LIFESTREET

Altinity

Migration to ClickHouse Practical Guide

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LifeSteet, Altinity

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Who am I

- Graduated Moscow State University in 1999
- Software engineer since 1997
- Developed distributed systems since 2002
- Focused on high performance analytics since 2007
- Director of Engineering in LifeStreet
- Co-founder of Altinity


LIFESTREET

- Ad Tech company (ad exchange, ad server, RTB, DMP etc.) since 2006
- 10,000,000,000+ events/day
- 2K/event
- 3 months retention (90-120 days)

10B * 2K * [90-120] = [1.8-2.4]PB

LIFESTREET

- Tried/used/evaluated:
  - MySQL (TokuDB, ShardQuery)
  - InfiniDB
  - MonetDB
  - InfoBright EE
  - Paraccel (now RedShift)
  - Oracle
  - Greenplum
  - Snowflake DB
  - Vertica

ClickHouse

Before you go:

- ✓ Confirm your use case
- ✓ Check benchmarks
- ✓ Run your own
- ✓ Consider limitations, not features
- ✓ Make a POC

LifeStreet Use Case

- Event Stream analysis
- Publisher/Advertiser performance
- Campaign/Creative performance optimization/prediction
- Realtime programmatic bidding
- DMP

LifeStreet Requirements

- Load 10B events/day, 500 dimensions/event
- Ad-hoc reports on 3 months of detail data
- Low data and query latency
- High Availability

ClickHouse limitations:

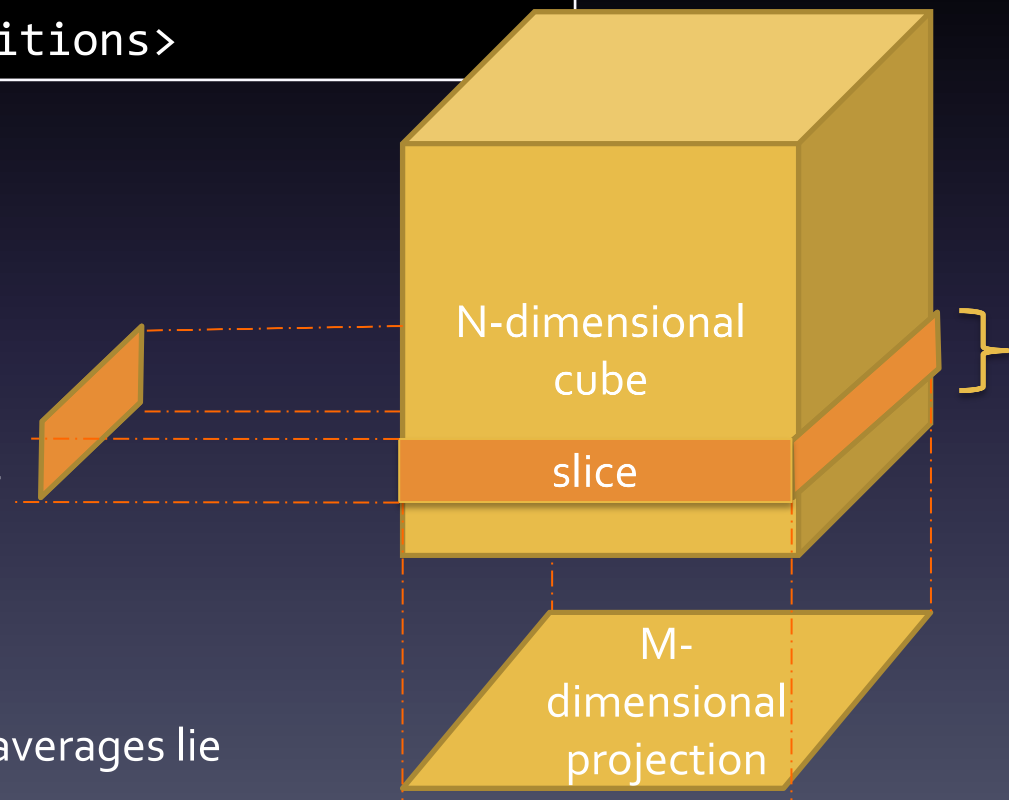
- No Transactions
- No Constraints
- Eventual Consistency
- No UPDATE/DELETE
- No NULLs (added few months ago)
- No milliseconds
- No Implicit type conversions
- Non-standard SQL
- No partitioning by any column (monthly only)
- No Enterprise operation tools

