TSAR

# A TimeSeries AggregatoR

Anirudh Todi | Twitter | @anirudhtodi | TSAR

# What is TSAR?

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TSAR is a framework and service infrastructure for specifying, deploying and operating timeseries aggregation jobs.

# TimeSeries Aggregation at Twitter

# TimeSeries Aggregation at Twitter

A common problem

- Data products (analytics.twitter.com, embedded analytics, internal dashboards)
- Business metrics
- Site traffic, service health, and user engagement monitoring

Hard to do at scale

- 10s of billions of events/day in real time

Hard to maintain aggregation services once deployed -

- Complex tooling is required

# TimeSeries Aggregation at Twitter

# TimeSeries Aggregation at Twitter

Many time-series applications look similar

- Common types of aggregations
- Similar service stacks

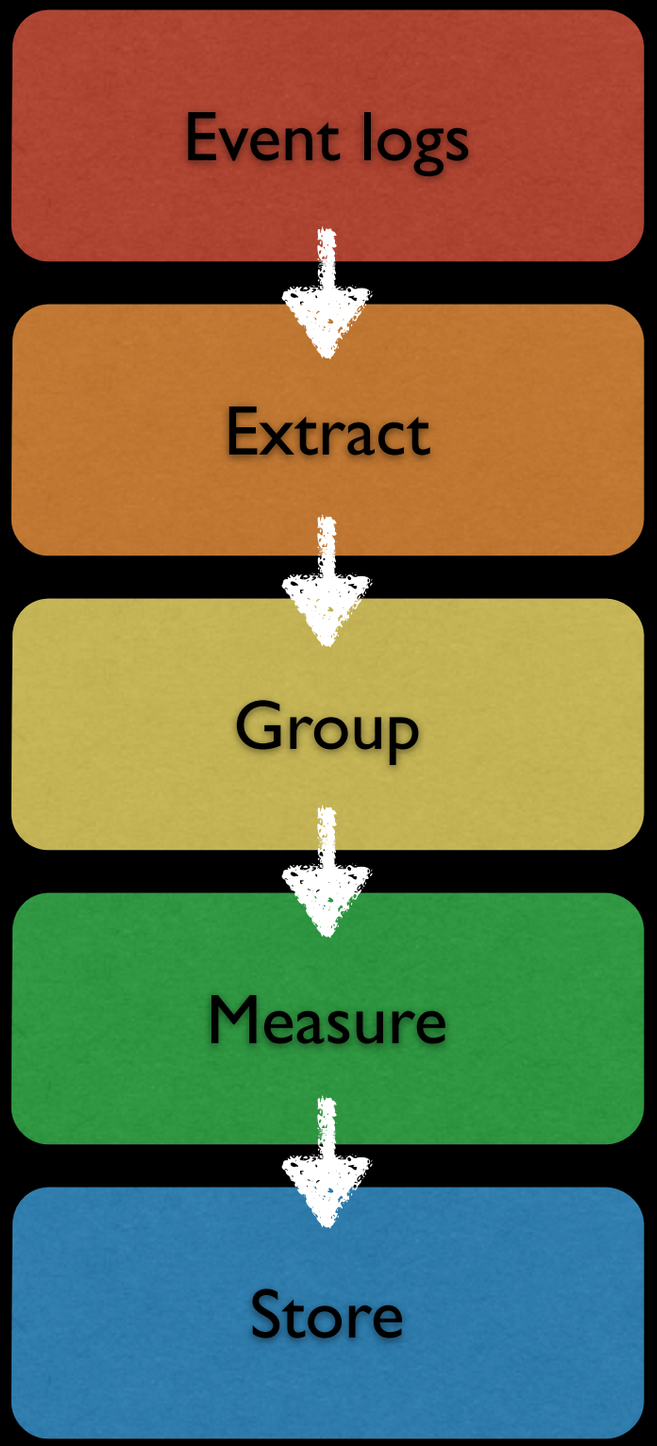
Multi-year effort to build general solutions

- Summingbird - abstraction library for generalized distributed computation

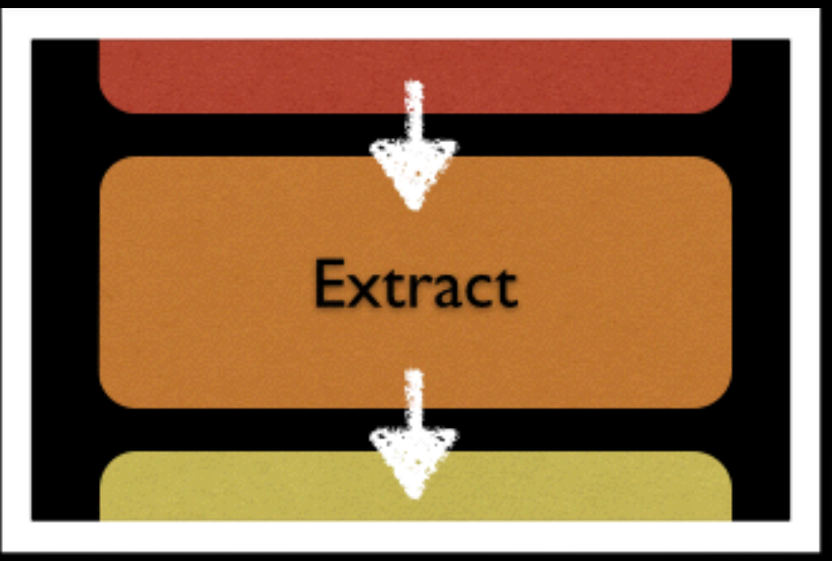
TSAR - an end-to-end aggregation service built on Summingbird

