Druid for real-time analysis

Yann Esposito

7 Avril 2016

Abstract

Druid explained with high altitude point of view

Contents

1 Druid the Sales Pitch

- Sub-Second Queries
- Real-time Streams
- Scalable to Petabytes
- Deploy Anywhere
- Vibrant Community (Open Source)

- Ideal for powering user-facing analytic applications
- Deploy anywhere: cloud, on-premise, integrate with Haddop, Spark, Kafka, Storm, Samza

2 Intro

2.1 Experience

- Real Time Social Media Analytics

2.2 Real Time?

- Ingestion Latency: seconds
- Query Latency: seconds

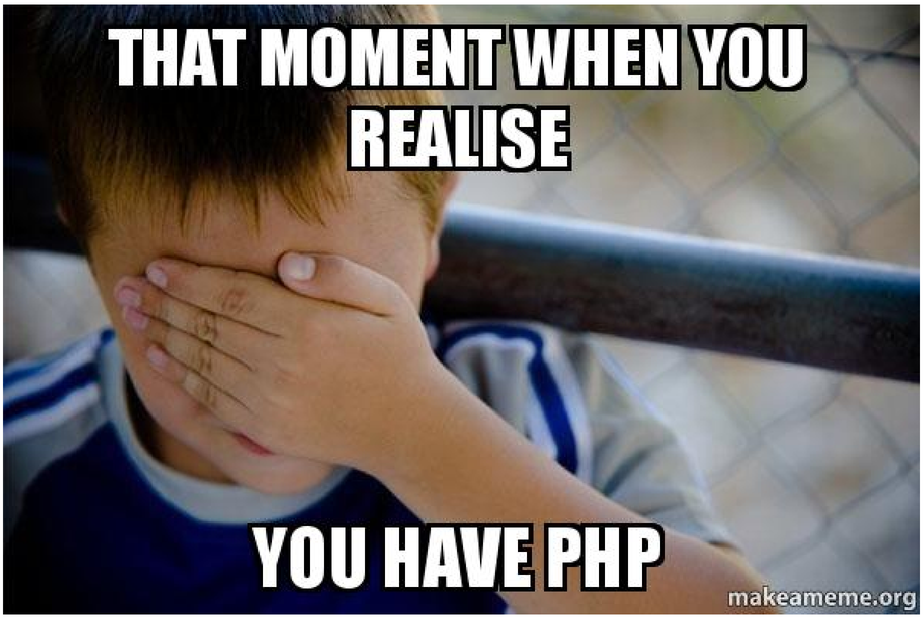
2.3 Demand

- Twitter: `20k msg/s`, `1msg = 10ko` during 24h
- Facebook public: 1000 to 2000 msg/s continuously
- Low Latency

2.4 Reality

- Twitter: 400 msg/s continuously, burst to 1500
- Facebook: 1000 to 2000 msg/s

3 Origin (PHP)



4 1st Refactoring (Node.js)

- Ingestion still in PHP
- Node.js, Perl, Java & R for sentiment analysis
- MongoDB
- Manually made time series (Incremental Map/Reduce)
- Manually coded HyperLogLog in js

5 Return of Experience

6 Return of Experience

- Ingestion still in PHP (600 msg/s max)
- Node.js, Perl, Java (10 msg/s max)

7 2nd Refactoring

- Haskell
- Clojure / Clojurescript
- Kafka / Zookeeper
- Mesos / Marathon
- Elasticsearch
- **Druid**

