



# Exploring data analysis in time series databases

Aliaksandr Valialkin, CTO at VictoriaMetrics

November 19-21, 2024

• I'm software engineer



osa con 24

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- I like writing fast programs in Go
  - Go is easy to use
  - Go is productive
  - Go programs can be fast



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- I'm inspired by ClickHouse focus on performance



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# IF YOUR DATA HAS A TIME STAMP

## YOU'RE A TIME SERIES ANALYST, HARRY





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- Every time series may have arbitrary set of (label=value) labels:
  - temperature{city="NY",country="US"}
  - o memory\_usage{host="foo",env="prod",az="us-east"}
- The set of (label=value) labels remain constant across all the (timestmap; value) samples, which belong to the same time series

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- Example time series:
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  - o cpu\_usage\_percent{host="foo",env="prod"}: (10:20:30; 50%), ... (23:34:59; 12%)

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  - Structured logs aka events every value contains a set of (field=value) fields:
    - (t1; fields1), ... (tN; fieldsN)
  - Wide events every value contains hundreds of (field=value) fields



## My knowledge about TV series



#### My knowledge about time series



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• A database optimized for efficient storing and querying of large volumes of time series data



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  - Trillions of rows (raw samples)



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  - OpenTelemetry for logs, traces and metrics
  - Prometheus text exposition format
  - Graphite metrics format
  - Influx line protocol
  - Elasticsearch for logs



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  - Events VictoriaLogs
  - Traces Grafana Tempo
  - Mixed InfluxDB, ClickHouse

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    - Traditional RDBMS: 1TB of logs occupies 2TB of disk space
    - Database optimized for logs: 1TB of logs occupies 20GB of disk space

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    - Database optimized for time series data: makes a few sequential reads for fetching a million of samples for the typical query, while reading 1MB of data from disk

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    - Time series database: occupies a few GiB of RAM for sparse index over 10 trillions of rows

## I LIKE WHEN MY DATABASE IS RUNNING SLOW

## CAUSE I SPEND MORE TIME ON REDDIT



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• Typical Kubernetes clusters contain thousands of containers





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  - A thousand of containers, which expose 500 metrics each, and these metrics are stored into database per every 10 seconds, generate 1000\*500\*(24\*3600/10)=4.32 billions of samples per day
  - A thousand of containers, which generate 100 events (logs) per second each, result in 1000\*10\*24\*3600=8.64 billions of events per day



• All these samples must be efficiently stored, so they occupy the smallest possible amounts of disk space





- All these samples must be efficiently stored, so they occupy the smallest possible amounts of disk space
- All these samples must be efficiently queried with a query language optimized for typical monitoring tasks: alerting, analyzing dashboards with graphs for the requested metrics/logs/events over the selected time range



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### Kubernetes monitoring: which database to use?



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- Analytical databases such as ClickHouse? Yes if you know how to create the best database schema for Kubernetes monitoring use cases in order to get the maximum performance and storage efficiency
- Specialized databases such as VictoriaMetrics and VictoriaLogs? Yes, since they work great for particular cases (metrics, logs, events and wide events) without any configuration and tuning. They may work slower than optimized ClickHouse database schema though



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- Specialized query language: PromQL, MetricsQL, LogsQL
  - Easier to write queries for typical monitoring use cases
  - You need to learn yet another query language
  - Some queries are harder or impossible to write

• Select time series with the given set of labels

SQL

SELECT id FROM series WHERE hasAll(labels, ['label1=value1', ... 'labelN=valueN']) osa con 24

• Select time series with the given set of labels

**PromQL** 

{label1="value1", ... labelN="valueN"}



- Select time series with the given set of labels
- Select samples for the selected time series on the given time range
   SQL

SELECT series\_id timestamp, value FROM samples WHERE series\_id IN (<query\_from\_the\_previous\_slide>) AND timestamp > \$start AND timestamp <= \$end



Select samples for the selected time series on the given time range
 PromQL

{label1="value1", ... labelN="valueN"}[\$\_\_\_range]

/api/v1/query?time=\$end&query=...



