Analyzing Billion Row Datasets with ClickHouse

Alexander Zaitsev and Robert Hodges

About Us

Robert Hodges - Altinity CEO

30+ years on DBMS plus virtualization and security. ClickHouse is database #20.

Alexander Zaitsev - Altinity CTO

Expert in data warehouse with petabyte-scale deployments. Altinity Founder

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

ClickHouse Overview

ClickHouse is a powerful data warehouse that handles many use cases

Understands SQL

Runs on bare metal to cloud

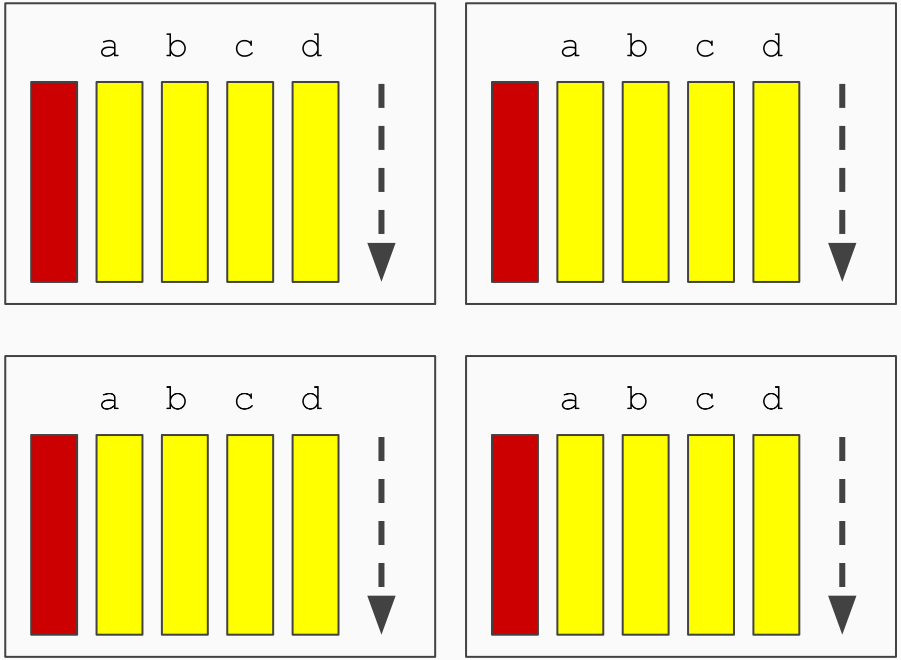
Stores data in columns

Parallel and vectorized execution

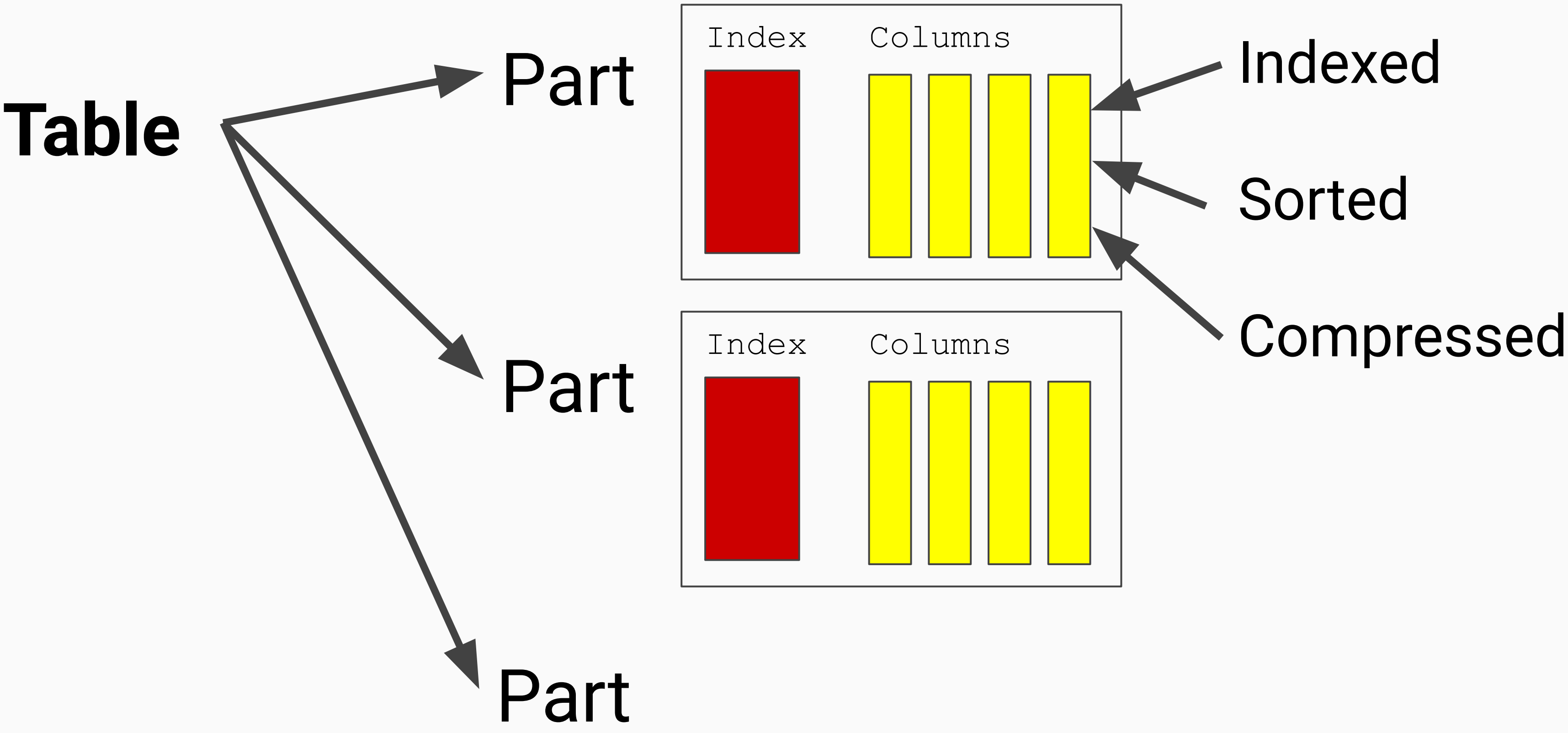
Scales to many petabytes

Is Open source (Apache 2.0)

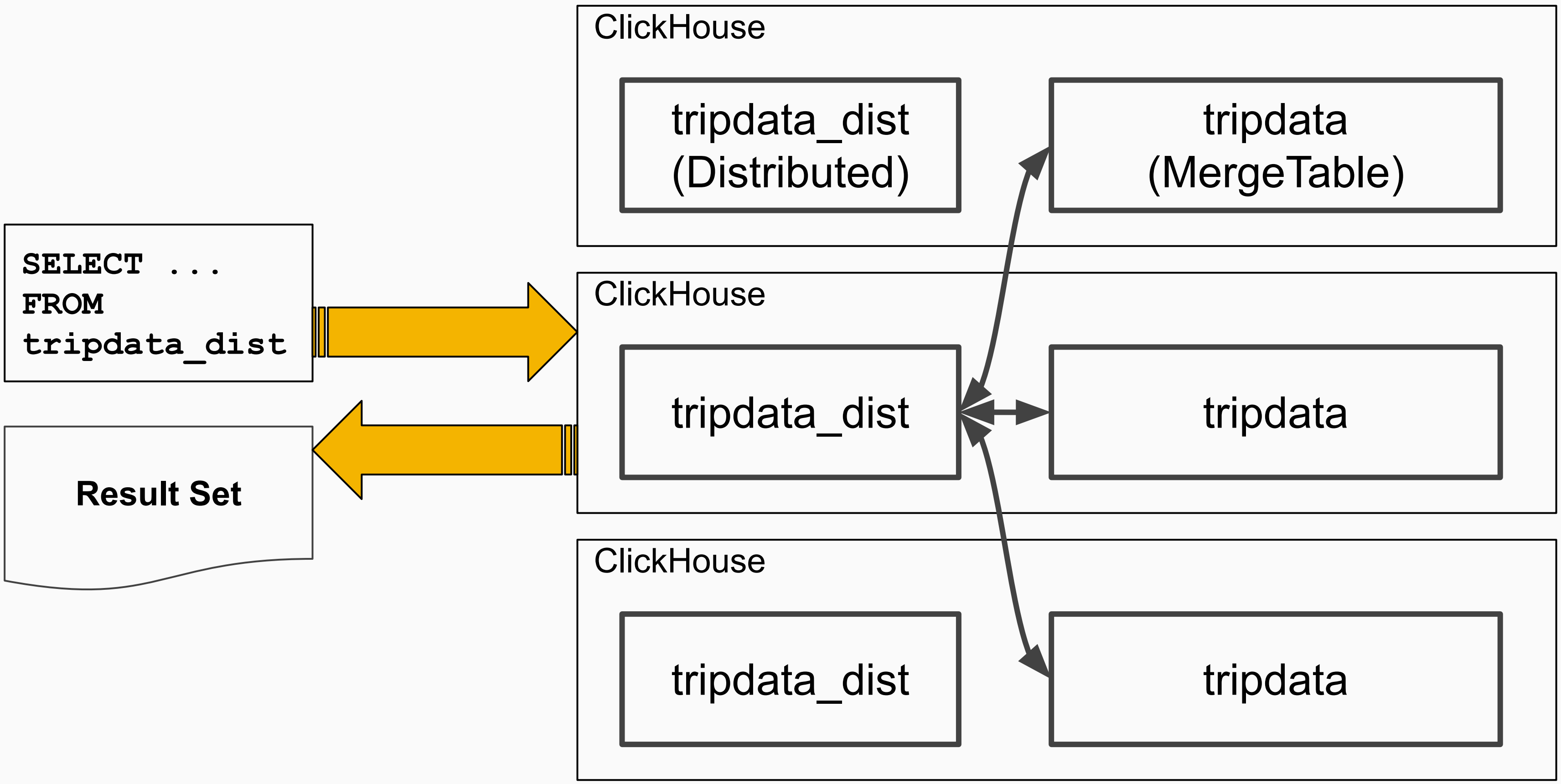
Is WAY fast!