- Abstracts away everything except application's data model and business logic

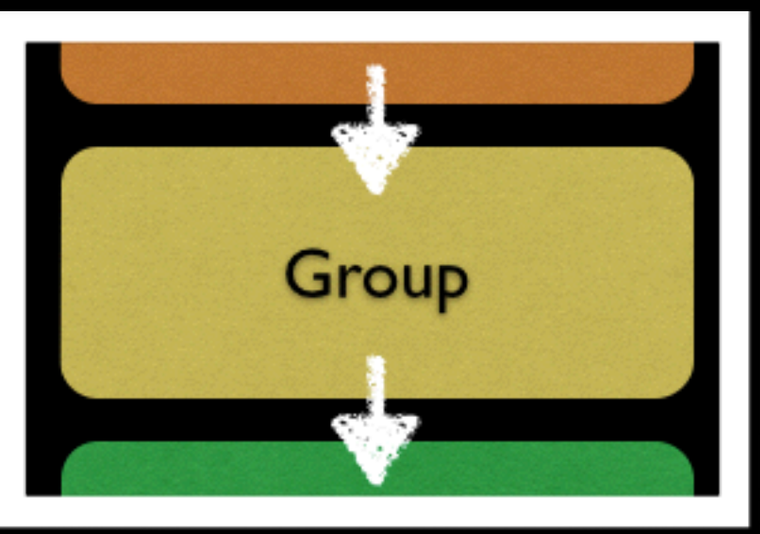
# A typical aggregation



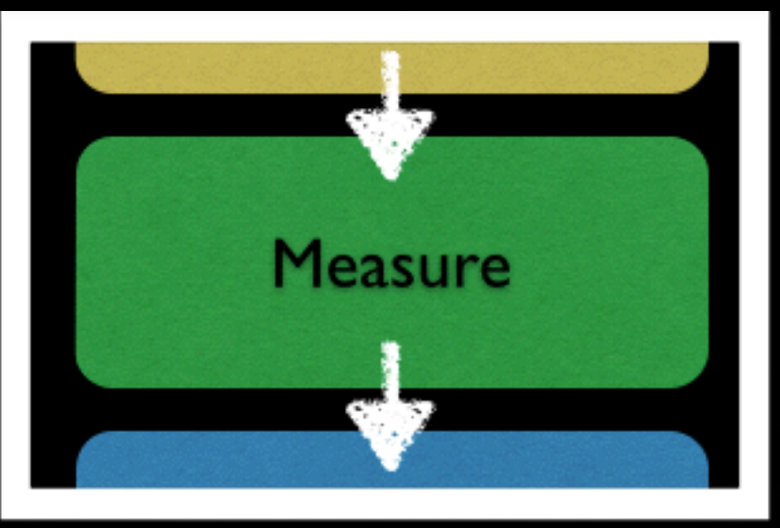

```
[ (“/“          , 300, iPhone,…)
, (“/favorites”, 300, iPhone,…)
, (“/replies”  , 300, Anroid,…)
, (“/“          , 200, Web,…)
, (“/favorites”, 200, Web,…)
, (“/“          , 200, iPhone,…)
]
```




```
[ (“/“           , 300)
, (“/favorites”, 300)
, (“/replies”  , 300)
, (“/“           , 200)
, (“/favorites”, 200)
, (“/“           , 200)
]
```