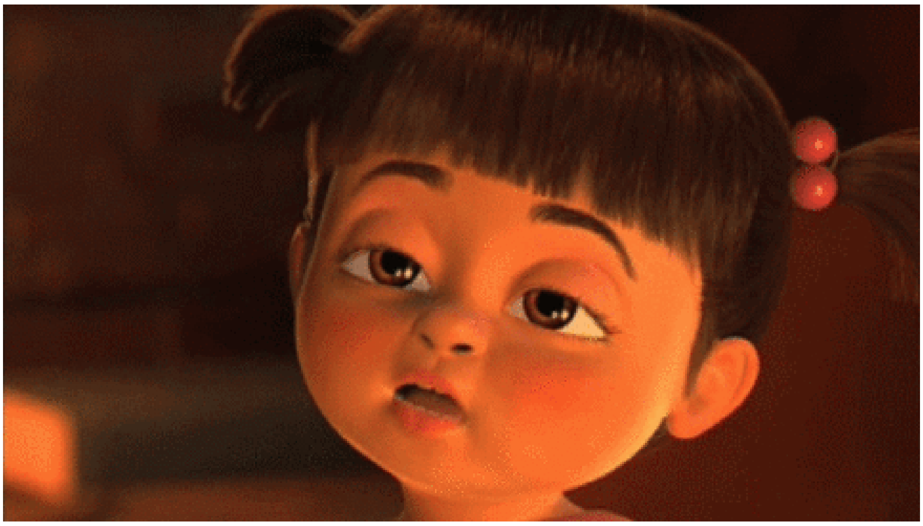


Figure 1: Too Slow, Bored

8 2nd Refactoring (FTW!)

9 2nd Refactoring return of experience

- No limit, everything is scalable
- High availability
- Low latency: Ingestion & User faced querying
- Cheap if done correctly

Thanks Druid!

10 Demo

- Low Latency High Volume of Data Analysis
- Typically `pulse`

DEMO Time

11 Pre Considerations

11.1 Discovered vs Invented

Try to conceptualize a s.t.

- Ingest Events
- Real-Time Queries
- Scalable
- Highly Available

Analytics: timeseries, alerting system, top N, etc…

11.2 In the End

Druid concepts are always emerging naturally

12 Druid

12.1 Who?

Metamarkets

Powered by Druid

- Alibaba, Cisco, Criteo, eBay, Hulu, Netflix, Paypal…

12.2 Goal

Druid is an open source store designed for real-time exploratory analytics on large data sets.

hosted dashboard that would allow users to arbitrarily explore and visualize event streams.

12.3 Concepts

- Column-oriented storage layout
- distributed, shared-nothing architecture
- advanced indexing structure

12.4 Key Features

- Sub-second OLAP Queries
- Real-time Streaming Ingestion
- Power Analytic Applications
- Cost Effective
- High Available
- Scalable

12.5 Right for me?

- require fast aggregations
- exploratory analytics
- analysis in real-time
- lots of data (trillions of events, petabytes of data)
- no single point of failure

13 High Level Architecture

13.1 Inspiration

- Google's BigQuery/Dremel
- Google's PowerDrill

13.2 Index / Immutability

Druid indexes data to create mostly immutable views.

13.3 Storage

Store data in custom column format highly optimized for aggregation & filter.

13.4 Specialized Nodes

- A Druid cluster is composed of various type of nodes
- Each designed to do a small set of things very well
- Nodes don't need to be deployed on individual hardware
- Many node types can be colocated in production

14 Druid vs X

14.1 Elasticsearch

- resource requirement much higher for ingestion & aggregation
- No data summarization (100x in real world data)

14.2 Key/Value Stores (HBase/Cassandra/OpenTSDB)

- Must Pre-compute Result
  - Exponential storage
  - Hours of pre-processing time
- Use the dimensions as key (like in OpenTSDB)
  - No filter index other than range
  - Hard for complex predicates

14.3 Spark

- Druid can be used to accelerate OLAP queries in Spark
- Druid focuses on the latencies to ingest and serve queries
- Too long for end user to arbitrarily explore data

14.4 SQL-on-Hadoop (Impala/Drill/Spark SQL/Presto)

- Queries: more data transfer between nodes
- Data Ingestion: bottleneck by backing store
- Query Flexibility: more flexible (full joins)

15 Data

15.1 Concepts

- **Timestamp column**: query centered on time axis
- **Dimension columns**: strings (used to filter or to group)
- **Metric columns**: used for aggregations (count, sum, mean, etc…)

15.2 Indexing

- Immutable snapshots of data
- data structure highly optimized for analytic queries
- Each column is stored separately
- Indexes data on a per shard (segment) level

15.3 Loading

- Real-Time
- Batch

15.4 Querying

- JSON over HTTP
- Single Table Operations, no joins.