Tables are split into indexed, sorted parts for fast queries



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

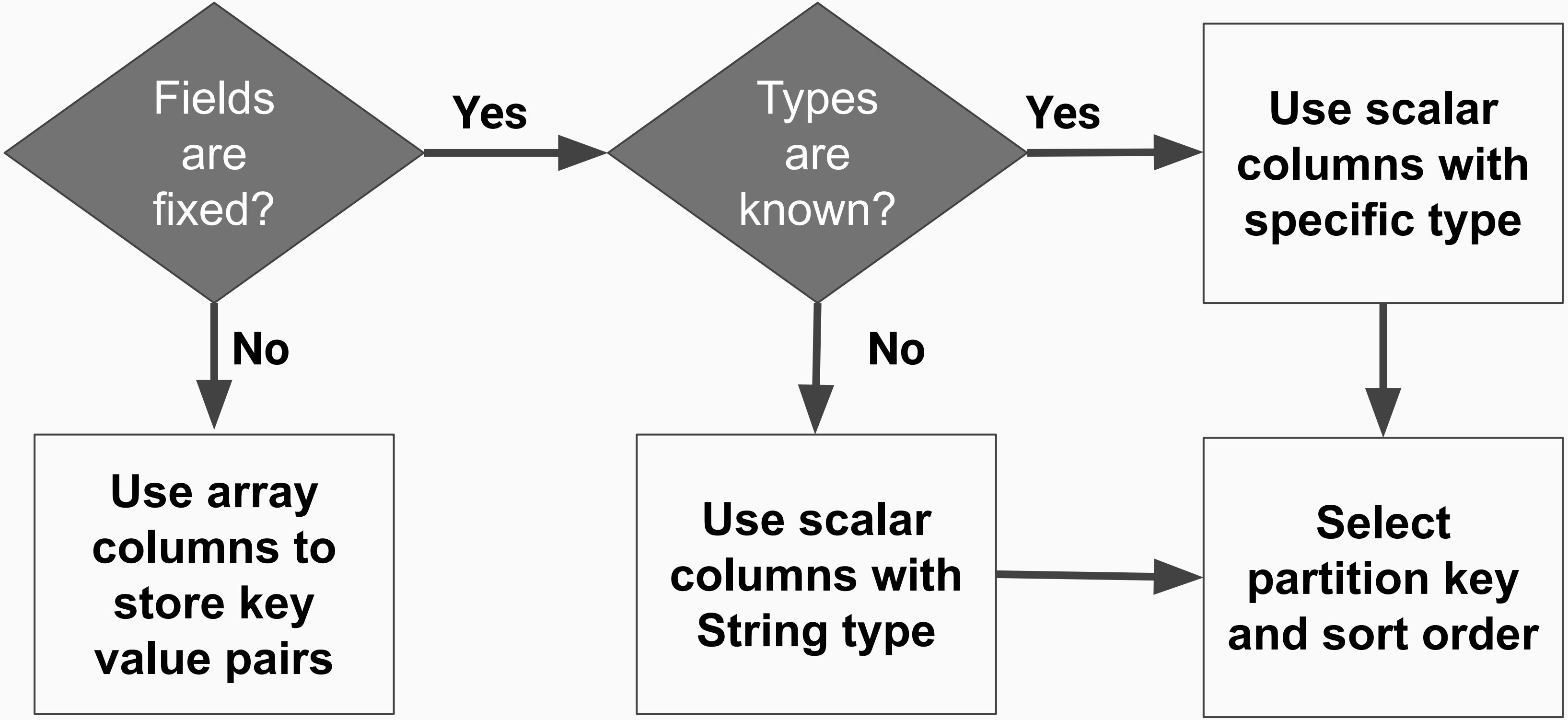


Getting Started: Data Loading

Installation: Use packages on Linux host

```
$ sudo apt -y install clickhouse-client=19.6.2 \
 clickhouse-server=19.6.2 \
 clickhouse-common-static=19.6.2
...
$ sudo systemctl start clickhouse-server
...
$ clickhouse-client
11e99303c78e :) select version()
...
┌─version()─┐
│ 19.6.2.11 │
└───────────┘
```