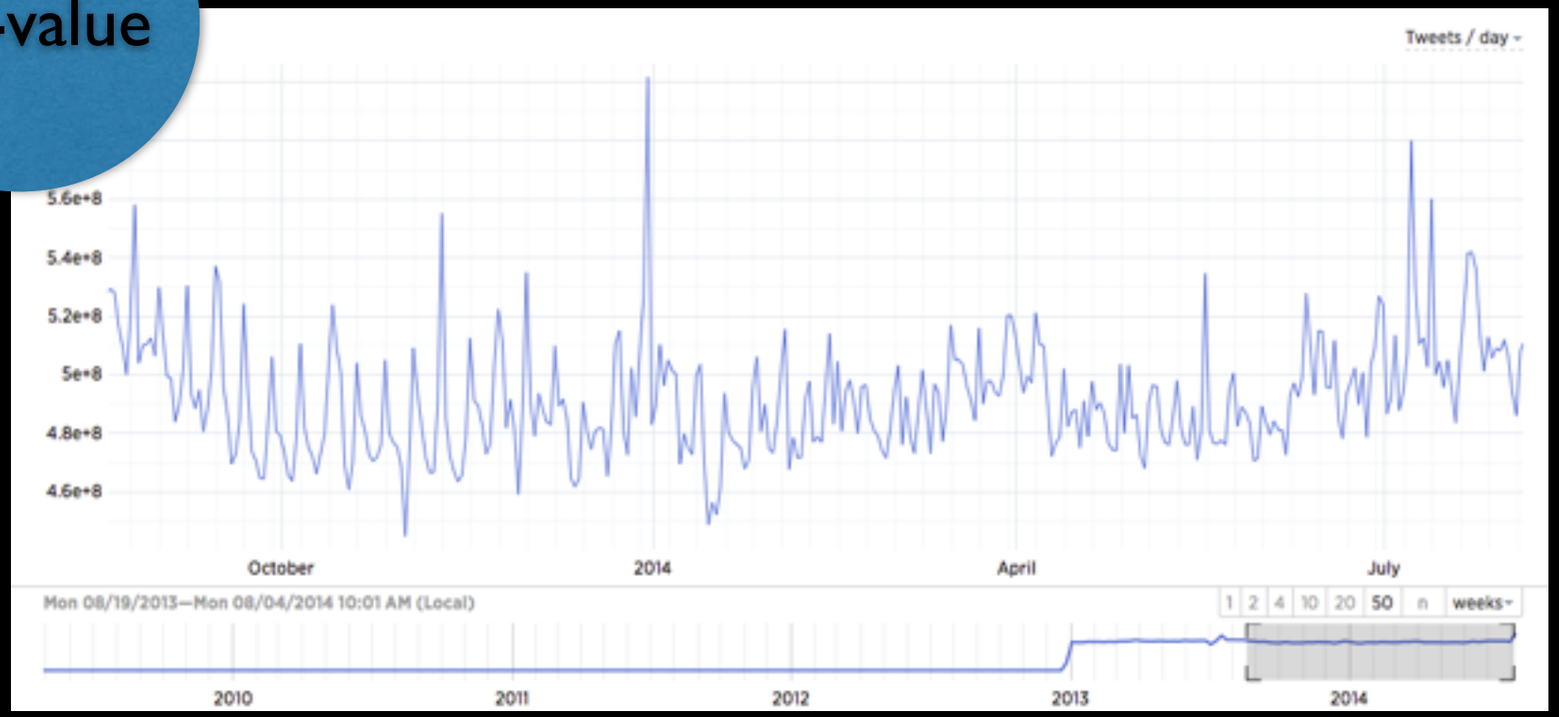


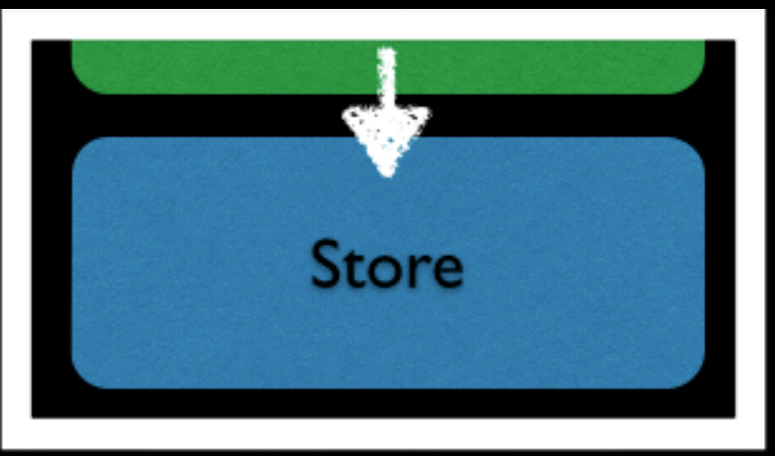

```
[ (“/“
  , [ (“/“, 300)
    , (“/“, 200 )
    , (“/“, 200 )
    ]
  )
, (“/favorites”
  , [ (“/favorites”, 300)
    , (“/favorites”, 300)
    ]
  )
, (“/replies”
  , [ (“/replies”, 300)
    ]
  )
]
```




```
[ (“/“           , 3)
, (“/favorites”, 2)
, (“/replies”  , 1)
]
```

key-value




Vertica

```
OM platform_analytics.tfe_requests_by_client_daily WHERE date_id = 20140520 AND client_ap
          |          created_at          | date_id  | bucket_start_millis | client_application_id | po
 1485     | 2014-05-21 12:00:25.365622 | 20140520 | 2014-05-20 00:00:00 |                176056 | f
 41298910 | 2014-05-20 11:15:24.221067 | 20140520 | 2014-05-20 00:00:00 |                176056 | f
 41458592 | 2014-05-22 11:16:37.581903 | 20140520 | 2014-05-20 00:00:00 |                176056 | f
(3 rows)
```

# Example: API aggregates

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- Bucket each API call
- Dimensions - endpoint, datacenter, client application ID
- Compute - total event count, unique users, mean response time etc
- Write the output to Vertica

# Example: Impressions by Tweet

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- Bucket each impressions by tweet ID
- Compute total count, unique users
- Write output to a key-value store
- Expose output via a high-SLA query service
- Write sample of data to Vertica for cross-validation

# Problems

# Problems

- Service interruption: Can we retrieve lost data?
- Data schema coordination: Store output as log data, in a key-value data store, in cache, and in relational databases
- Flexible schema change
- Easy to backfill and update/repair historical data

Most important: Solve these problems in a general way

# TSAR's design principles

# TSAR's design principles

1) Hybrid computation: Build on *Summingbird*, process each event twice - in real time & in batch (at a later time)

- Gives stability and reproducibility of batch
- Streaming (recency) of realtime

Leverage the Summingbird ecosystem:

- Abstraction framework over computing platforms
- Rich library of approximation monoids (Algebird)
- Storage abstractions (Storehaus)