Main Challenges

- Efficient schema
  - Use ClickHouse bests
  - Workaround limitations
- Reliable data ingestion
- Sharding and replication
- Client interfaces

Multi-Dimensional Analysis

```
SELECT d1, … , dn, sum(m1), … , sum(mk)
  FROM T
 WHERE <where conditions>
 GROUP BY d1, … , dn
HAVING <having conditions>
```



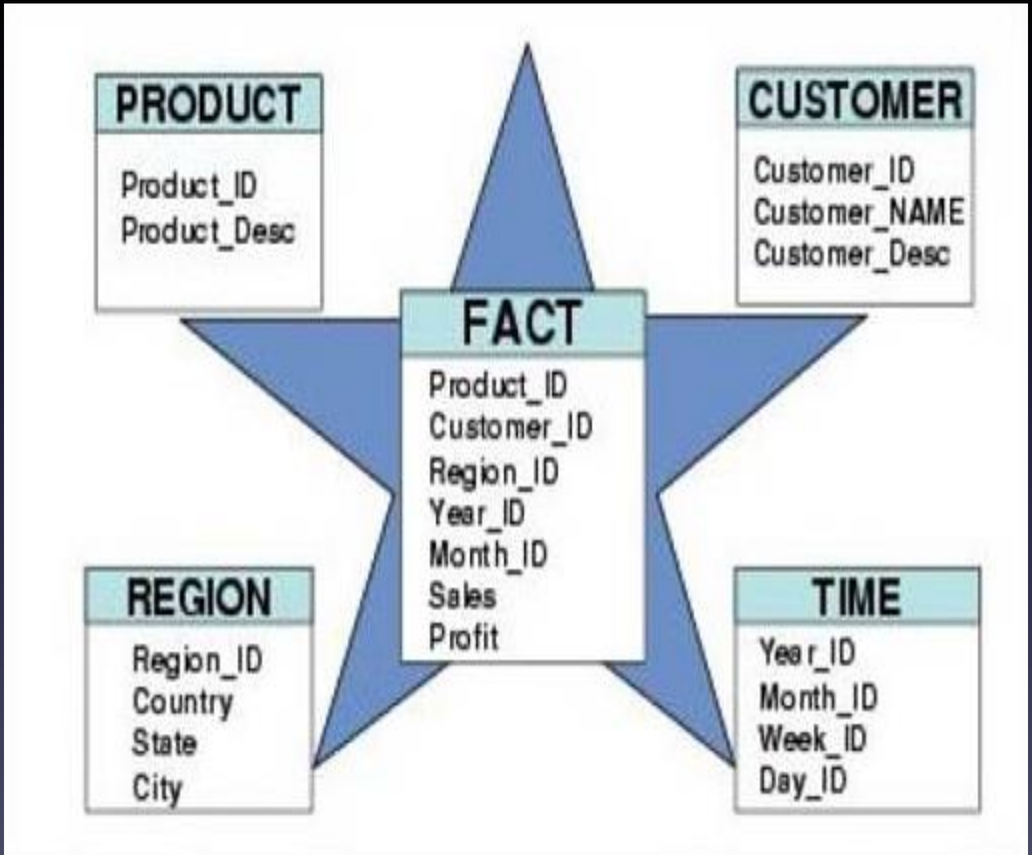
Range filter

Query result

Disclaimer: averages lie

Typical schema: “star”