Decision tree for ClickHouse basic schema design



Tabular data structure typically gives the best results

```
CREATE TABLE tripdata (
  `pickup_date` Date DEFAULT
    toDate(tpep_pickup_datetime),
  `id` UInt64,
   `vendor_id` String,
  `tpep_pickup_datetime` DateTime,
  `tpep_dropoff_datetime` DateTime,
  ...
) ENGINE = MergeTree
PARTITION BY toYYYYMM(pickup_date)
ORDER BY (pickup_location_id, dropoff_location_id, vendor_id)
```

- Scalar columns
- Specific datatypes
- Time-based partition key
- Sort key to index parts

Use clickhouse-client to load data quickly from files

CSV Input Data

```
"Pickup_date","id","vendor_id","tpep_pickup_datetime"…
"2016-01-02",0,"1","2016-01-02 04:03:29","2016-01-02…
"2016-01-29",0,"1","2016-01-29 12:00:51","2016-01-29…
"2016-01-09",0,"1","2016-01-09 17:22:05","2016-01-09…
```

Reading CSV Input with Headers

```
clickhouse-client --database=nyc_taxi_rides --query='INSERT
INTO tripdata FORMAT CSVWithNames' < data.csv
```

Reading Gzipped CSV Input with Headers

```
gzip -d -c | clickhouse-client --database=nyc_taxi_rides
--query='INSERT INTO tripdata FORMAT CSVWithNames'
```

Wouldn't it be nice to run in parallel over a lot of input files?

Altinity Datasets project does exactly that!

- Dump existing schema definitions and data to files
- Load files back into a database
- Data dump/load commands run in parallel

See https://github.com/Altinity/altinity-datasets

How long does it take to load 1.3B rows?

```
$ time ad-cli dataset load nyc_taxi_rides --repo_path=/data1/sample-data
Creating database if it does not exist: nyc_timed
Executing DDL: /data1/sample-data/nyc_taxi_rides/ddl/taxi_zones.sql
. . .
Loading data: table=tripdata, file=data-200901.csv.gz
. . .
Operation summary: succeeded=193, failed=0

real     11m4.827s
user     63m32.854s
sys      2m41.235s
```

(Amazon md5.2xlarge: Xeon(R) Platinum 8175M, 8vCPU, 30GB RAM, NVMe SSD)

Do we really have 1B+ table?

```
:) select count() from tripdata;

SELECT count()
FROM tripdata

┌────count()─┐
│ 1310903963 │
└────────────┘

1 rows in set. Elapsed: 0.324 sec. Processed 1.31 billion rows, 1.31 GB (4.05
billion rows/s., 4.05 GB/s.)
```

1,310,903,963/11m4s = 1,974,253 rows/sec!!!

Getting Started on Queries

Let’s try to predict maximum performance

```
SELECT avg(number)
FROM
(
    SELECT number
    FROM system.numbers
    LIMIT 1310903963
)

┌─avg(number)─┐
│   655451981 │
└─────────────┘

1 rows in set. Elapsed: 3.420 sec. Processed 1.31 billion rows, 10.49 GB (383.29
million rows/s., 3.07 GB/s.)
```

system.numbers -- internal generator for testing

Now we try with real data

```
SELECT avg(passenger_count)
FROM tripdata

┌─avg(passenger_count)─┐
│    1.6817462943317076 │
└──────────────────────┘

1 rows in set. Elapsed: ?
```

Guess how fast?

Now we try with the real data

```
SELECT avg(passenger_count)
FROM tripdata

┌─avg(passenger_count)─┐
│    1.6817462943317076 │
└───────────────────────┘

1 rows in set. Elapsed: 1.084 sec. Processed 1.31 billion rows, 1.31 GB (1.21 billion rows/s., 1.21 GB/s.)
```

Even faster!!!!

Data type and cardinality matters

What if we add a filter

```
SELECT avg(passenger_count)
FROM tripdata
WHERE toYear(pickup_date) = 2016

┌─avg(passenger_count)─┐
│   1.6571129913837774 │
└──────────────────────┘

1 rows in set. Elapsed: 0.162 sec. Processed 131.17 million rows, 393.50 MB (811.05 million rows/s., 2.43 GB/s.)
```

What if we add a group by

```
SELECT
    pickup_location_id AS location_id,
    avg(passenger_count),
    count()
FROM tripdata
WHERE toYear(pickup_date) = 2016
GROUP BY location_id LIMIT 10
...
10 rows in set. Elapsed: 0.251 sec. Processed 131.17 million rows, 655.83 MB
(522.62 million rows/s., 2.61 GB/s.)
```

What if we add a join

```
SELECT
    zone,
    avg(passenger_count),
    count()
FROM tripdata
INNER JOIN taxi_zones ON taxi_zones.location_id = pickup_location_id
WHERE toYear(pickup_date) = 2016
GROUP BY zone
LIMIT 10

10 rows in set. Elapsed: 0.803 sec. Processed 131.17 million rows, 655.83 MB (163.29
million rows/s., 816.44 MB/s.)
```