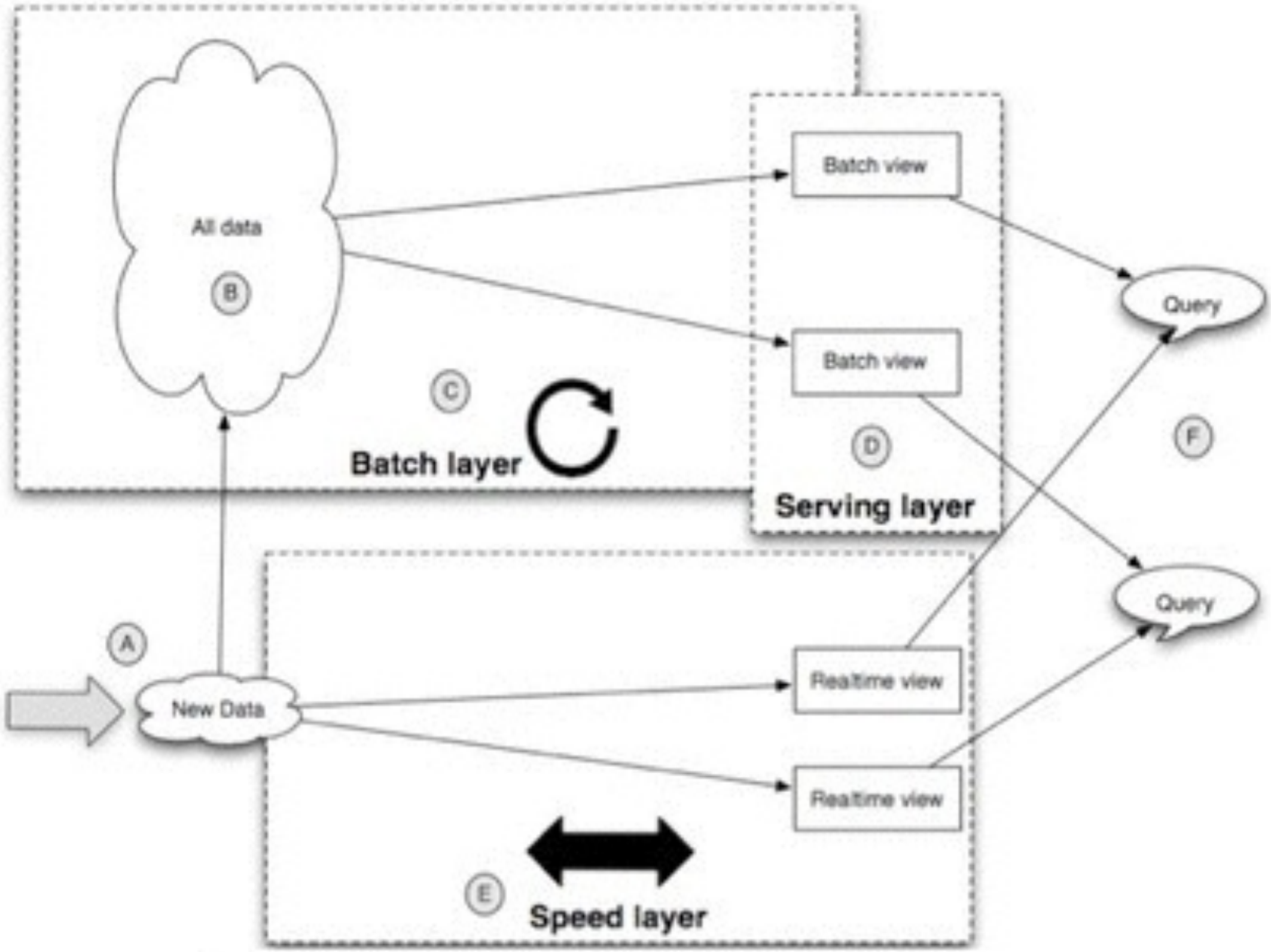


**Figure 1.11 Lambda Architecture diagram**

# TSAR's design principles

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2) Separate *event production* from *event aggregation*

