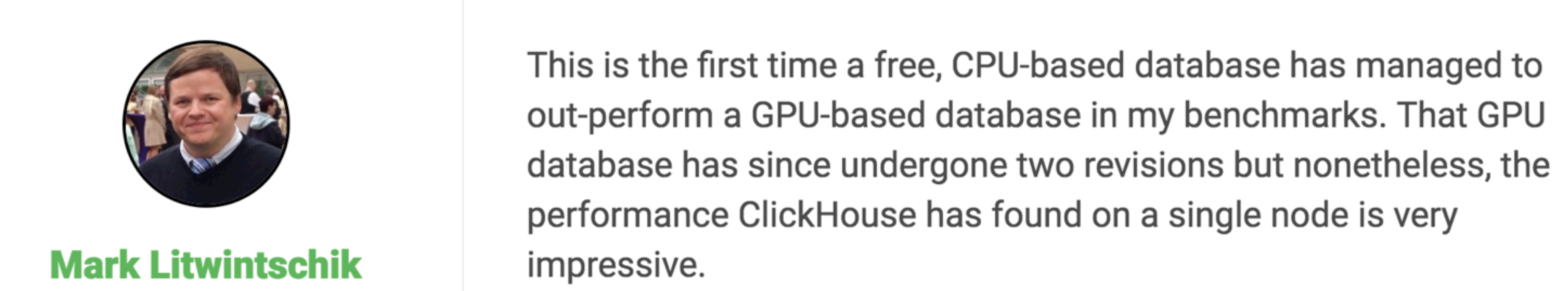
Is Open source (Apache 2.0)

Is WAY fast!



http://clickhouse.yandex

ClickHouse is FAST!

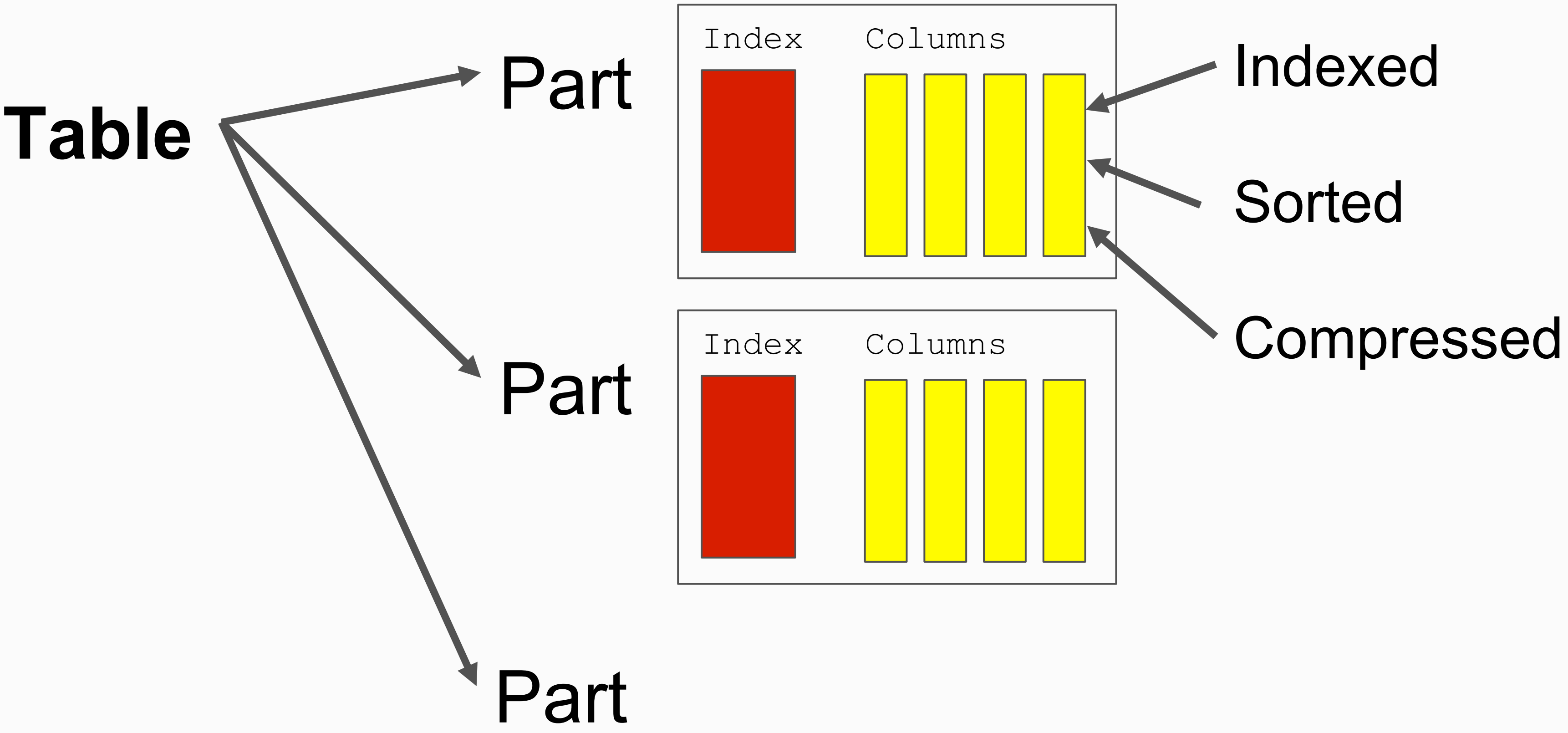


Mark Litwintschik

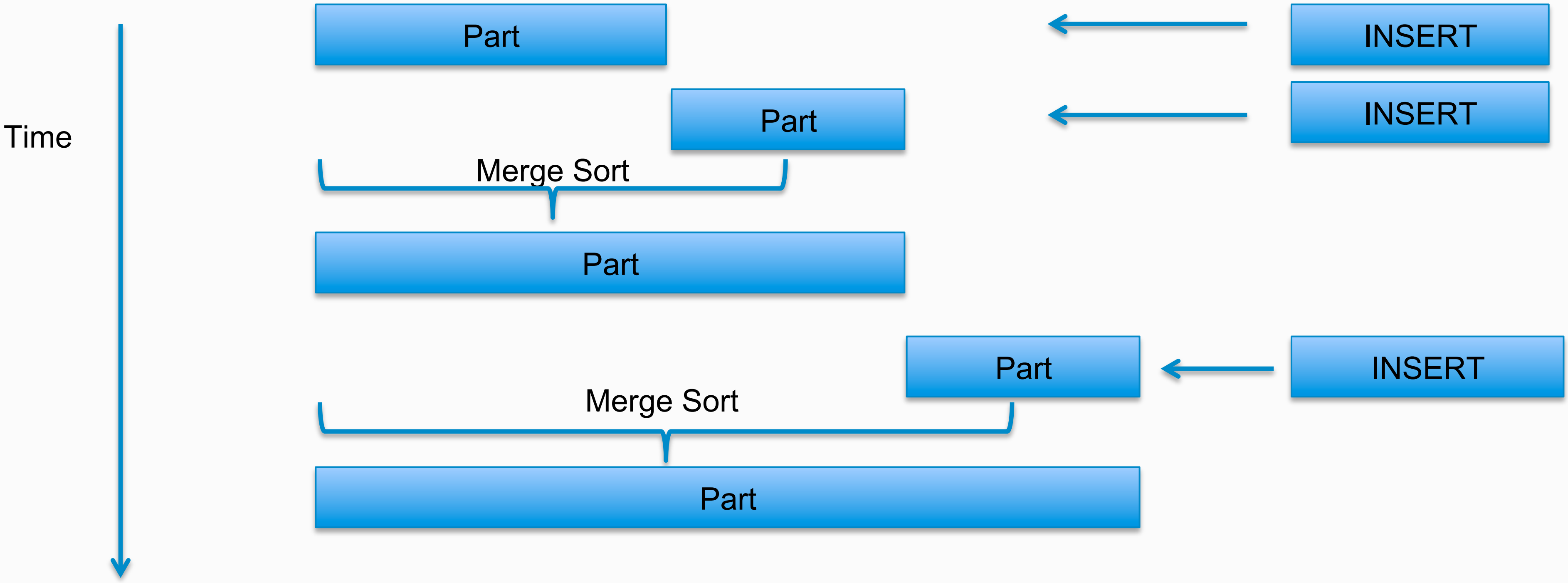
This is the first time a free, CPU-based database has managed to out-perform a GPU-based database in my benchmarks. That GPU database has since undergone two revisions but nonetheless, the performance ClickHouse has found on a single node is very impressive.