Yes, 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

Optimization Techniques

How to make ClickHouse even faster

You can optimize

Server settings

Schema (index, dictionaries, arrays, special table engines)

Column storage (encoding, compression)

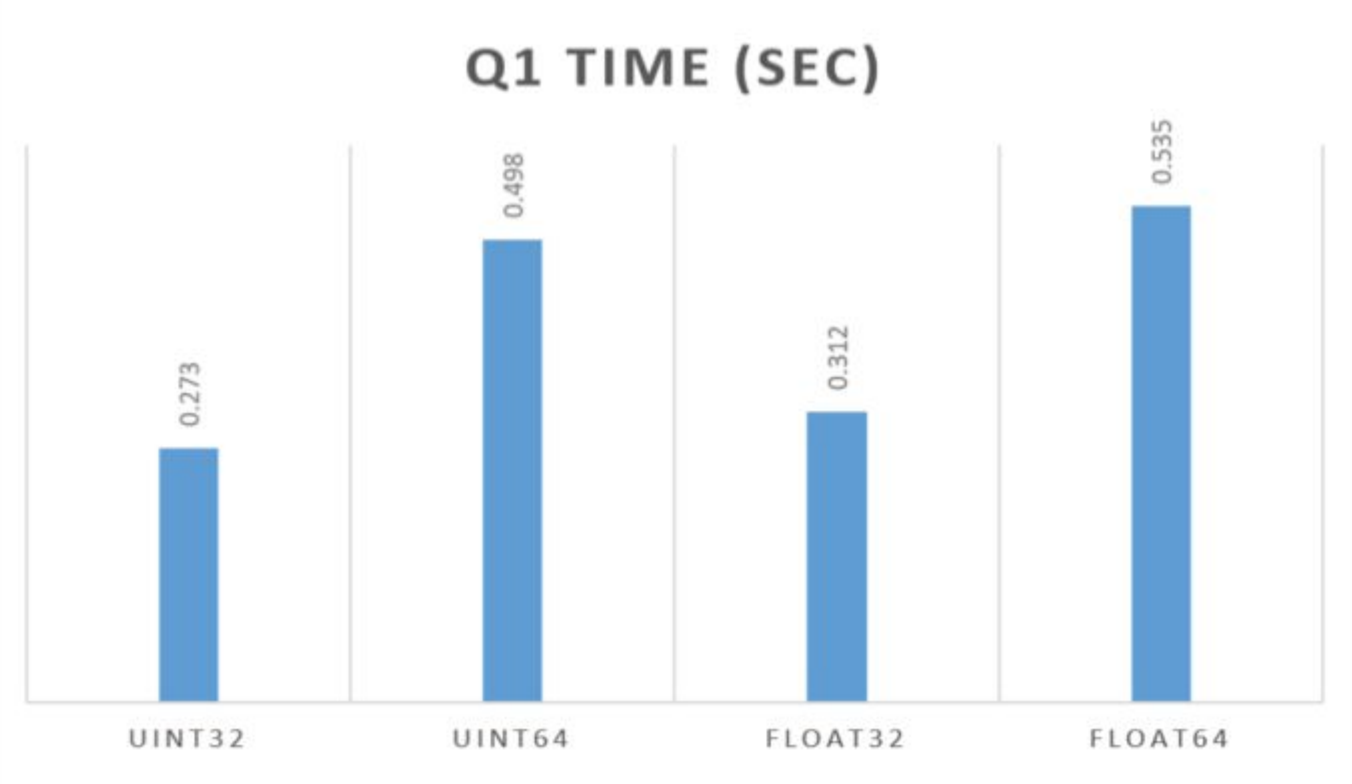
Queries

Settings

```
SELECT avg(passenger_count)
FROM tripdata
SETTINGS max_threads = 1

...

1 rows in set. Elapsed: 4.855 sec. Processed 1.31 billion rows, 1.31 GB
(270.04 million rows/s., 270.04 MB/s.)

SELECT avg(passenger_count)
FROM tripdata
SETTINGS max_threads = 8

...

1 rows in set. Elapsed: 1.092 sec. Processed 1.31 billion rows, 1.31 GB (1.20
billion rows/s., 1.20 GB/s.)
```

Default is half of available cores -- good enough to start

Data Types matter!



https://www.percona.com/blog/2019/02/15/clickhouse-performance-uint32-vs-uint64-vs-float32-vs-float64/

Schema optimization

```
SELECT
    zone,
    avg(passenger_count),
    count()
FROM tripdata
INNER JOIN taxi_zones ON taxi_zones.location_id =
pickup_location_id
WHERE toYear(pickup_date) = 2016
GROUP BY zone
LIMIT 10

10 rows in set. Elapsed: 0.803 sec. Processed 131.17 million rows,
655.83 MB (163.29 million rows/s., 816.44 MB/s.)
```

Can we do it any faster?