- Facts
- Dimensions
- Metrics
- Projections



Star Schema Approach

De-normalized: **dimensions in a fact table**	**Normalized:** **dimension keys in a fact table** **separate dimension tables**
Single table, simple	Multiple tables
Simple queries, no joins	More complex queries with joins
Data can not be changed	Data in dimension tables can be changed
Sub-efficient storage	Efficient storage
Sub-efficient queries	More efficient queries

Normalized schema: traditional approach - joins

- Limited support in ClickHouse (1 level, cascade sub-selects for multiple)
- Dimension tables are not updatable

Normalized schema: ClickHouse approach - dictionaries

- Lookup service: key -> value
- Supports different external sources (files, databases etc.)
- Refreshable

Dictionaries. Example

```
SELECT country_name,
       sum(imps)
  FROM T
  ANY INNER JOIN dim_geo USING (geo_key)
 GROUP BY country_name;
```

vs

```
SELECT dictGetString('dim_geo', 'country_name', geo_key)
country_name,
       sum(imps)
  FROM T
 GROUP BY country_name;
```

Dictionaries. Sources

- mysql table
- clickhouse table
- odbc data source
- file
- executable script
- http service

Dictionaries. Configuration

```
<dictionary>
    <name></name>
    <source> … </source>
    <lifetime> ... </lifetime>
    <layout> … </layout>
    <structure>
        <id> ... </id>
        <attribute> ... </attribute>
        <attribute> ... </attribute>
        ...
    </structure>
</dictionary>
```

In config.xml: `<dictionaries_config>*_dictionary.xml</dictionaries_config>`

Dictionaries. Update values

- By timer (default)
- Automatic for MySQL MyISAM
- Using ‘invalidate_query’

```
<source>
   <invalidate_query>
       SELECT max(update_time) FROM  dictionary_source
   </invalidate_query>
```

- SYSTEM RELOAD DICTIONARY
- Manually touching config file
- Warning: N dict * M nodes = N * M DB connections

Dictionaries. Restrictions

- ‘Normal’ keys are only UInt64
- Only full refresh is possible
- Every cluster node has its own copy
- XML config (DDL would be better)

Dictionaries Pros-and-Cons

+ No JOINs
+ Updatable
+ Always in memory for flat/hash (faster)

- Not a part of the schema
- Somewhat inconvenient syntax

Tables

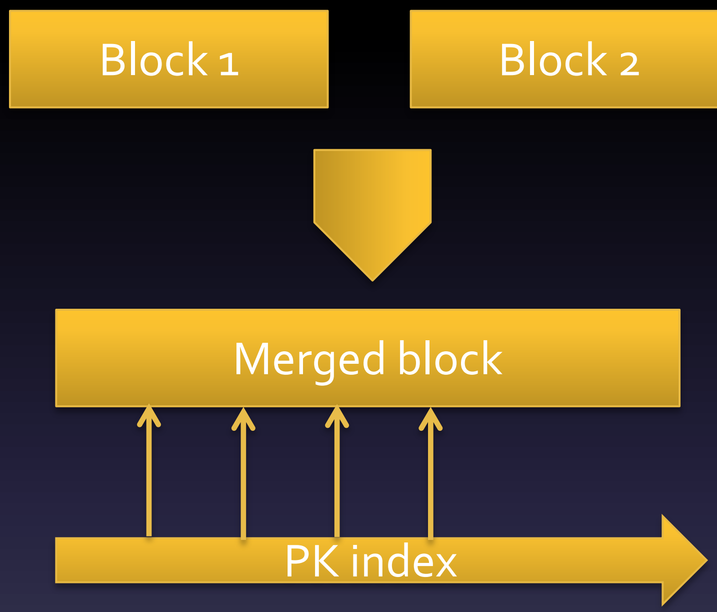
- Engines
- Sharding/Distribution
- Replication

Engine = ?