https://tech.marksblogg.com/benchmarks.html

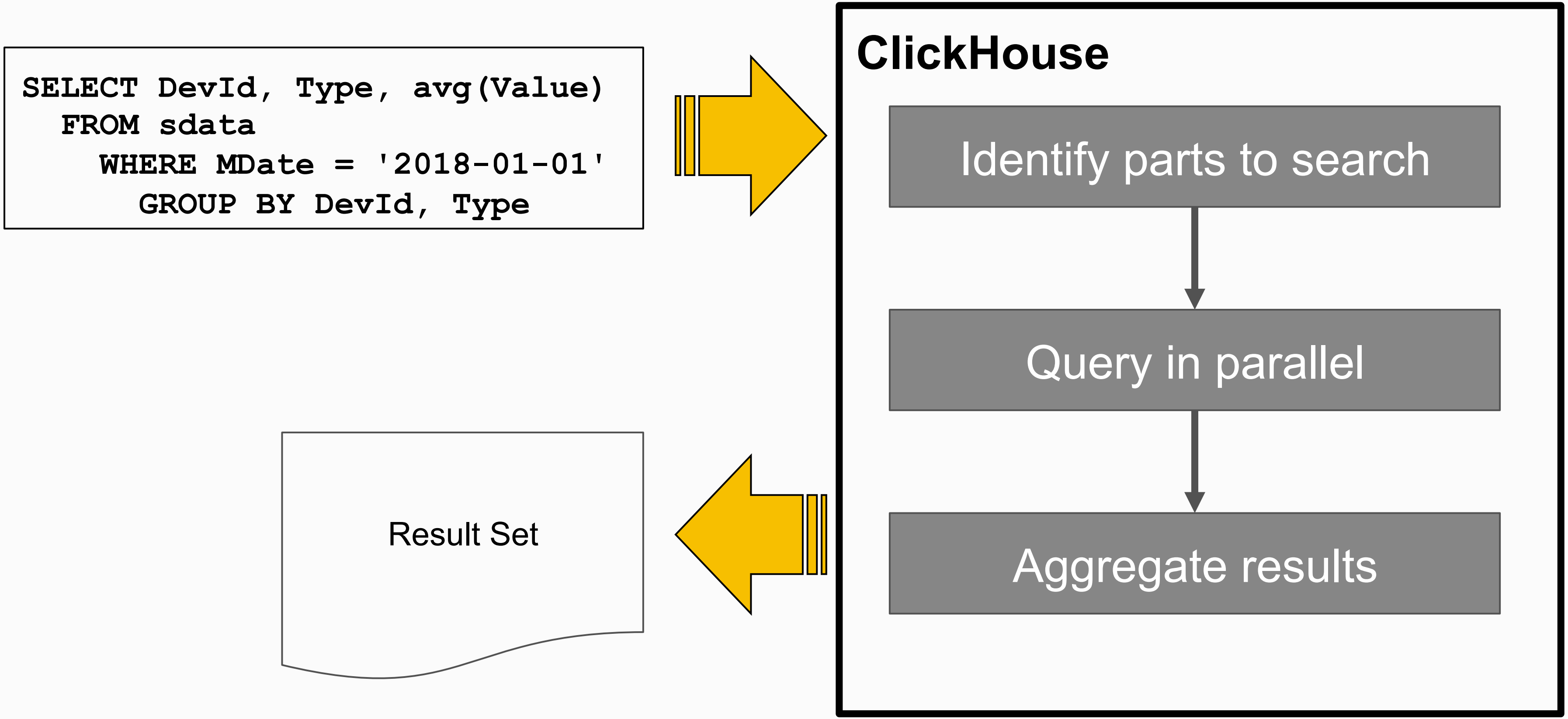
Tables are split into indexed, sorted parts for fast queries