15.5 Segments

- Per time interval
  - skip segments when querying
- Immutable
  - Cache friendly
  - No locking
- Versioned
  - No locking
  - Read-write concurrency

16 Roll-up

16.1 Example

```
timestamp             page    ... added  deleted
2011-01-01T00:01:35Z  Cthulhu     10      65
2011-01-01T00:03:63Z  Cthulhu     15      62
2011-01-01T01:04:51Z  Cthulhu     32      45
2011-01-01T01:01:00Z  Azatoth     17      87
2011-01-01T01:02:00Z  Azatoth     43      99
2011-01-01T02:03:00Z  Azatoth     12      53
```

```
timestamp             page    ... nb added deleted
2011-01-01T00:00:00Z  Cthulhu      2 25    127
2011-01-01T01:00:00Z  Cthulhu      1 32    45
2011-01-01T01:00:00Z  Azatoth      2 60    186
2011-01-01T02:00:00Z  Azatoth      1 12    53
```

16.2 as SQL

```
GROUP BY timestamp, page, nb, added, deleted
  :: nb = COUNT(1)
  ,  added = SUM(added)
  ,  deleted = SUM(deleted)
```

In practice can dramatically reduce the size (up to x100)

17 Segments

17.1 Sharding

```
sampleData_2011-01-01T01:00:00:00Z_2011-01-01T02:00:00:00Z_v1_0
```

```
timestamp             page    ... nb added deleted
2011-01-01T01:00:00Z  Cthulhu      1 20    45
2011-01-01T01:00:00Z  Azatoth      1 30    106
```

```
sampleData_2011-01-01T01:00:00:00Z_2011-01-01T02:00:00:00Z_v1_0
```

```
timestamp             page    ... nb added deleted
2011-01-01T01:00:00Z  Cthulhu      1 12    45
2011-01-01T01:00:00Z  Azatoth      2 30    80
```

17.2 Core Data Structure

Timestamp	Dimensions				Metrics	
Timestamp	**Page**	**Username**	**Gender**	**City**	**Characters Added**	**Characters Removed**
2011-01-01T01:00:00Z	Justin Bieber	Boxer	Male	San Francisco	1800	25
2011-01-01T01:00:00Z	Justin Bieber	Reach	Male	Waterloo	2912	42
2011-01-01T02:00:00Z	Ke$ha	Helz	Male	Calgary	1953	17
2011-01-01T02:00:00Z	Ke$ha	Xeno	Male	Taiyuan	3194	170

- dictionary
- a bitmap for each value
- a list of the columns values encoded using the dictionary

17.3 Example

```
dictionary: { "Cthulhu": 0
            , "Azatoth": 1 }

column data: [0, 0, 1, 1]

bitmaps (one for each value of the column):
value="Cthulhu": [1,1,0,0]
value="Azatoth": [0,0,1,1]
```

17.4 Example (multiple matches)

```
dictionary: { "Cthulhu": 0
            , "Azatoth": 1 }

column data: [0, [0,1], 1, 1]

bitmaps (one for each value of the column):
value="Cthulhu": [1,1,0,0]
value="Azatoth": [0,1,1,1]
```

17.5 Real-time ingestion

- Via Real-Time Node and Firehose
  - No redundancy or HA, thus not recommended
- Via Indexing Service and Tranquility API
  - Core API

  - Integration with Streaming Frameworks
  - HTTP Server
  - **Kafka Consumer**

17.6 Batch Ingestion

- File based (HDFS, S3, …)

17.7 Real-time Ingestion

```
Task 1: [   Interval          ][ Window ]
Task 2:                         [                     ]
------------------------------------------------------->
                                                   time
```

18 Querying

18.1 Query types

- Group by: group by multiple dimensions
- Top N: like grouping by a single dimension
- Timeseries: without grouping over dimensions
- Search: Dimensions lookup
- Time Boundary: Find available data timeframe
- Metadata queries

18.2 Example(s)

```
{"queryType": "groupBy",
 "dataSource": "druidtest",
 "granularity": "all",
 "dimensions": [],
 "aggregations": [
     {"type": "count", "name": "rows"},
   {"type": "longSum", "name": "imps", "fieldName": "impressions"},
     {"type": "doubleSum", "name": "wp", "fieldName": "wp"}
 ],
 "intervals": ["2010-01-01T00:00/2020-01-01T00"]}
```