- In memory:
  - Memory
  - Buffer
  - Join
  - Set
- On disk:
  - Log, TinyLog
  - MergeTree family
- Interface:
  - Distributed
  - Merge
  - Dictionary
- Special purpose:
  - View
  - Materialized View
  - Null

Merge tree

- What is 'merge'
- PK sorting and index
- Date partitioning
- Query performance



See details at: https://medium.com/@f1yegor/clickhouse-primary-keys-2cf2a45d7324

MergeTree family

Replicated + Replacing / Collapsing / Summing / Aggergating / Graphite + MergeTree

- Replacing
- Collapsing
- Summing
- Aggergating
- Graphite

Data Load

- Load from CSV, TSV, JSONs, native binary
- clickhouse-client of HTTP/TCP API
- Error handling
  - input_format_allow_errors_num
  - input_format_allow_errors_ratio
- Simple Transformations
- Load to local or distributed table

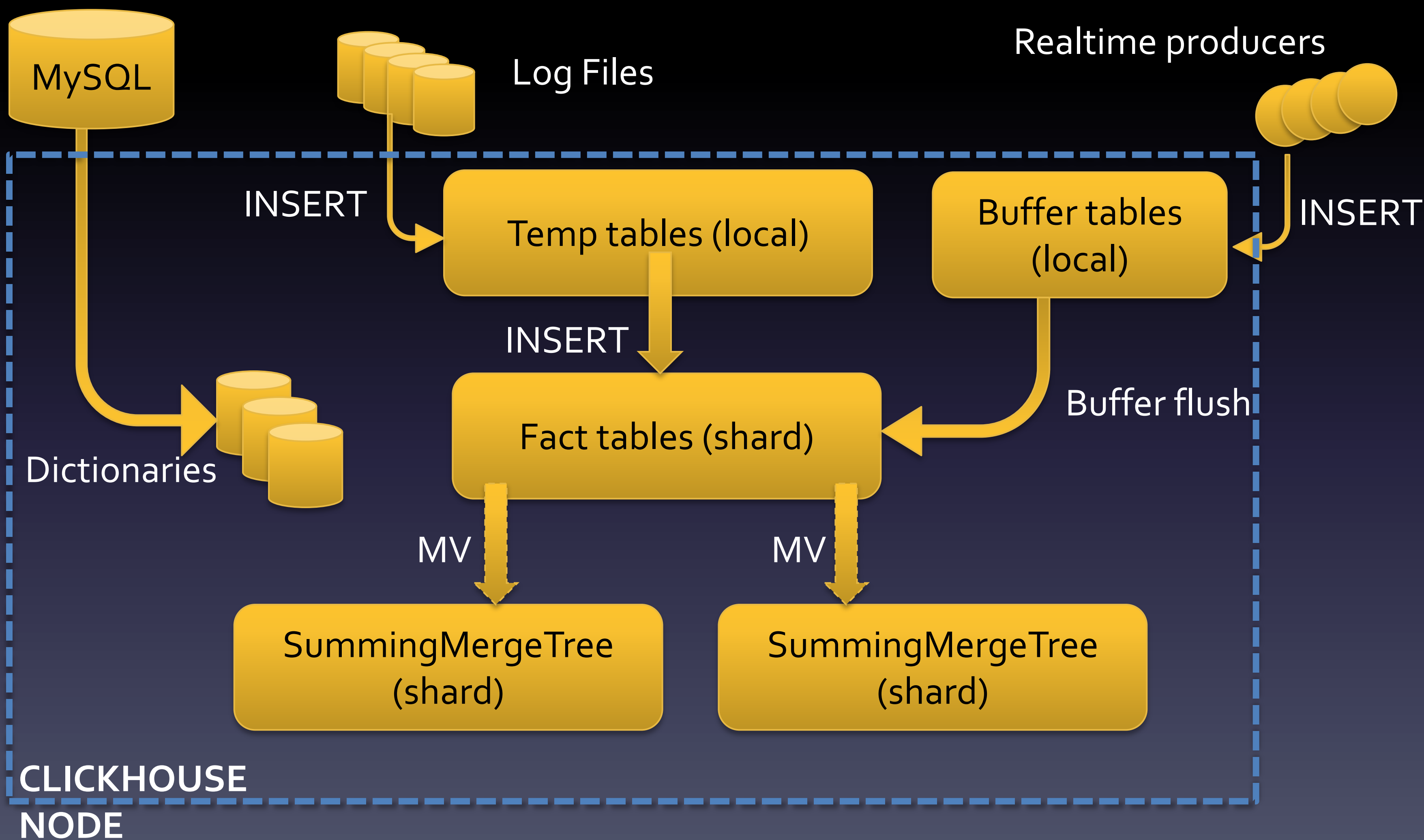
Data Load Tricks

- ClickHouse loves big blocks!
- max_insert_block_size = 1,048,576 rows – atomic insert
  - API only, not for clickhouse-client
- What to do with clickhouse-client?
  1. Load data to temp table, reload on error
  2. Set max_block_size = <size of your data>
  3. INSERT into <perm_table> SELECT FROM <temp_table>
- What if there are no big blocks?
  - Ok if <10 inserts/sec
  - Buffer tables

The power of Materialized Views

- MV is a table, i.e. engine, replication etc.
- Updated synchronously
- Summing/AggregatingMergeTree – consistent aggregation
- Alters are problematic

Data Load Diagram



Updates and deletes

- Dictionaries are refreshable
- Replacing and Collapsing merge trees
  - eventually updates
  - SELECT … FINAL
- Partitions

Sharding and Replication

- Sharding and Distribution => Performance
  - Fact tables and MVs – distributed over multiple shards
  - Dimension tables and dicts – replicated at every node (local joins and filters)
- Replication => Reliability
  - 2-3 replicas per shard
  - Cross DC