Merge Process re-sortes data in the background

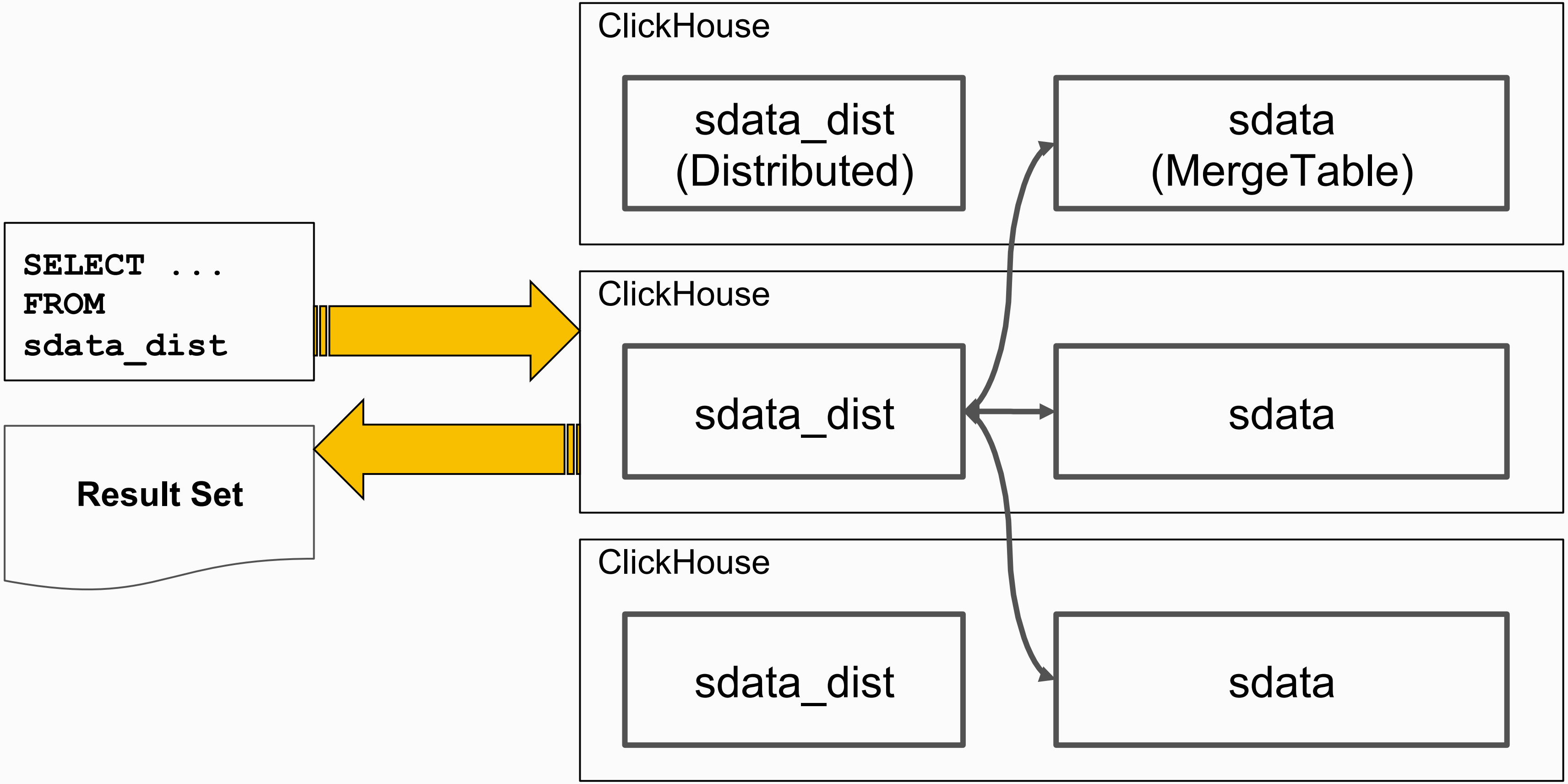


Now we can follow how query works on a single server

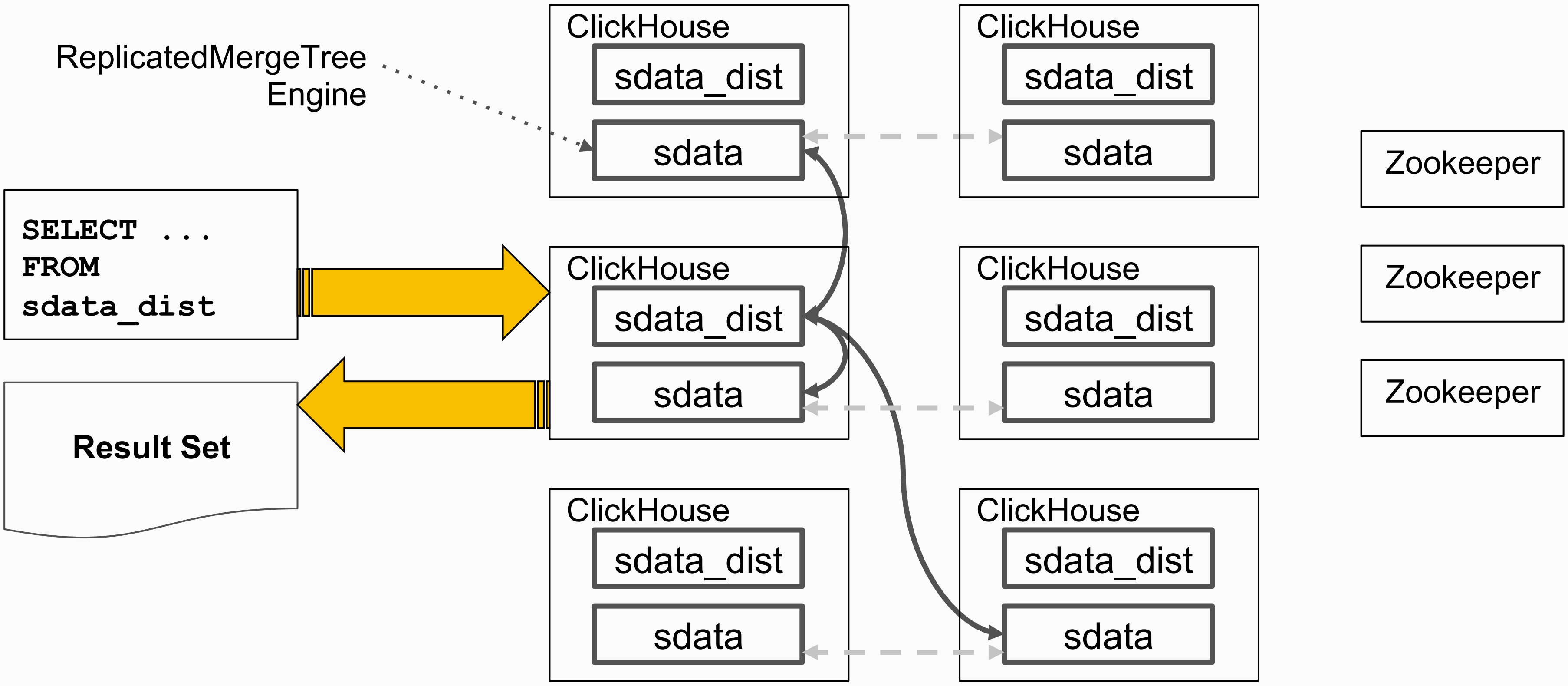


```
SELECT DevId, Type, avg(Value)
  FROM sdata
    WHERE MDate = '2018-01-01'
      GROUP BY DevId, Type
```

If one server is not enough -- ClickHouse can scale out easily



Built-in Replication and Failover provide high availability



ReplicatedMergeTree Engine

```
SELECT ...
FROM
sdata_dist
```

Result Set

ClickHouse
sdata_dist
sdata

ClickHouse
sdata_dist
sdata

ClickHouse
sdata_dist
sdata

ClickHouse
sdata_dist
sdata

ClickHouse
sdata_dist
sdata

ClickHouse
sdata_dist
sdata

Zookeeper

Zookeeper

Zookeeper

What are the main ClickHouse use patterns?

- Fast, scalable data warehouse for online services (SaaS and in-house apps)
- Built-in data warehouse for installed analytic applications
- Monitoring and Log Storage in-house solutions
- Exploration -- throw in a bunch of data and go crazy!

ClickHouse’s Four “F”-s:

Fast!

Flexible!

Free!

Fun!

ClickHouse for Time Series

Does ClickHouse fit for time series?

Does ClickHouse fit for time series?

“One size does not fit all!”

Michael Stonebraker. 2005

Does ClickHouse fit for time series?

“ClickHouse не тормозит!”

Alexey Milovidov. 2016

Does ClickHouse fit for time series?

“One size does not fit all!”

Michael Stonebraker

?

“ClickHouse не тормозит!”