User specifies how to extract events from source data

Bucketing and aggregating events is managed by TSAR

# TSAR's design principles

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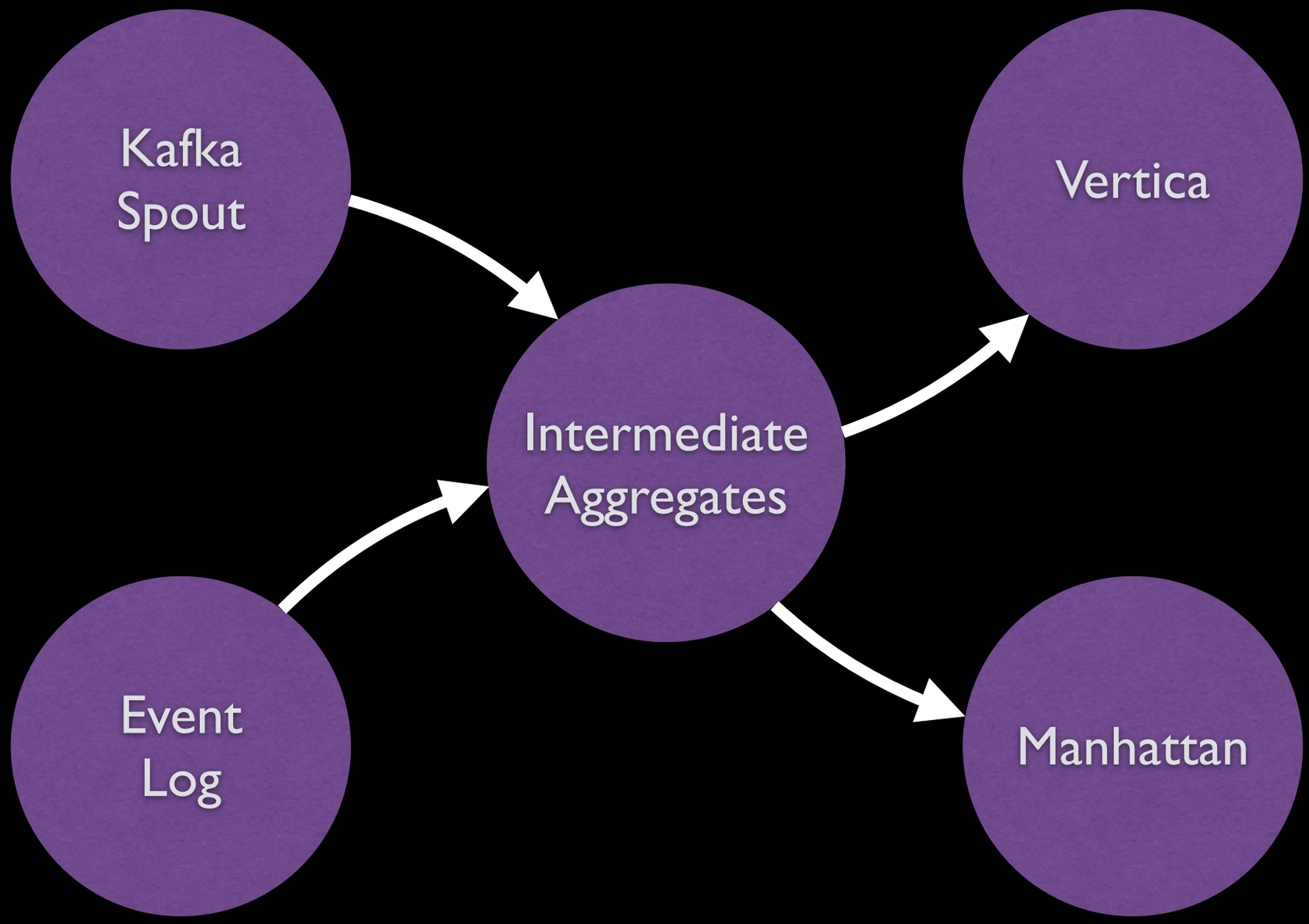
3) Unified data schema:
- Data schema specified in datastore-independent way
- Managed schema evolution & data transformation

Store data on:
- HDFS
- Manhattan (key-value)
- Vertica/MySQL
- Cache

Easily extensible to other schemas (Cassandra, HBase, etc)

# Data Schema Coordination




- Schema consistent across stores
- Update stores when schema evolves

# TSAR's design principles

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4) Integrated service toolkit

- One-stop deployment tooling
- Data warehousing
- Query capability
- Automatic observability and alerting
- Automatic data integrity checks

# Tweet Impressions in TSAR

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- Annotate each tweet with an impression count
- Count = unique users who saw that tweet
- Massive scalability challenge:
  - > 500MM tweets/day
  - tens of billions of impressions
- Want realtime updates
- Production ready and robust

# A minimal Tsar project

Scala Tsar job

Configuration File

Thrift IDL

Thrift IDL

```
struct TweetAttributes
{
    1: optional i64 tweet_id
}
```

# Tweet Impressions Example

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```
aggregate {
      onKeys(
          (TweetId)
      ) produce (
          Count
      ) sinkTo (Manhattan)
} fromProducer {
  ClientEventSource(“client_events”)
    .filter { event => isImpressionEvent(event) }
    .map { event =>
       val impr = ImpressionAttributes(event.tweetId)
       (event.timestamp, impr)
    }
}
```

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Dimensions for job aggregation

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Metrics to compute

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What datastores to write to

# Tweet Impressions Example

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Summingbird fragment to describe event production.

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    .map { event =>
       val impr = ImpressionAttributes(event.tweetId)
       (event.timestamp, impr)
    }
}
```

Summingbird fragment to describe event production.

There is no aggregation logic specified here

Configuration File

```
Config(
  base = Base(
    namespace             = 'tsar-examples',
    name                  = 'tweets',
    user                  = 'tsar-shared',
    thriftAttributesName = 'TweetAttributes',
    origin                = '2014-05-15 00:00:00 UTC',
    jobclass              = 'com.twitter.platform.analytics.examples.TweetJob',

    outputs               =  [
      Output(sink = Sink.IntermediateThrift, width = 1 * Day),
      Output(sink = Sink.Manhattan1, width = 1 * Day)
    ],
    ...
```

# What has been specified?

# What has been specified?

- Our event schema (in thrift)
- How to produce these events
- Dimensions to aggregate on
- Time granularities to aggregate on
- Sinks (Manhattan / MySQL) to use

# What do you ***not*** specify?

- How to represent the aggregated data
- How to represent the schema in MySQL / Manhattan
- How to perform the aggregation
- How to locate and connect to underlying services (Hadoop, Storm, MySQL, Manhattan, …)