Distributed Query

SELECT foo FROM distributed_table GROUP by col1

Server 1, 2 or 3

SELECT foo FROM local_table GROUP BY col1

- Server 1

SELECT foo FROM local_table GROUP BY col1

- Server 2

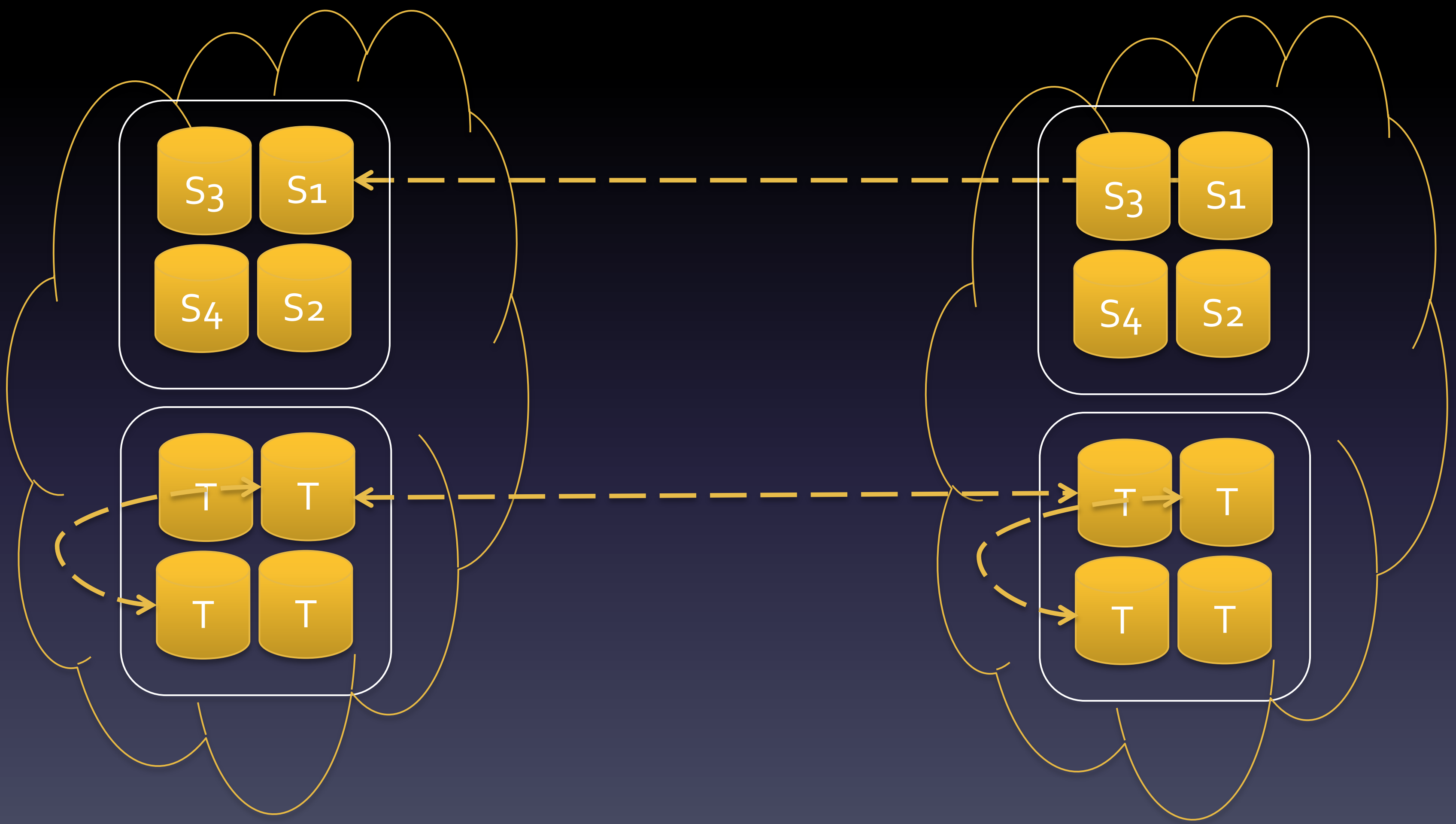
SELECT foo FROM local_table GROUP BY col1

- Server 3

Replication

- Per table topology configuration:
  - Dimension tables – replicate to any node
  - Fact tables – replicate to mirror replica
- Zookeeper to communicate the state
  - State: what blocks/parts to replicate
- Asynchronous => faster and reliable enough
- Synchronous => slower
- Isolate query to replica
- Replication queues

Cluster Topology Example



SQL

- Supports basic SQL syntax
- Supports JOINs with non-standard syntax
- Aliasing everywhere
- Array and nested data types, lambda-expressions, ARRAY JOIN
- GLOBAL IN, GLOBAL JOIN
- Approximate queries
- A lot of domain specific functions
- Basic analytic functions (e.g. runningDifference)

SQL Limitations

- JOIN syntax is different:
  - ANY|ALL
  - only 'USING' is supported, no ON
  - multiple joins using nesting
- dictionaries are not supported by BI tools
- strict data types for inserts, function calls etc.
- no windowed analytic functions
- No transaction statements, update, delete