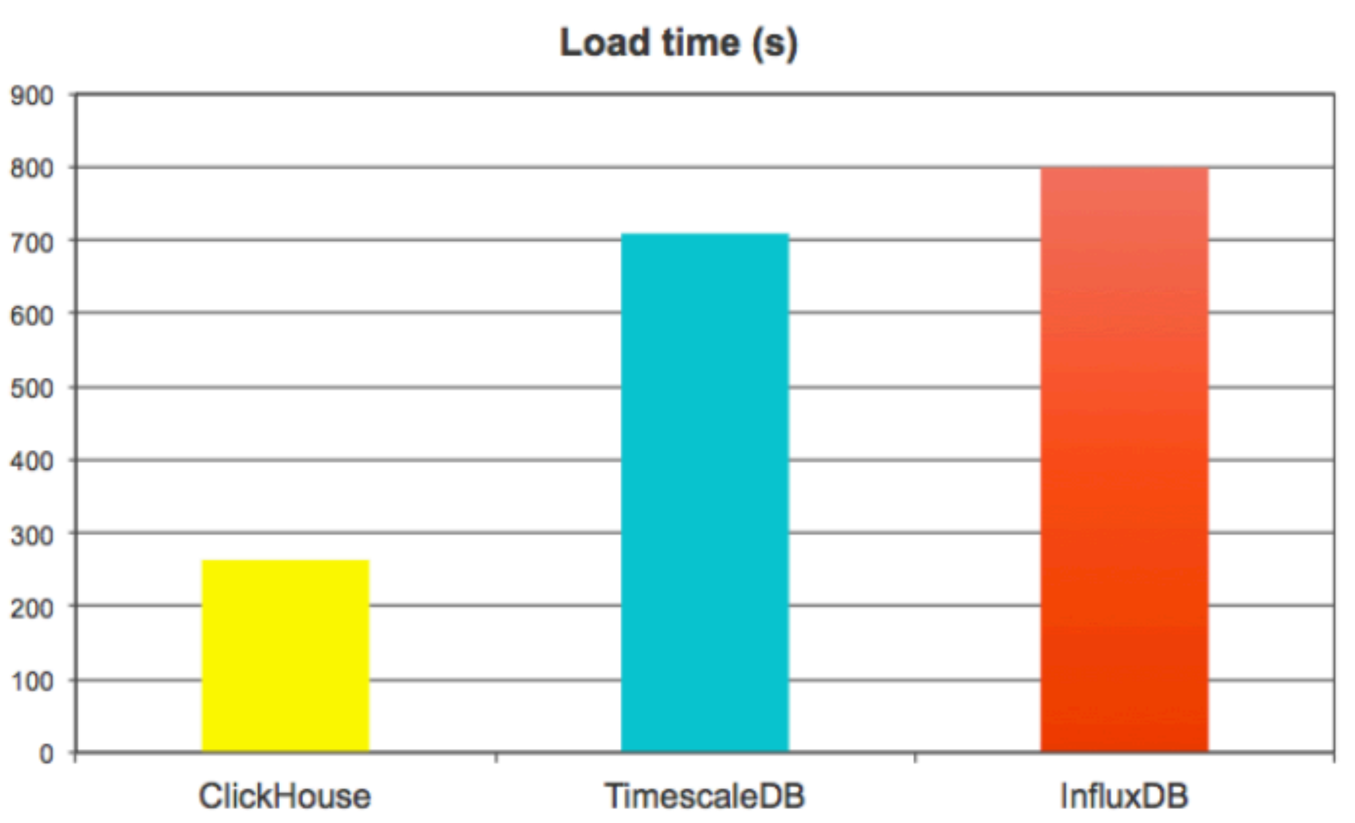
Alexey Milovidov

November 2018 benchmark. TSBS

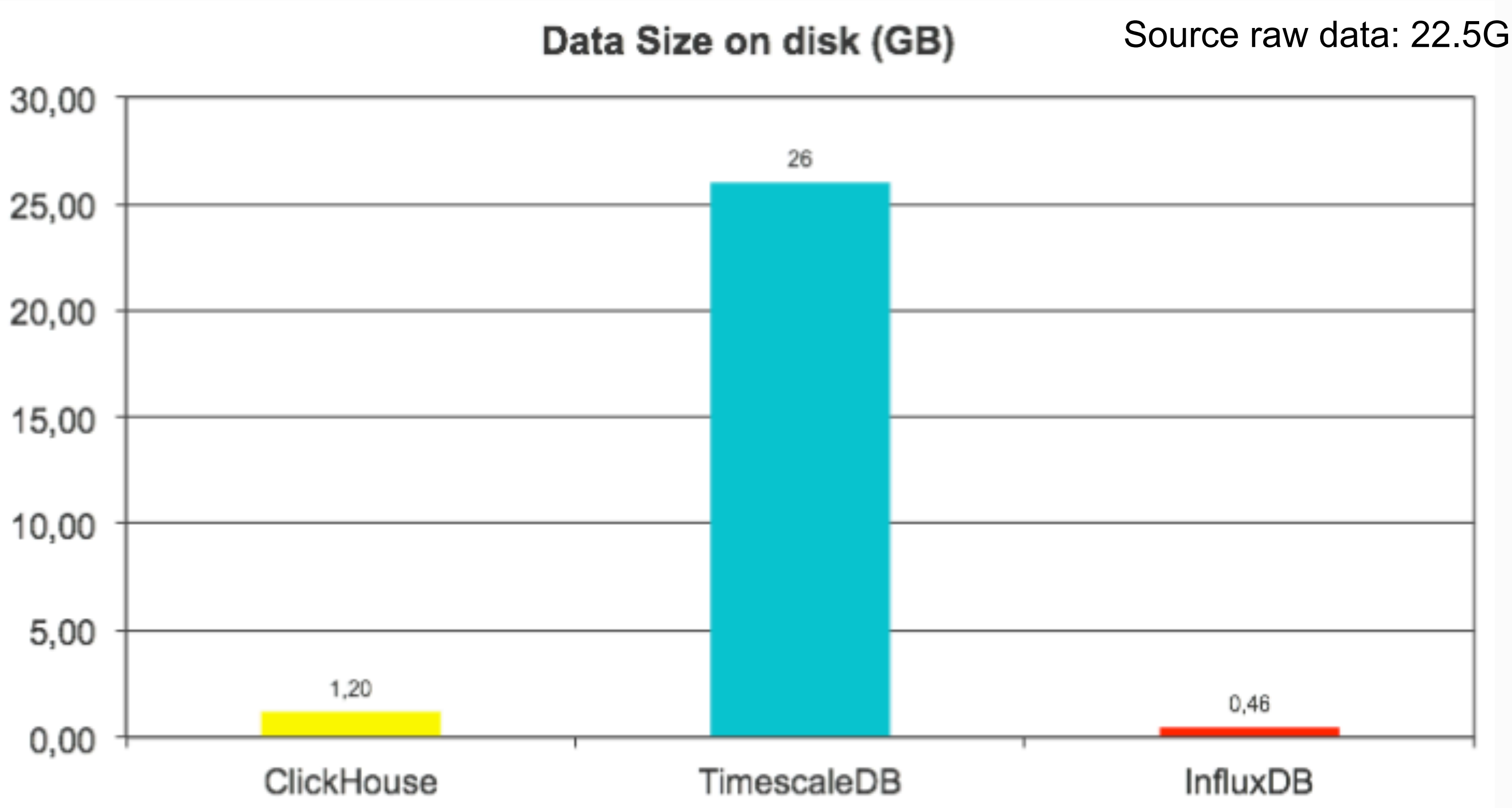
- https://github.com/timescale/tsbs
- ClickHouse vs TimescaleDB vs InfluxDB (vs Cassandra)
- Amazon r5.2xlarge instance, 8 vCPUs, 64GB RAM, EBS storage
- 100M rows, 10 metrics (columns) + metadata
- 15 test queries common for time series use cases, 8 threads