We can optimize JOIN

```
SELECT
    zone,
    sum(pc_sum) / sum(pc_cnt) AS pc_avg,
    sum(pc_cnt)
FROM
(
    SELECT
        pickup_location_id,
        sum(passenger_count) AS pc_sum,
        count() AS pc_cnt
    FROM tripdata
    WHERE toYear(pickup_date) = 2016
    GROUP BY pickup_location_id
)
INNER JOIN taxi_zones ON taxi_zones.location_id = pickup_location_id
GROUP BY zone LIMIT 10

10 rows in set. Elapsed: 0.248 sec. Processed 131.17 million rows, 655.83
MB (529.19 million rows/s., 2.65 GB/s.)
```

Subquery minimizes data scanned in parallel; joins on GROUP BY results

Can we do it any faster?

MaterializedView with SummingMergeTree

```
CREATE MATERIALIZED VIEW tripdata_mv
ENGINE = SummingMergeTree
PARTITION BY toYYYYMM(pickup_date)
ORDER BY (pickup_location_id, dropoff_location_id, vendor_id) AS
SELECT
    pickup_date,
    vendor_id,
    pickup_location_id,
    dropoff_location_id,
    sum(passenger_count) AS passenger_count_sum,
    sum(trip_distance) AS trip_distance_sum,
    sum(fare_amount) AS fare_amount_sum,
    sum(tip_amount) AS tip_amount_sum,
    sum(tolls_amount) AS tolls_amount_sum,
    sum(total_amount) AS total_amount_sum,
    count() AS trips_count
FROM tripdata
GROUP BY
    pickup_date,
    vendor_id,
    pickup_location_id,
    dropoff_location_id
```

MaterializedView works as an INSERT trigger

SummingMergeTree automatically aggregates data in the background

MaterializedView with SummingMergeTree

```
INSERT INTO tripdata_mv SELECT
    pickup_date,
    vendor_id,
    pickup_location_id,
    dropoff_location_id,
    passenger_count,
    trip_distance,
    fare_amount,
    tip_amount,
    tolls_amount,
    total_amount,
    1
FROM tripdata;

Ok.

0 rows in set. Elapsed: 303.664 sec. Processed 1.31 billion rows,
50.57 GB (4.32 million rows/s., 166.54 MB/s.)
```

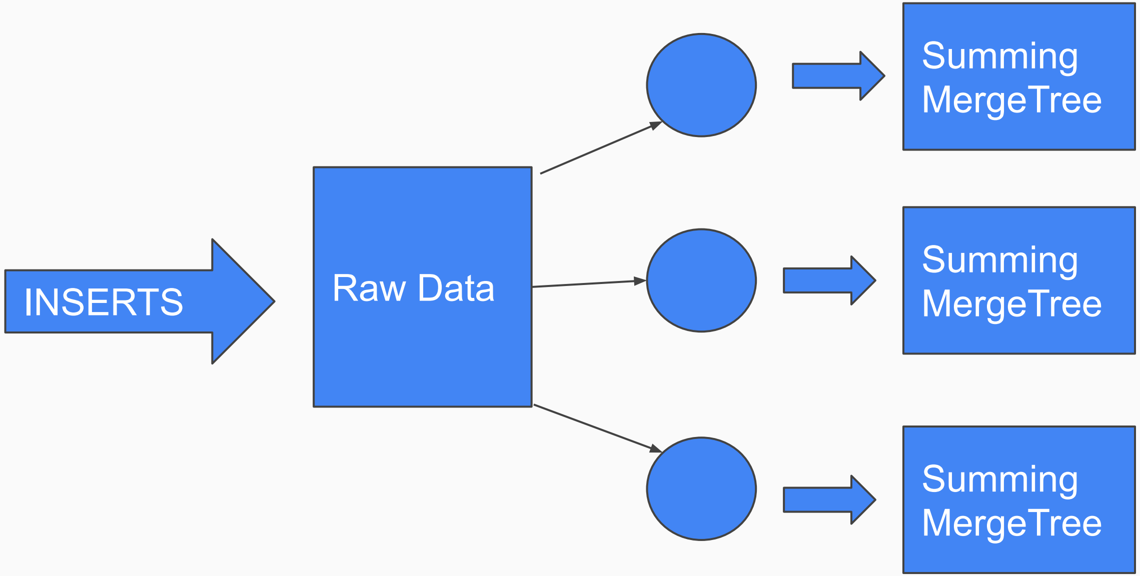
Note, no group by!