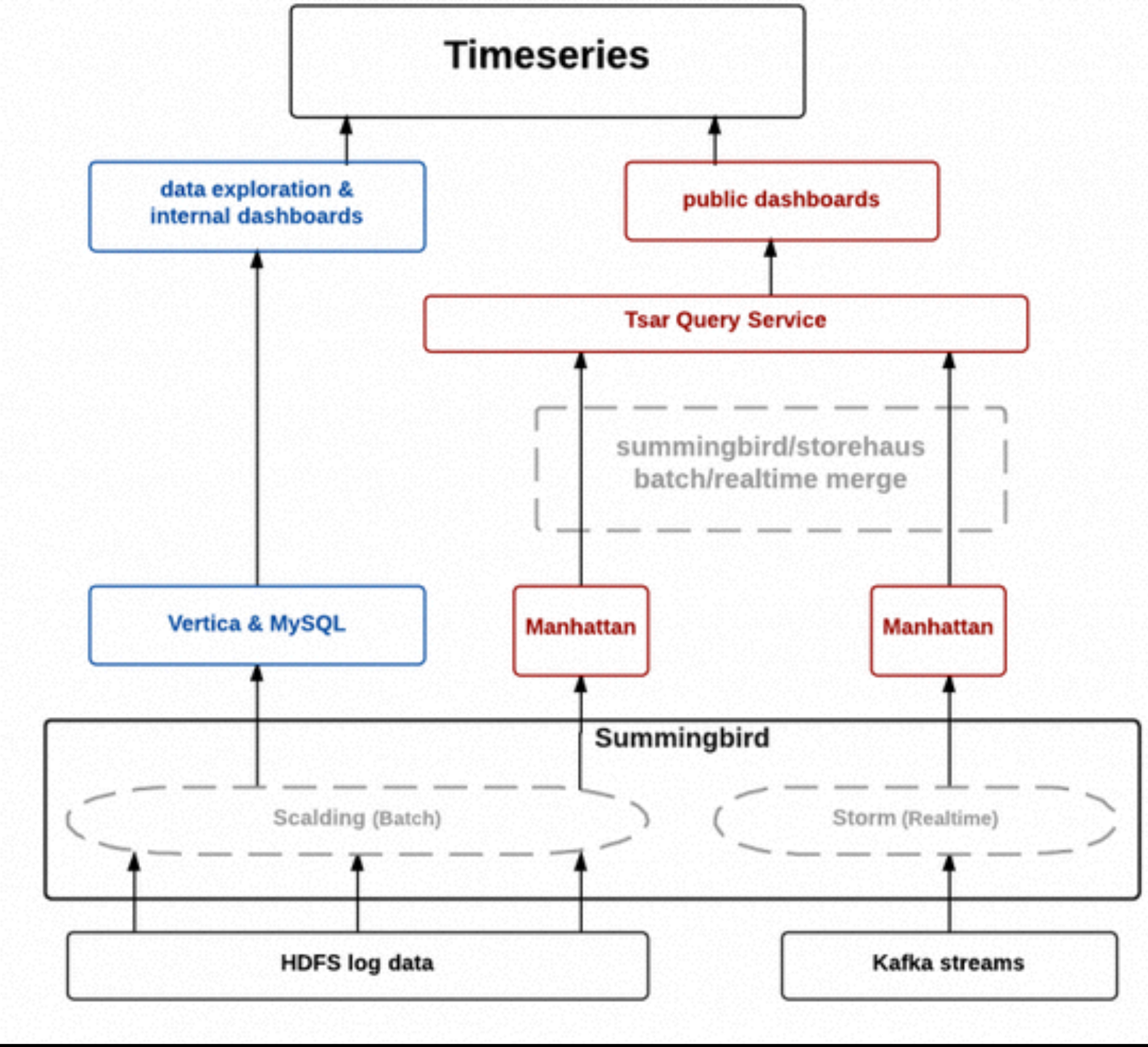
# Operational simplicity

End-to-end service infrastructure with a *single command*

```
$ tsar deploy --env=prod
```

- Launch Hadoop jobs
- Launch Storm jobs
- Launch Thrift query service
- Launch loader processes to load data into MySQL / Manhattan
- Mesos configs for all of the above
- Alerts for the batch & storm jobs and the query service
- Observability for the query service
- Auto-create tables and views in MySQL or Vertica
- Automatic data regression and data anomaly checks

# Bird’s eye view of the TSAR pipeline



# Seamless Schema evolution

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Break down impressions by the client application
(Twitter for iPhone, Twitter for Android etc)


```
aggregate {
      onKeys(
          (TweetId),
          (TweetId, ClientApplicationId)
      ) produce (
          Count
      ) sinkTo (Manhattan)
} fromProducer {
  ClientEventSource(“client_events”)
    .filter { event => isImpressionEvent(event) }
    .map { event =>
      val impr = ImpressionAttributes(event.client, event.tweetId)
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# Seamless Schema evolution

Scala Tsar job

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```

# Seamless Schema evolution

Break down impressions by the client application
(Twitter for iPhone, Twitter for Android etc)

Scala Tsar job

New aggregation dimension