https://www.altinity.com/blog/clickhouse-for-time-series

November 2018 benchmark. TSBS

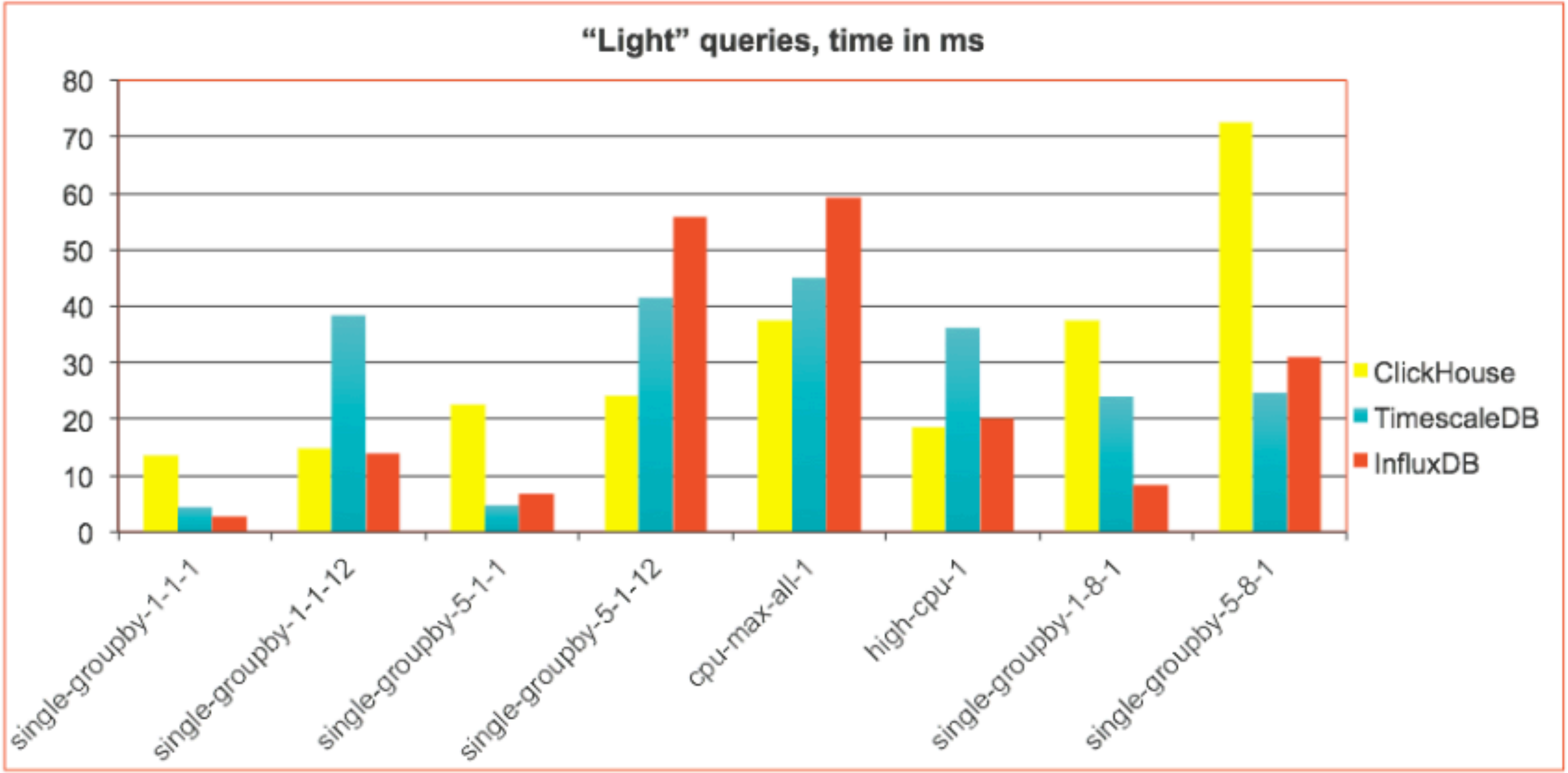


November 2018 benchmark. TSBS

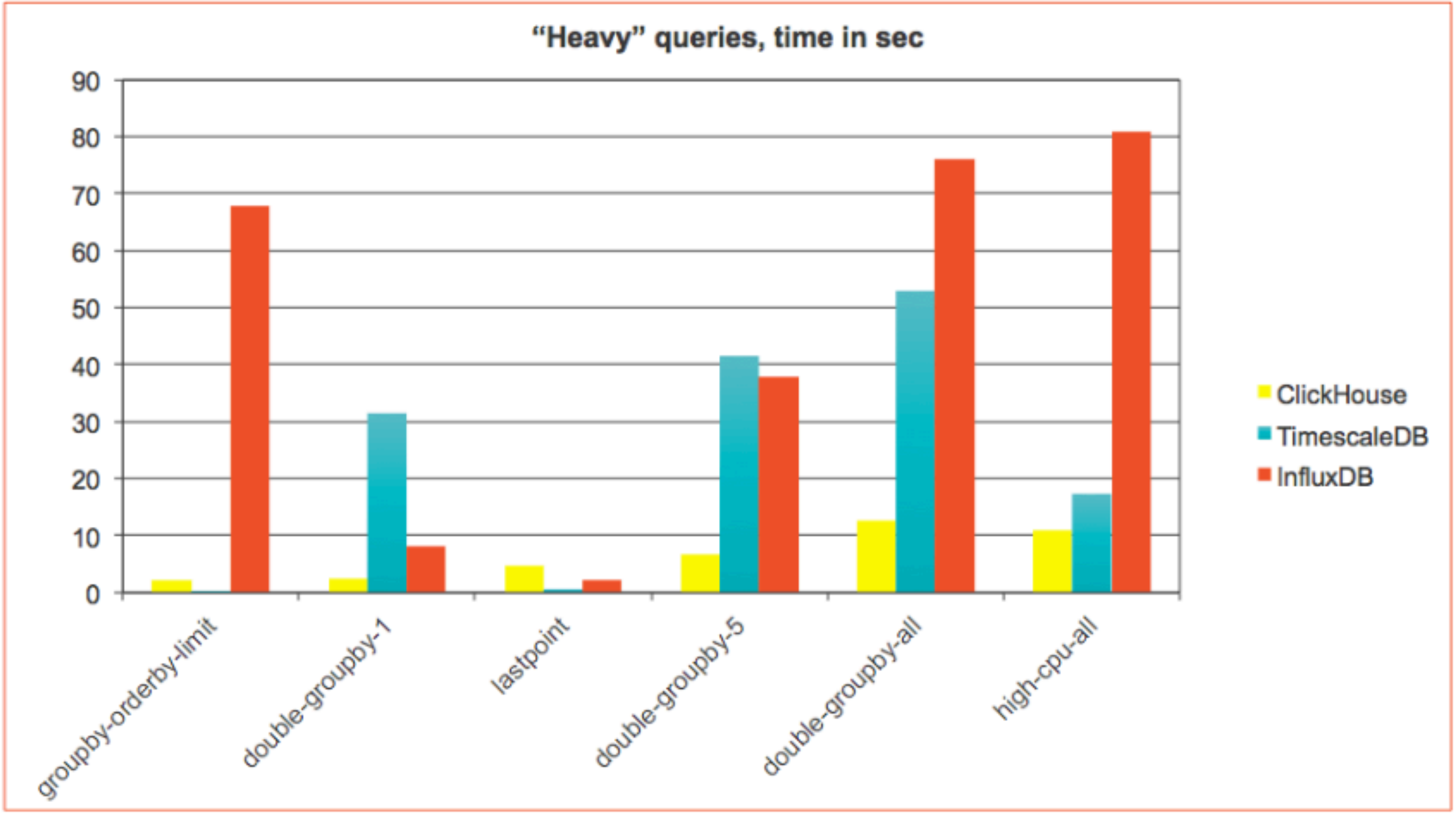


Source raw data: 22.5GB

November 2018 benchmark. TSBS



November 2018 benchmark. TSBS



What have we learned?

- ClickHouse load performance is outstanding! *
- Compression is efficient, but not as good as InfluxDB’s
- Queries are fast, but can be even faster

** It turned out later, it has been limited by storage performance reading source data*

ClickHouse as time series DBMS

Time series performance

with

flexibility of feature rich analytical SQL DBMS

How to build time series apps with ClickHouse

Schema

Basic model:

timestamp | device (user, etc.) | metric | value | attrs, tags

Options:

- Well-structured data (all metrics are known)
- Semi-structured data (metrics are not known)
- Non-structured tags

Schema options: column per metric

```
CREATE TABLE cpu (
  created_date Date DEFAULT today(),
  created_at DateTime DEFAULT now(),
  time String,
  tags_id UInt32,  /* join to dim_tag */
  usage_user Float64,
  usage_system Float64,
  usage_idle Float64,
  usage_nice Float64,
  usage_iowait Float64,
  usage_irq Float64,
  usage_softirq Float64,
  usage_steal Float64,
  usage_guest Float64,
  usage_guest_nice Float64
) ENGINE = MergeTree(created_date, (tags_id, created_at), 8192);
```

Schema options: arrays

```
CREATE TABLE cpu_alc (
  created_date Date,
  created_at DateTime,
  time String,
  tags_id UInt32,
  metrics Nested(
    name LowCardinality(String),
    value Float64
  )
) ENGINE = MergeTree(created_date, (tags_id, created_at), 8192);


SELECT max(metrics.value[indexOf(metrics.name,'usage_user')]) FROM ...
```