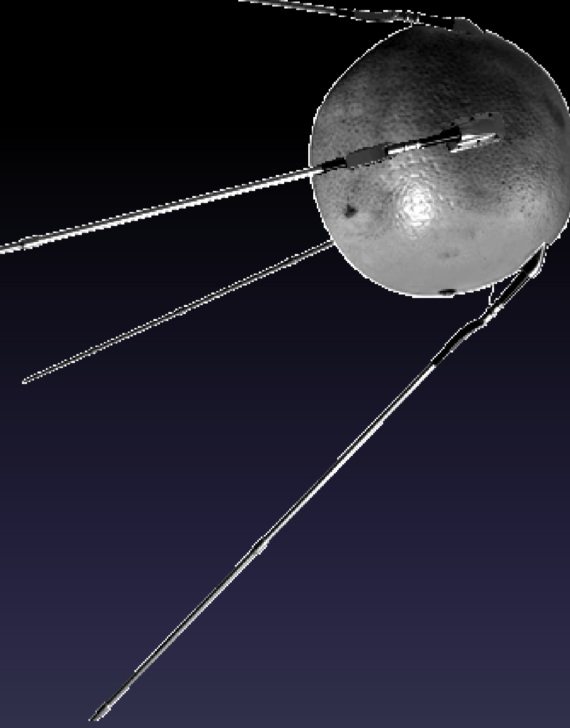
Hardware and Deployment

- Load is CPU intensive => more cores
- Query is disk intensive => faster disks
- Huge sorts are memory intensive => more memory
- 10-12 SATA RAID10
  - SAS/SSD => x2 performance for x2 price for x0.5 capacity
- 192GB RAM, 10 TB/server seems optimal
- Zookeper – keep in one DC for fast quorum
- Remote DC works bad (e.g. East an West coast in US)

Main Challenges Revisited

- Design efficient schema
  - Use ClickHouse bests
  - Workaround limitations
- Design sharding and replication
- Reliable data ingestion
- Client interfaces

LifeStreet project timelines



- June 2016: Start
- August 2016: POC
- October 2016: first test runs
- December 2016: production scale data load:
  - 10-50B events/ day, 20TB data/day
  - 12 x 2 servers with 12x4TB RAID10
- March 2017: Client API ready, starting migration
  - 30+ client types, 20 req/s query load
- May 2017: extension to 20 x 3 servers
- June 2017: migration completed!
  - 2-2.5PB uncompressed data

Few examples

```
:) select count(*) from dw.ad8_fact_event;

SELECT count(*)
FROM dw.ad8_fact_event

┌──────count()─┐
│ 900627883648 │
└──────────────┘

1 rows in set. Elapsed: 3.967 sec. Processed 900.65 billion rows,
900.65 GB (227.03 billion rows/s., 227.03 GB/s.)
```

```
:) select count(*) from dw.ad8_fact_event where access_day=today()-1;

SELECT count(*)
FROM dw.ad8_fact_event
WHERE access_day = (today() - 1)

┌────count()─┐
│ 7585106796 │
└────────────┘

1 rows in set. Elapsed: 0.536 sec. Processed 14.06 billion rows,
28.12 GB (26.22 billion rows/s., 52.44 GB/s.)
```

```
:)  select dictGetString('dim_country', 'country_code',
toUInt64(country_key)) country_code, count(*) cnt from dw.ad8_fact_event
where access_day=today()-1 group by country_code order by cnt desc limit
5;

SELECT
    dictGetString('dim_country', 'country_code', toUInt64(country_key))
AS country_code,
    count(*) AS cnt
FROM dw.ad8_fact_event
WHERE access_day = (today() - 1)
GROUP BY country_code
ORDER BY cnt DESC
LIMIT 5

┌─country_code─┬────────cnt─┐
│ US           │ 2159011287 │
│ MX           │  448561730 │
│ FR           │  433144172 │
│ GB           │  352344184 │
│ DE           │  336479374 │
└──────────────┴────────────┘

5 rows in set. Elapsed: 2.478 sec. Processed 12.78 billion rows, 55.91 GB
(5.16 billion rows/s., 22.57 GB/s.)
```

```
:) SELECT
    dictGetString('dim_country', 'country_code', toUInt64(country_key)) AS
country_code,
    sum(cnt) AS cnt
FROM
(
    SELECT
        country_key,
        count(*) AS cnt
    FROM dw.ad8_fact_event
    WHERE access_day = (today() - 1)
    GROUP BY country_key
    ORDER BY cnt DESC
    LIMIT 5
)
GROUP BY country_code
ORDER BY cnt DESC

┌─country_code─┬────────cnt─┐
│ US           │ 2159011287 │
│ MX           │  448561730 │
│ FR           │  433144172 │
│ GB           │  352344184 │
│ DE           │  336479374 │
└──────────────┴────────────┘

5 rows in set. Elapsed: 1.471 sec. Processed 12.80 billion rows, 55.94 GB (8.70
billion rows/s., 38.02 GB/s.)
```

```
:) SELECT
    countDistinct(name) AS num_cols,
    formatReadableSize(sum(data_compressed_bytes) AS c) AS comp,
    formatReadableSize(sum(data_uncompressed_bytes) AS r) AS raw,
    c / r AS comp_ratio
FROM lf.columns
WHERE table = 'ad8_fact_event_shard'

┌─num_cols─┬─comp───────┬─raw──────┬─────────comp_ratio─┐
│      308 │ 325.98 TiB │ 4.71 PiB │ 0.06757640834769944 │
└──────────┴────────────┴──────────┴─────────────────────┘

1 rows in set. Elapsed: 0.289 sec. Processed 281.46 thousand rows, 33.92
MB (973.22 thousand rows/s., 117.28 MB/s.)
```