```
aggregate {
      onKeys(
          (TweetId),
          (TweetId, ClientApplicationId)
      ) produce (
          Count
      ) sinkTo (Manhattan)
} fromProducer {
  ClientEventSource("client_events")
    .filter { event => isImpressionEvent(event) }
    .map { event =>
      val impr = ImpressionAttributes(event.client, event.tweetId)
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    }
}
```

# Backfill tooling

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But what about historical data?

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tsar backfill —start=<start> —end=<end>

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But what about historical data?

tsar backfill —start=<start> —end=<end>

Backfill runs parallel to the production job

Useful for repairing historical data as well

# Aggregating on different granularities

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Configuration File

We have been computing only *daily aggregates*
We now wish to add *alltime aggregates*

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```
Output(sink = Sink.Manhattan, width = 1 * Day)
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```

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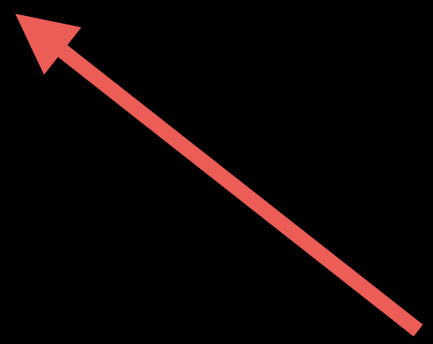

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```
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```

New aggregation granularity

# Automatic metric computation

# Automatic metric computation

So far, only total view counts.
Now, add # unique users viewing each tweet


```
aggregate {
      onKeys(
          (TweetId),
          (TweetId, ClientApplicationId)
      ) produce (
          Count,
          Unique(UserId)
      ) sinkTo (Manhattan)
} fromProducer {
  ClientEventSource(“client_events”)
    .filter { event => isImpressionEvent(event) }
    .map { event =>
       val impr = ImpressionAttributes(
          event.client, event.userId, event.tweetId
       )
       (event.timestamp, impr)
    }
```

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       val impr = ImpressionAttributes(
          event.client, event.userId, event.tweetId
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       (event.timestamp, impr)
    }
```

New metric

# Support for multiple sinks

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So far, only persisting data to Manhattan

Persist data to MySQL as well

# Support for multiple sinks


So far, only persisting data to Manhattan

Persist data to MySQL as well

```
Output(sink = Sink.Manhattan, width = 1 * Day)
Output(sink = Sink.Manhattan, width = Alltime)
Output(sink = Sink.MySQL, width = Alltime)
```

# Support for multiple sinks

Configuration File

So far, only persisting data to Manhattan

Persist data to MySQL as well

Output(sink = Sink.Manhattan, width = 1 * Day)
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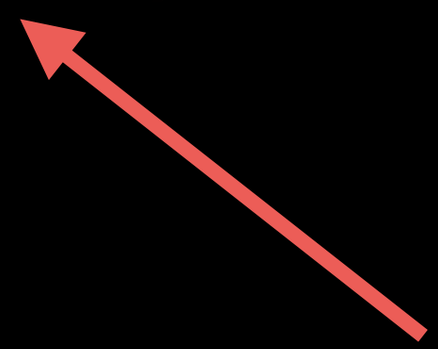
Output(sink = Sink.MySQL, width = Alltime)



# Support for multiple sinks

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Persist data to MySQL as well

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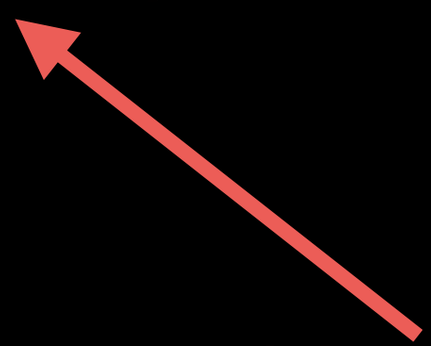
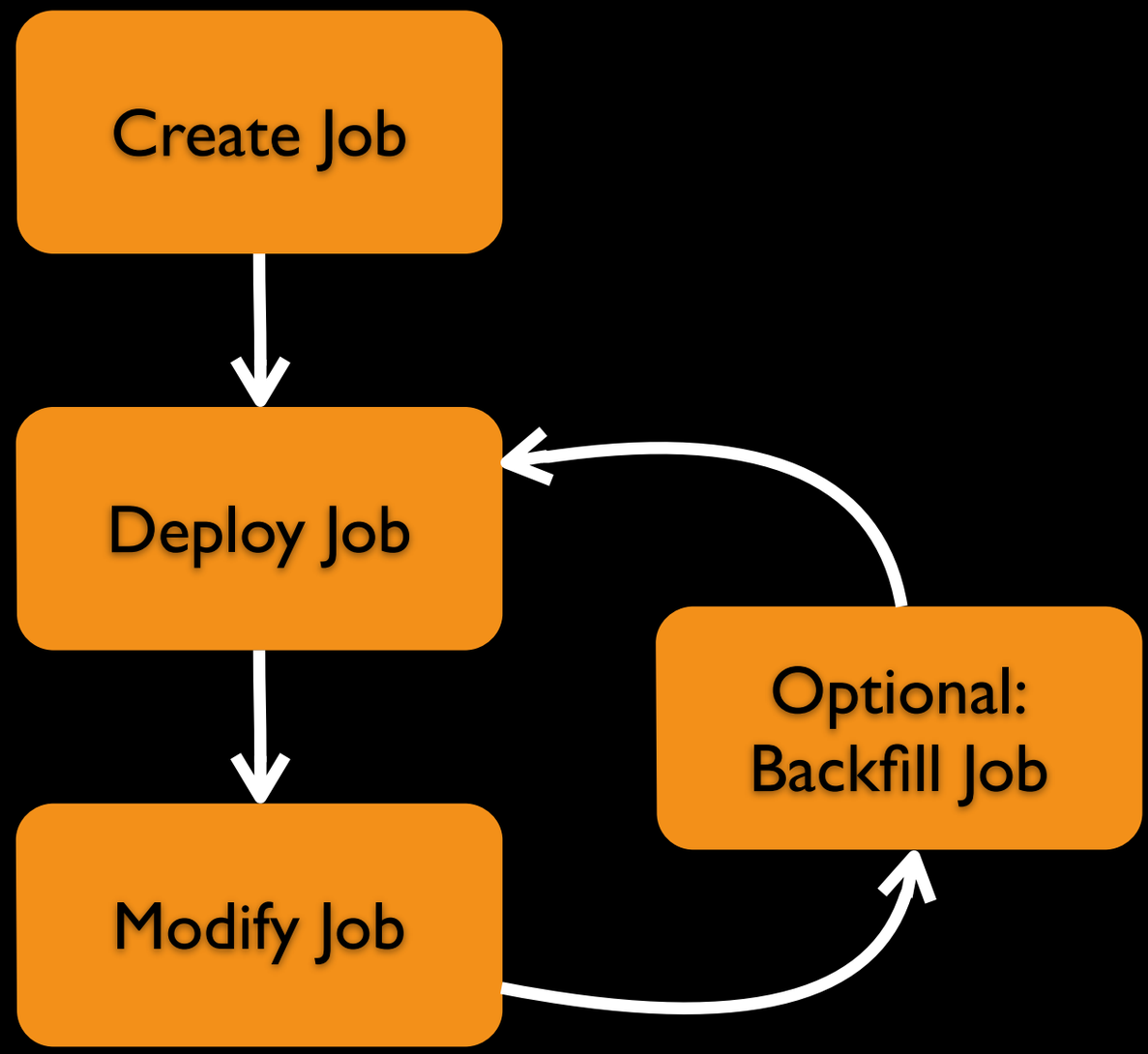