Schema options: row per metric

```
CREATE TABLE cpu_rlc (
  created_date Date,
  created_at DateTime,
  time String,
  tags_id UInt32,
  metric_name LowCardinality(String),
  metric_value Float64
) ENGINE = MergeTree(created_date, (metric_name, tags_id, created_at),
8192);


SELECT
    maxIf(metric_value, metric_name = 'usage_user'),
    ...
FROM cpu_r
WHERE metric_name IN ('usage_user', ...)
```

Schema options: let’s compare

Schema type	Size on disk	Pros	Cons
Columns	1.23 GB	- Best compression - Best insert/query performance	- Schema is fixed
Arrays	1.48 GB	- Good compression - Works for semi-structured data	- Speed degrades with array size
Rows	4.7 GB	- Simplest - Excellent speed for a single metric	- Bad compression, too many rows - Performance degrades when multiple metrics are queried together

Details: https://www.altinity.com/blog/2019/5/23/handling-variable-time-series-efficiently-in-clickhouse

Compression and Encoding

- Compression vs Encoding
- Example of encodings:
  - RLE
  - Dictionary encoding
  - Entropy coding

Codecs in ClickHouse

- LowCardinality – special data type
- Delta – for ordered time stamps
- DoubleDelta – for ordered time stamps
- Gorilla – for float gauges
- T64 – for integers

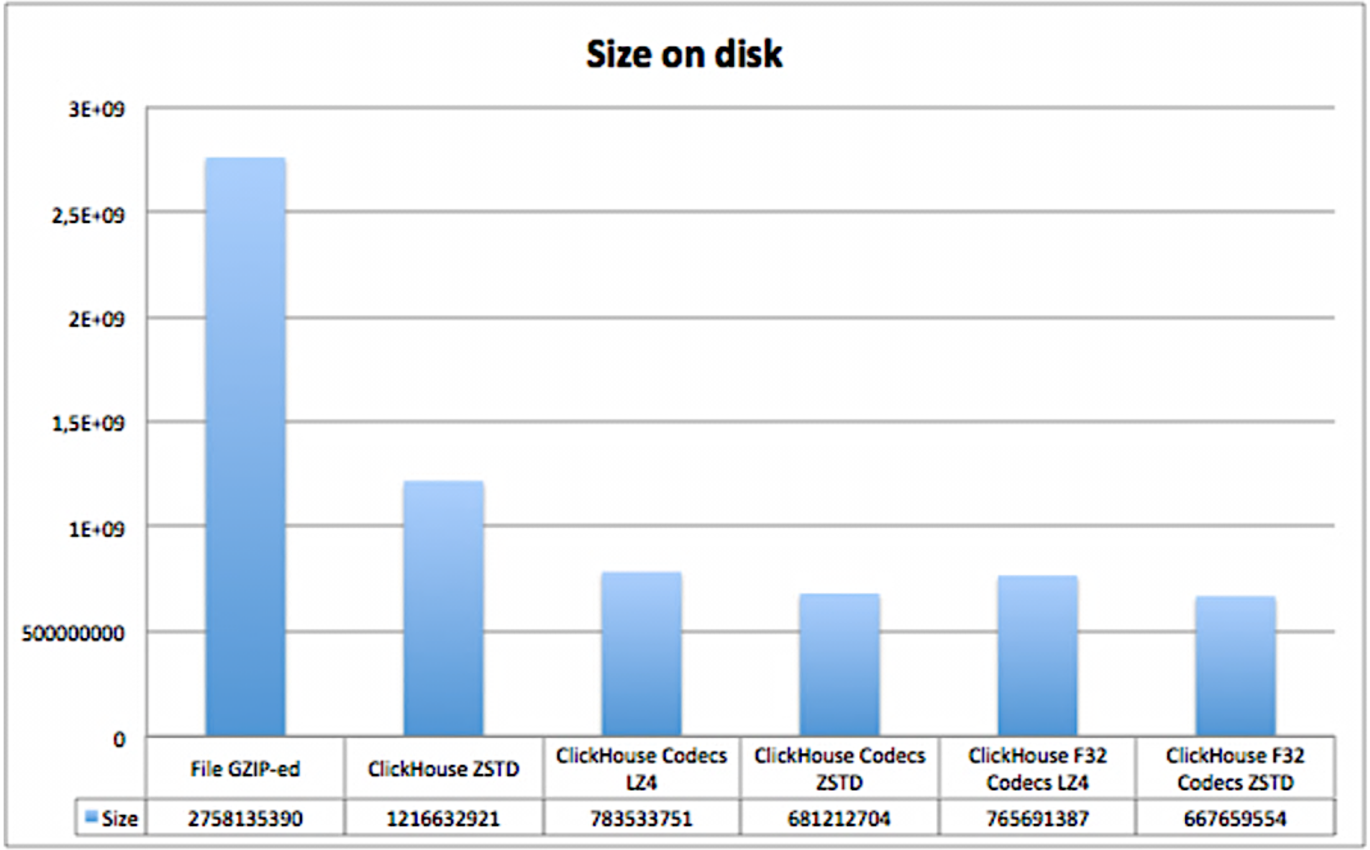
.. and

- LZ4 and ZSTD
- Codecs can be “chained”

Codecs in ClickHouse

```
CREATE TABLE benchmark.cpu_codecs_lz4 (
    created_date Date DEFAULT today(),
    created_at DateTime DEFAULT now() Codec(DoubleDelta, LZ4),
    tags_id UInt32,
    usage_user Float64 Codec(Gorilla, LZ4),
    usage_system Float64 Codec(Gorilla, LZ4),
    usage_idle Float64 Codec(Gorilla, LZ4),
    usage_nice Float64 Codec(Gorilla, LZ4),
    usage_iowait Float64 Codec(Gorilla, LZ4),
    usage_irq Float64 Codec(Gorilla, LZ4),
    usage_softirq Float64 Codec(Gorilla, LZ4),
    usage_steal Float64 Codec(Gorilla, LZ4),
    usage_guest Float64 Codec(Gorilla, LZ4),
    usage_guest_nice Float64 Codec(Gorilla, LZ4),
    additional_tags String DEFAULT ''
)
ENGINE = MergeTree(created_date, (tags_id, created_at), 8192);
```