ClickHouse at Oct 2017

- 1+ year Open Source
- 100+ prod installs worldwide
- Public changelogs, roadmap, and plans
- 5+2 Yandex devs, community contributors
- Active community, blogs, case studies
- A lot of features added by community requests
- Support by Altinity

Final Words

- Try ClickHouse for your Big Data case – it is easy now
- Need more info - http://clickhouse.yandex
- Need fast take off - Altinity Demo Appliance
- Need help for the safe ClickHouse journey:
  - http://www.altinity.com
  - @AltinityDB twitter

Questions?

Contact me:

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ClickHouse and MySQL

- MySQL is widespread but weak for analytics
  - TokuDB, InfiniDB somewhat help
- ClickHouse is best in analytics

How to combine?

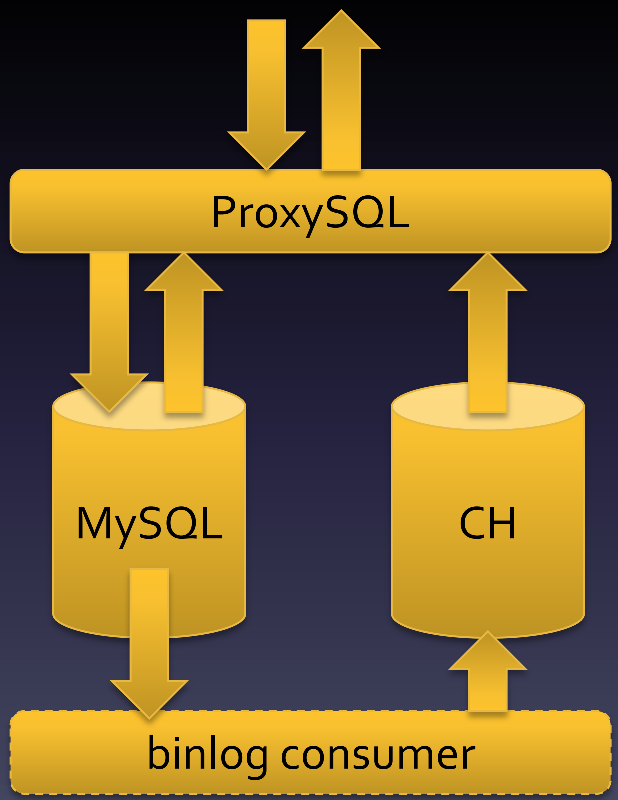
Imagine

MySQL flexibility at ClickHouse speed?


Dreams....

ClickHouse *with* MySQL

- ProxySQL to access ClickHouse data via MySQL protocol (more at the next session)
- Binlogs integration to load MySQL data in ClickHouse in realtime (in progress)



ClickHouse *instead of* MySQL

- Web logs analytics
- Monitoring data collection and analysis
  – Percona's PMM
  – Infinidat InfiniMetrics
- Other time series apps
- .. and more!