- Select time series with the given set of labels
- Select samples for the selected time series on the given time range
- Apply some aggregations over the selected time series
   SQL

```
SELECT
series_id,
avg(value) AS avg_value
FROM (<query_from_the_prevous_slide>)
GROUP BY
series_id
```



- Select time series with the given set of labels
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   PromQL

avg\_over\_time({label1="value1", ... labelN="valueN"}[\$\_\_range])

- Select time series with the given set of labels
- Select samples for the selected time series on the given time range
- Apply some aggregations over the selected time series
- Apply some filters on the calculated aggregates

### SQL

SELECT series\_id, avg\_value FROM (<query\_from\_the\_prevous\_slide>) WHERE avg\_value > \$threshold

- Select time series with the given set of labels
- Select samples for the selected time series on the given time range
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PromQL

avg\_over\_time(
 {label1="value1", ... labelN="valueN"}[\$\_\_range]
) > \$threshold

# The resulting SQL query

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```
SELECT
series_id,
 avg_value
FROM (
SELECT
  series_id,
  avg(value) AS avg_value
 FROM (
  SELECT
   series_id,
  value
  FROM samples
  WHERE
   series_id IN (
    SELECT id FROM series WHERE hasAll(labels, ['label1=value1', ... 'labelN=valueN'])
   AND timestamp > $start AND timestamp <= $end
 GROUP BY series_id
WHERE avg_value > $threshold
```





# Example queries: SQL vs PromQL Select temperature in NY city on the given time range



# Example queries: SQL vs PromQL

Select temperature in NY city on the given time range

### SQL

```
SELECT

date_trunc('$__step', timestamp) AS timestamp_truncated,

last_value(value) AS temperature

FROM

metrics

WHERE

series_id IN (

SELECT id FROM series

WHERE __name__ = 'temperature' AND city = 'NY'

)
```

AND timestamp > now() - \$\_\_range AND timestamp < now() GROUP BY timestamp\_truncated ORDER BY timestamp\_truncated



# Example queries: SQL vs PromQL

Select temperature in NY city on the given time range

### SQL

ORDER BY

timestamp\_truncated

```
SELECT

date_trunc('$__step', timestamp) AS timestamp_truncated,

last_value(value) AS temperature

FROM

metrics

WHERE

series_id IN (

SELECT id FROM series

WHERE __name__ = 'temperature' AND city = 'NY'

)

AND timestamp > now() - $__range AND timestamp < now()

GROUP BY

timestamp truncated
```

**PromQL or MetricsQL** 

temperature{city="NY"}





Select top 5 applications with the biggest number of error logs, which do not contain "broken pipe" phrase during the last day





Select top 5 applications with the biggest number of error logs, which do not contain "broken pipe" phrase during the last day

### SQL

```
SELECT

app,

count(*) hits

FROM

logs

WHERE

timestamp > now() - 1 day AND timestamp <= now()

AND level = 'error'

AND positionUTF8(_msg, 'broken pipe') = 0

GROUP BY

app

ORDER BY

hits DESC

LIMIT 5
```



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### LogsQL

\_time:1d level:=error -"broken pipe" | top 5 by (app)

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Select the number of apps with more than 10 error logs per each step on the graph



CON CON

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| SQL  |
|--|
| SELECT   |
| timestamp_trucated,  |
| count()  |
| FROM (   |
| SELECT   |
| <pre>date_trunc('\$step', timestamp) AS timestamp_truncated,</pre> |
| app,   |
| count(*) hits  |
| FROM logs  |
| WHERE  |
| timestamp >= now() - \$range AND timestamp < now()                 |
| AND level = 'error'  |
| GROUP BY timestamp_truncated, app                                  |
| HAVING hits > 10   |
|  |
| GROUP BY timestamp_truncated                                       |

ORDER BY timestamp\_truncated



Select the number of apps with more than 10 error logs per each step on the graph

| SQL  |
|--|
| SELECT   |
| timestamp_trucated,  |
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| app,   |
| count(*) hits  |
| FROM logs  |
| WHERE  |
| timestamp >= now() - \$range AND timestamp < now()                 |
| AND level = 'error'  |
| GROUP BY timestamp_truncated, app                                  |
| HAVING hits > 10   |
|  |
| GROUP BY timestamp_truncated                                       |
| ORDER BY timestamp_truncated                                       |

### LogsQL

```
level:=error
| stats by (app) count() as hits
| hits:>10
| count()
```

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  - /api/v1/query\_range?start=...&end=...&step=...&query=...
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  - /select/logsql/stats\_query\_range?start=...&end=...&step=...&query=...
- The query is automatically executed per every step on the [start ... end] time range
- The query results are grouped and returned per each step at the following timestamps: start, start+step, start+2\*step, ... end

# Conclusions

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  - What about traces?

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- Typical time series data volumes do not fit relational databases
- Prefer specialized databases for storing and querying time series data
- Time series data includes: metrics, logs, events and wide events
- Prefer specialized databases for particular time series data types





#### Questions?



- ClickHouse docs <u>https://clickhouse.com/docs</u>
- VictoriaMetrics docs <u>https://docs.victoriametrics.com/</u>
- VictoriaLogs docs <a href="https://docs.victoriametrics.com/victorialogs/">https://docs.victoriametrics.com/victorialogs/</a>
- LogsQL docs https://docs.victoriametrics.com/victorialogs/logsql/