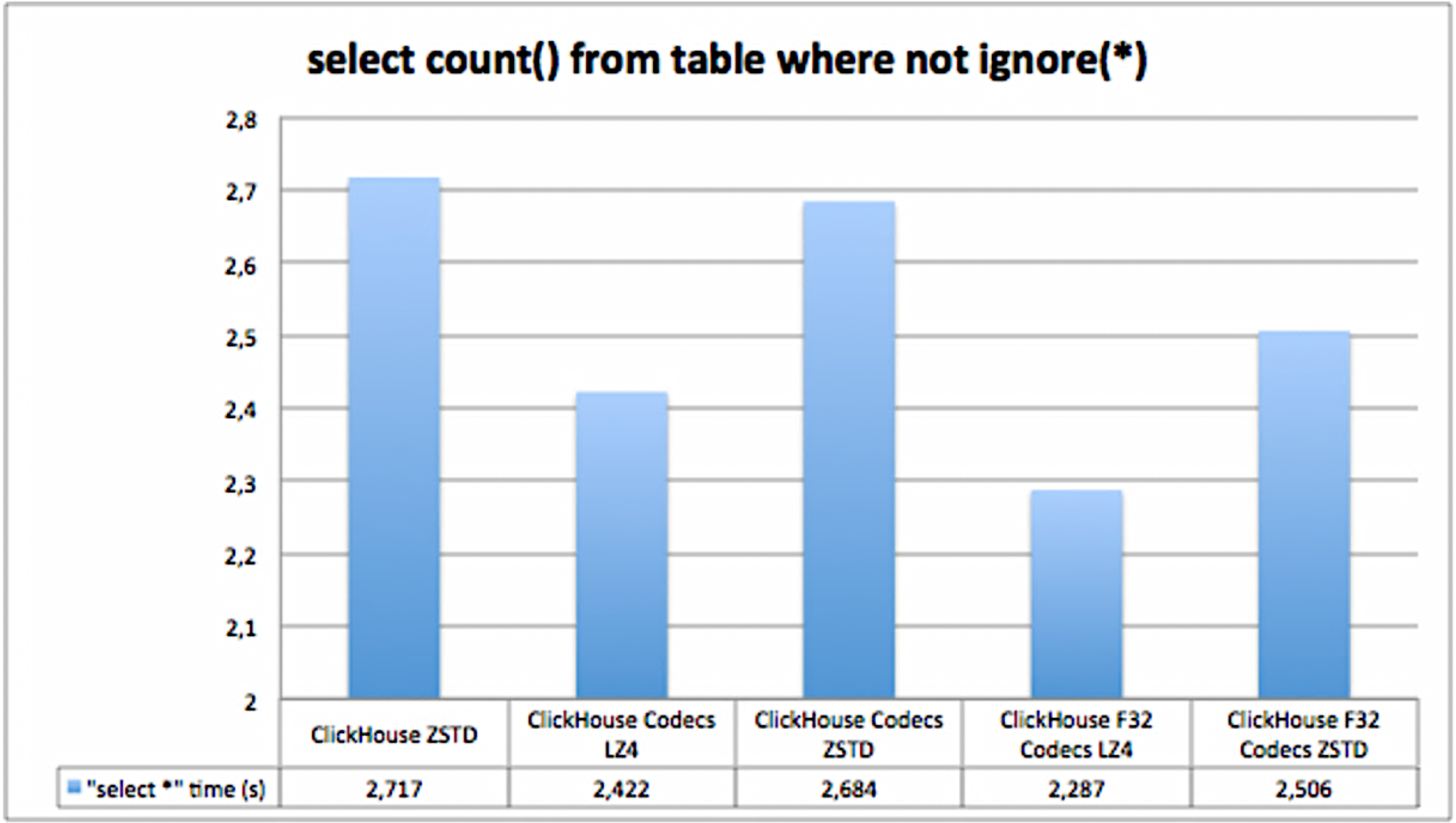
Codecs in ClickHouse: size



	File GZIP-ed	ClickHouse ZSTD	ClickHouse Codecs LZ4	ClickHouse Codecs ZSTD	ClickHouse F32 Codecs LZ4	ClickHouse F32 Codecs ZSTD
▨ Size	2758135390	1216632921	783533751	681212704	765691387	667659554

InfluxDB:
456MB :-/

Codecs in ClickHouse: query performance



select count() from table where not ignore(*)

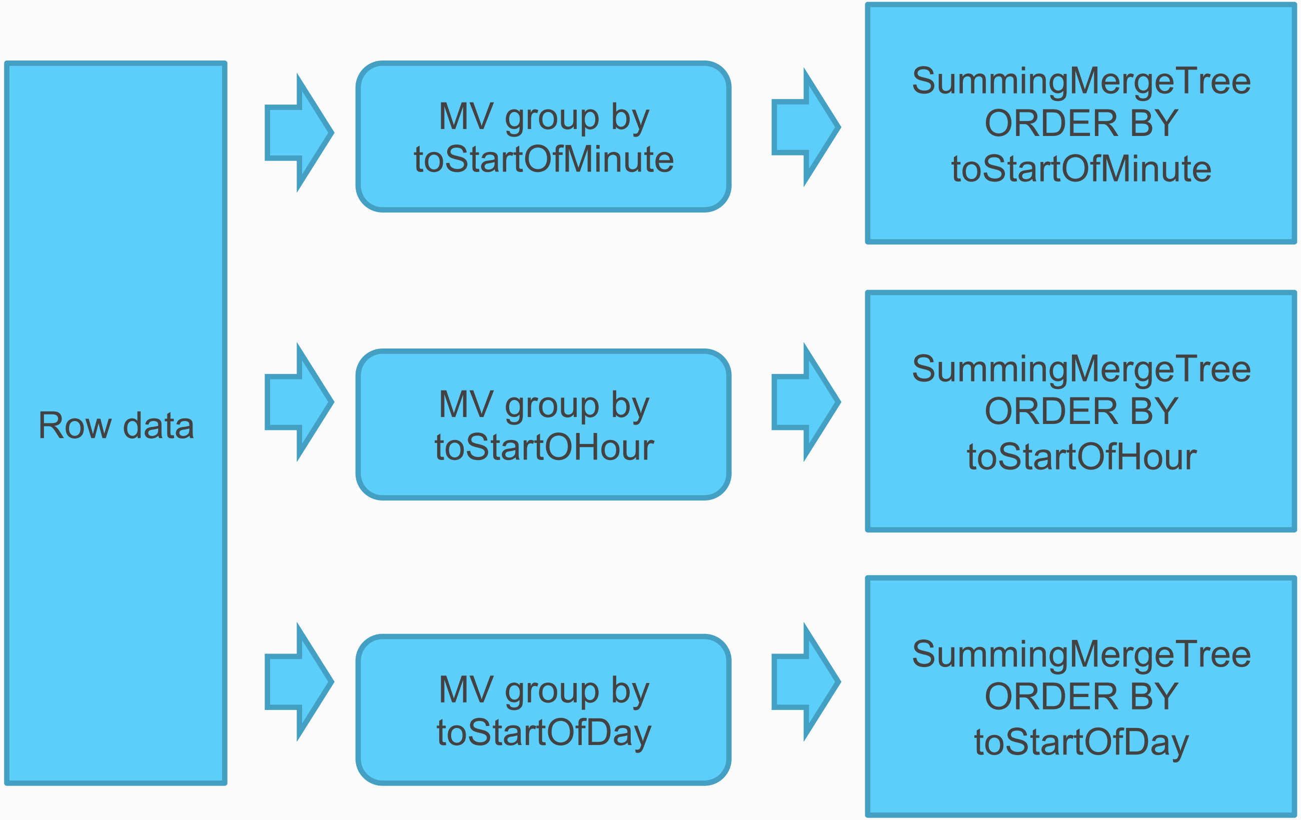
	ClickHouse ZSTD	ClickHouse Codecs LZ4	ClickHouse Codecs ZSTD	ClickHouse F32 Codecs LZ4	ClickHouse F32 Codecs ZSTD
■ "select *" time (s)	2,717	2,422	2,684	2,287	2,506

Codecs in ClickHouse: summary

- Codecs are good! (ClickHouse 19.11.7 and above)
- Could be better (examples InfluxDB, VictoriaMetrics)
- Will be improved:
  - Encoding in frames for better performance (middle-out algorithm)
  - Convert floats to integers before encoding (VictoriaMetrics)
  - Do not perform bit instrumentation, rely on ZSTD instead

More details: https://github.com/yandex/clickhouse-presentations/blob/master/meetup26/time_series.pdf

Aggregation and downsampling


Row data
MV group by toStartOfMinute
MV group by toStartOHour
MV group by toStartOfDay
SummingMergeTree ORDER BY toStartOfMinute
SummingMergeTree ORDER BY toStartOfHour
SummingMergeTree ORDER BY toStartOfDay

- Realtime!
- Performance boost x100-1000 times!
- Aggregation of sums and uniques!
- Cascades since 19.14

TTLs – data retention policies

```
CREATE TABLE aggr_by_minute
…
TTL time + interval 1 day

CREATE TABLE aggr_by_day
…
TTL time + interval 30 day

CREATE TABLE aggr_by_week
…
/* no TTL */
```