SummingMergeTree automatically aggregates data in the background

MaterializedView with SummingMergeTree

```
SELECT
    count(),
    sum(trips_count)
FROM tripdata_mv

┌──count()─┬─sum(trips_count)─┐
│ 20742525 │       1310903963 │
└──────────┴──────────────────┘

1 rows in set. Elapsed: 0.029 sec. Processed 20.74 million rows, 165.94 MB (712.56 million
rows/s., 5.70 GB/s.)

SELECT
    zone,
    sum(passenger_count_sum)/sum(trips_count),
    sum(trips_count)
FROM tripdata_mv
INNER JOIN taxi_zones ON taxi_zones.location_id = pickup_location_id
WHERE toYear(pickup_date) = 2016
GROUP BY zone LIMIT 10

10 rows in set. Elapsed: 0.036 sec. Processed 3.23 million rows, 64.57 MB (89.14 million
rows/s., 1.78 GB/s.)
```

Realtime Aggreation with Materialized Views



One more example at:
https://www.altinity.com/blog/clickhouse-continues-to-crush-time-series

Column storage optimizations

Compression

LowCardinality

Column encodings

LowCardinality example. Another 1B rows.

```
:) create table test_lc (
    a String, a_lc LowCardinality(String) DEFAULT a) Engine = MergeTree
PARTITION BY tuple() ORDER BY tuple();

:) INSERT INTO test_lc (a) SELECT
concat('openconfig-interfaces:interfaces/interface/subinterfaces/subinter
face/state/index', toString(rand() % 1000))
 FROM system.numbers LIMIT 1000000000;
```

table	name	type	compressed	uncompressed
test_lc	a	String	4663631515	84889975226
test_lc	a_lc	LowCardinality(String)	2010472937	2002717299

LowCardinality encodes column with a dictionary encoding

Storage is dramatically reduced

LowCardinality example. Another 1B rows

```
:) select a a, count(*) from test_lc group by a order by count(*) desc limit 10;

┌─a──────────────────────────────────────────────────────────────────────┬─count()─┐
│ openconfig-interfaces:interfaces/interface/subinterfaces/subinterface/state/index396 │ 1002761 │
...
│ openconfig-interfaces:interfaces/interface/subinterfaces/subinterface/state/index5   │ 1002203 │
└────────────────────────────────────────────────────────────────────────┴─────────┘

10 rows in set. Elapsed: 11.627 sec. Processed 1.00 billion rows, 92.89 GB (86.00 million rows/s., 7.99 GB/s.)
```


```
:) select a_lc a, count(*) from test_lc group by a order by count(*) desc limit 10;
...
10 rows in set. Elapsed: 1.569 sec. Processed 1.00 billion rows, 3.42 GB (637.50 million rows/s., 2.18 GB/s.)
```

Array example. Another 1B rows

```
create table test_array (
 s String,
 a Array(LowCardinality(String)) default arrayDistinct(splitByChar(',', s))
) Engine = MergeTree PARTITION BY tuple() ORDER BY tuple();

INSERT INTO test_array (s)
WITH ['Percona', 'Live', 'Altinity', 'ClickHouse', 'MySQL', 'Oracle', 'Austin', 'Texas',
'PostgreSQL', 'MongoDB'] AS keywords
SELECT concat(keywords[((rand(1) % 10) + 1)], ',',
              keywords[((rand(2) % 10) + 1)], ',',
              keywords[((rand(3) % 10) + 1)], ',',
              keywords[((rand(4) % 10) + 1)])
FROM system.numbers LIMIT 1000000000;
```

Arrays efficiently model 1-to-N relationship

Note the use of complex default expression

Array example. Another 1B rows

Array efficiently models 1-to-N relationship

Data sample:

s	a
Texas,ClickHouse,Live,MySQL	['Texas','ClickHouse','Live','MySQL']
Texas,Oracle,Altinity,PostgreSQL	['Texas','PostgreSQL','Oracle','Altinity']
Percona,MySQL,MySQL,Austin	['MySQL','Percona','Austin']
PostgreSQL,Austin,PostgreSQL,Percona	['PostgreSQL','Percona','Austin']
Altinity,Percona,Percona,Percona	['Altinity','Percona']

Storage:

table	name	type	comp	uncomp
test_array	s	String	11239860686	31200058000
test_array	a	Array(LowCardinality(String))	4275679420	11440948123

Array example. Another 1B rows

```
:) select count() from test_array where s like '%ClickHouse%';

┌──count()─┐
│ 343877409 │
└───────────┘

1 rows in set. Elapsed: 7.363 sec. Processed 1.00 billion rows, 39.20 GB (135.81 million rows/s., 5.32 GB/s.)

:) select count() from test_array where has(a,'ClickHouse');

┌──count()─┐
│ 343877409 │
└───────────┘

1 rows in set. Elapsed: 8.428 sec. Processed 1.00 billion rows, 11.44 GB (118.66 million rows/s., 1.36 GB/s.)
```

Well, ‘like’ is very efficient, but we reduced I/O a lot.

* has() will be optimized by dev team

ClickHouse is fast,
but it is always possible to make
it even faster!

ClickHouse Integrations

...And a nice set of supporting ecosystem tools

Client libraries: JDBC, ODBC, Python, Golang, ...