18.3 Result

```
[ {
  "version" : "v1",
  "timestamp" : "2010-01-01T00:00:00.000Z",
  "event" : {
    "imps" : 5,
    "wp" : 15000.0,
    "rows" : 5
  }
} ]
```

18.4 Caching

- Historical node level
    - By segment
- Broker Level
    - By segment and query
    - `groupBy` is disabled on purpose!
- By default: local caching

19 Druid Components

19.1 Druid

- Real-time Nodes
- Historical Nodes
- Broker Nodes
- Coordinator
- For indexing:
    - Overlord
    - Middle Manager

19.2 Also

- Deep Storage (S3, HDFS, ...)
- Metadata Storage (SQL)
- Load Balancer
- Cache

19.3 Coordinator

- Real-time Nodes (pull data, index it)
- Historical Nodes (keep old segments)
- Broker Nodes (route queries to RT & Hist. nodes, merge)
- Coordinator (manage segemnts)
- For indexing:
  - Overlord (distribute task to the middle manager)
  - Middle Manager (execute tasks via Peons)

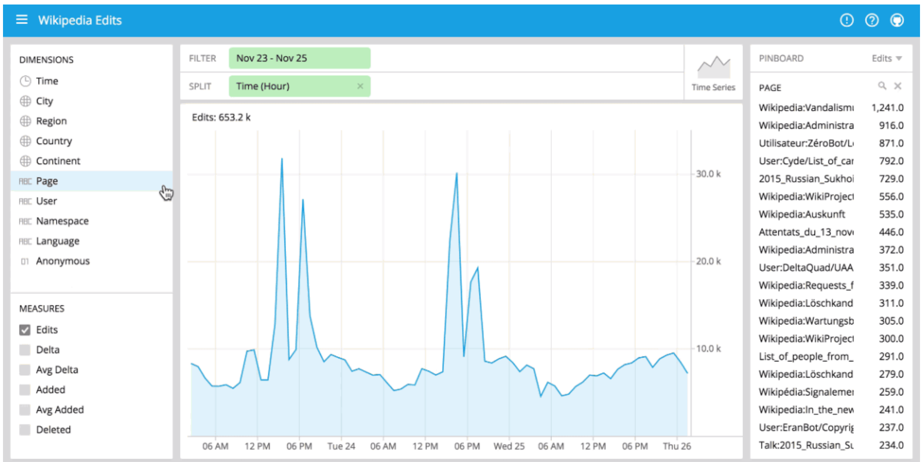
20 When *not* to choose Druid

- Data is not time-series
- Cardinality is *very* high
- Number of dimensions is high
- Setup cost must be avoided

21 Graphite (metrics)

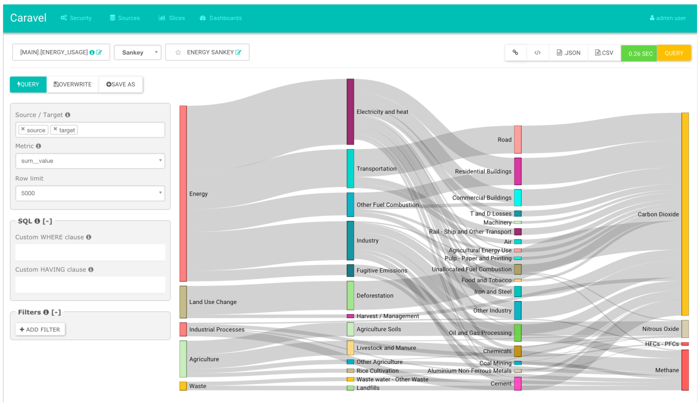
Graphite

22 Pivot (exploring data)



Pivot

23 Caravel



Caravel

24 Conclusions

24.1 Precompute your time series?

24.2 Don't reinvent it

- need a user facing API
- need time series on many dimensions
- need real-time
- big volume of data

24.3 Druid way is the right way!

1. Push in kafka
2. Add the right dimensions
3. Push in druid
4. ???
5. Profit!