Time series specific queries

- No Flux of other proprietary query language
- Standard SQL
- … enriched advanced functions

Query the last measurement for the device

```
SELECT *
  FROM cpu
 WHERE (tags_id, created_at) IN
    (SELECT tags_id, max(created_at)
        FROM cpu
        GROUP BY tags_id)
```

Tuple can be used with IN operator

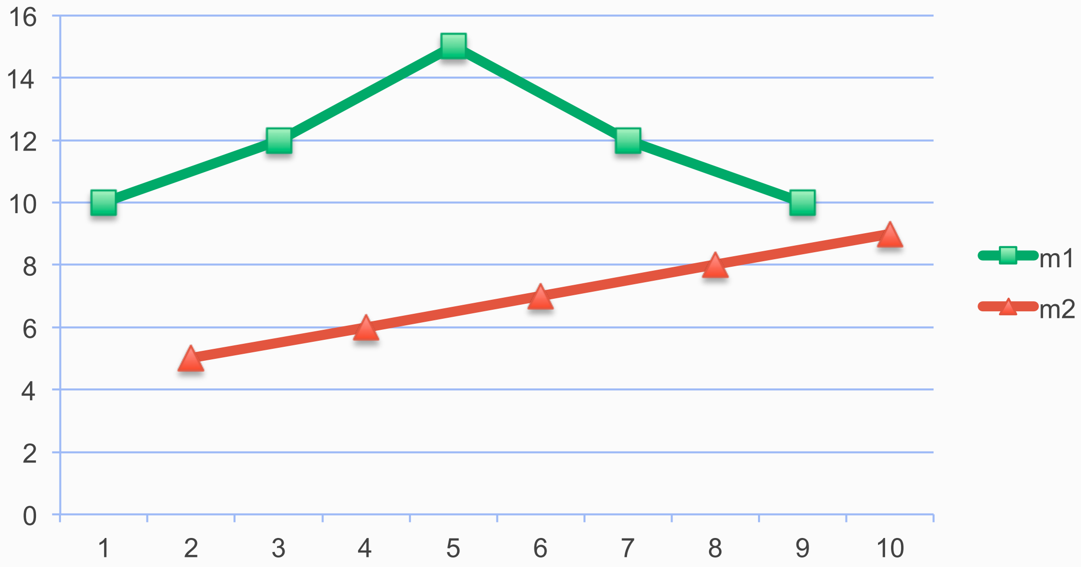
```
SELECT
    argMax(usage_user, created_at),
    argMax(usage_system, created_at),
...
 FROM cpu
```

Efficient argMax

```
SELECT now() as created_at,
       cpu.*
  FROM (SELECT DISTINCT tags_id from cpu) base
  ASOF LEFT JOIN cpu USING (tags_id, created_at)
```

ASOF

ASOF JOIN – «stitching» non-aligned time series



```
SELECT m1.*, m2.*
  FROM m1
  LEFT ASOF JOIN m2 USING (timestamp)
```

Analytical functions

```
SELECT origin,
       timestamp,
       timestamp -LAG(timestamp, 1) OVER (PARTITION BY origin ORDER BY
timestamp) AS duration,
       timestamp -MIN(timestamp) OVER (PARTITION BY origin ORDER BY
timestamp) AS startseq_duration,
       ROW_NUMBER() OVER (PARTITION BY origin ORDER BY timestamp) AS
sequence,
       COUNT() OVER (PARTITION BY origin ORDER BY timestamp) AS nb
  FROM mytable
ORDER BY origin, timestamp;
```

This is **NOT** ClickHouse

Analytical functions. ClickHouse way.

```
SELECT
    origin,
    timestamp,
    duration,
    timestamp - ts_min AS startseq_duration,
    sequence,
    ts_cnt AS nb
FROM (
    SELECT
        origin,
        groupArray(timestamp) AS ts_a,
        arrayMap((x, y) -> (x - y), ts_a, arrayPushFront(arrayPopBack(ts_a), ts_a[1])) AS ts_diff,
        min(timestamp) as ts_min,
        arrayEnumerate(ts_a) AS ts_row, -- generates array of indexes 1,2,3, ...
        count() AS ts_cnt
    FROM mytable
    GROUP BY origin
)
ARRAY JOIN ts_a AS timestamp, ts_diff AS duration, ts_row AS sequence
ORDER BY origin, timestamp
```

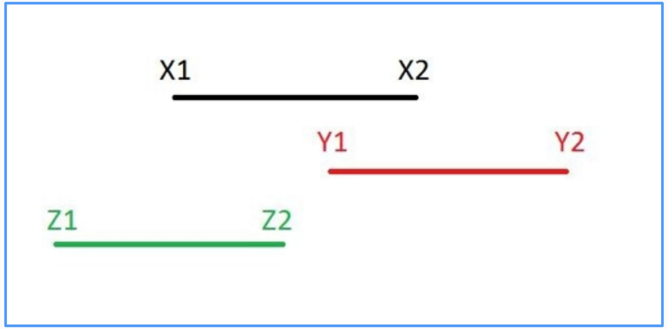
1. Convert time-series to an array with groupArray
2. Apply array magic
3. Convert arrays back to rows with ARRAY JOIN

-- not that easy but very flexible

Special functions for time series

How many sessions happened at the same time?

```
T:
---------
Sessionid
timestamp
. . .
```



```
SELECT
maxIntersections(toUInt32(start),
toUInt32(end)),
toDateTime(maxIntersectionsPosition(toUInt32(start), toUInt32(end)))
FROM (
        SELECT
        sessionid,
        min(timestamp) AS start,
        max(timestamp) AS end
        FROM T
        GROUP BY sessionid
)
```

Special functions for time series

sequenceMatch – “regular expressions” on time series data

```
SELECT userid
FROM hits
GROUP BY
        userid,
        sessionid
HAVING sequenceMatch('(?1).*(?2).*(?1).*(?2).*(?3)')(
   timestamp,
   event_type = 'product',
   event_type = 'checkout',
   event_type = 'purchase' )
```

Special functions for time series

Anomaly detection for counters:

```
SELECT
  host,
  round( boundingRatio(timestamp, read_bytes) ) as rate
FROM host_stats
GROUP by host
ORDER BY rate
```

```
boundingRatio(timestamp, value) =
 ( argMax(value, timestamp) - argMin(value, timestamp) )
  / ( max(timestamp) - min(timestamp) )
```

```
┌─host─┬───────rate─┐
│    0 │       2123 │
│    1 │       2102 │
│    2 │     120758 │ <- anomaly (!!!)
│    3 │       2087 │
└──────┴────────────┘
```

Special functions for time series

- runningDifference, runningAccumulate, neighbor
- sumMap(key, value)
- timeSeriesGroupSum(uid, timestamp, value)
- timeSeriesGroupRateSum(uid, timestamp, value)
- skewPop, skewSamp, kurtPop, kurtSamp
- ORDER BY WITH FILL – gaps filling
- simpleLinearRegression, stochasticLinearRegression
- windowFunnel, retention, rate, maxIntersection, sequenceMatch etc.

ClickHouse for time series usage

- GraphHouse – ClickHouse backend for Graphite monitoring
- PromHouse – ClickHouse backend for Prometheus
- Percona PMM – DB performance monitoring
- Apache Traffic Control – CDN monitoring
- ClickHouse itself – system.metric_log (since 19.14)
- … inside many companies for:
    - Netflow monitoring
    - CDN
    - IoT
    - Etc.

Summary

- Time series machine generated data volumes increase
- Time series requires specialized approach to data processing
- ClickHouse can do it effectively, thanks to its performance and flexibility
- ClickHouse is not a time series DBMS but much more

Questions?

Thank you!

P.S. We are hiring!

Contacts:
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