Kafka table engine to ingest from Kafka queues

Visualization tools: Grafana, Tableau, Tabix, SuperSet

Data science stack integration: Pandas, Jupyter Notebooks

Kubernetes ClickHouse operator

Integrations with MySQL

MySQL External Dictionaries (pull data from MySQL to CH)

MySQL Table Engine and Table Function (query/insert)

Binary Log Replication

ProxySQL supports ClickHouse

ClickHouse supports MySQL wire protocol (in June release)

..and with PostgreSQL

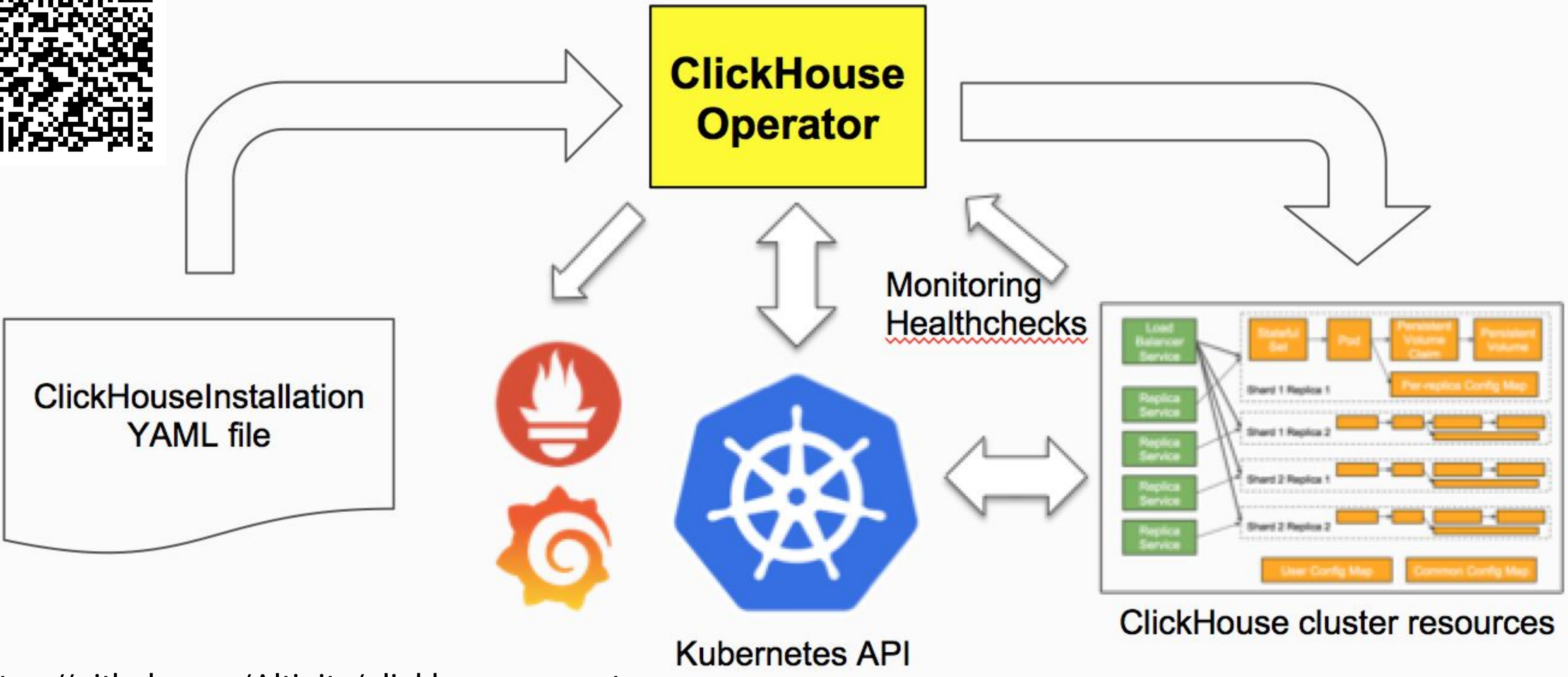
ODBC External Dictionaries (pull data from PostgreSQL to CH)

ODBC Table Engine and Table Function (query/insert)

Logical Replication: https://github.com/mkabilov/pg2ch

Foreign Data Wrapper:
https://github.com/Percona-Lab/clickhousedb_fdw

ClickHouse Operator -- an easy way to manage ClickHouse data warehouses in Kubernetes



https://github.com/Altinity/clickhouse-operator

Where to get more information

- ClickHouse Docs: https://clickhouse.yandex/docs/en/
- Altinity Blog: https://www.altinity.com/blog
- Meetups and presentations: https://www.altinity.com/presentations
  - 7 May -- Limassol, Cyprus ClickHouse Meetup
  - 28-30 May -- Austin, TX Percona Live 2019
  - 4 June -- San Francisco ClickHouse Meetup
  - 8 June -- Beijing ClickHouse Meetup
  - 13 August -- Silicon Valley ClickHouse Meetup
  - September -- ClickHouse Paris Meetup

Questions?

Thank you!

Contacts:
info@altinity.com

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https://www.altinity.com/blog