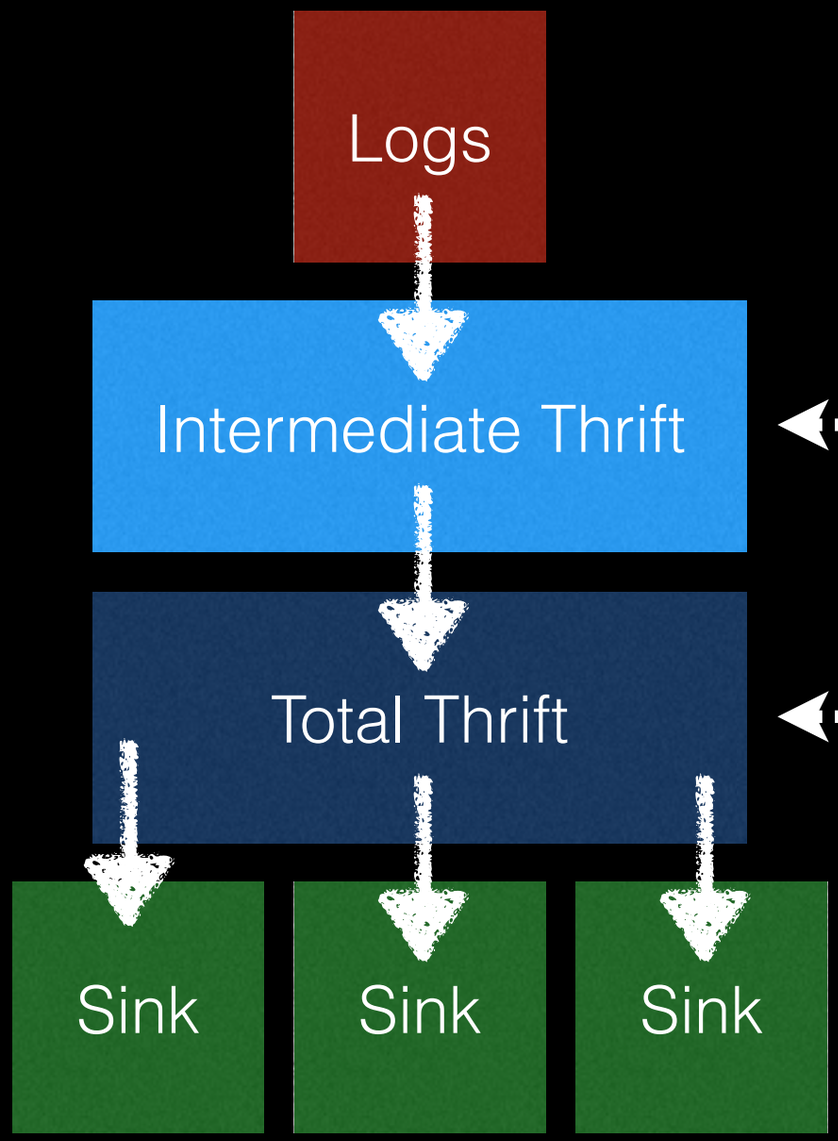
New sink

# Tsar Workflow



# TSAR Optimizations

# Cache TSAR Pipeline




Cache filtered events

Cache aggregation results

```
aggregate {
  onKeys (
    (TweetIdField),                                  // Total
    (ClientApplicationIdField),                      // Total
    (TweetIdField, ClientApplicationIdField)         // Intermediate
  ) produce (
    ...
  ) sinkTo (
    ...
  )
```

# Covering Template

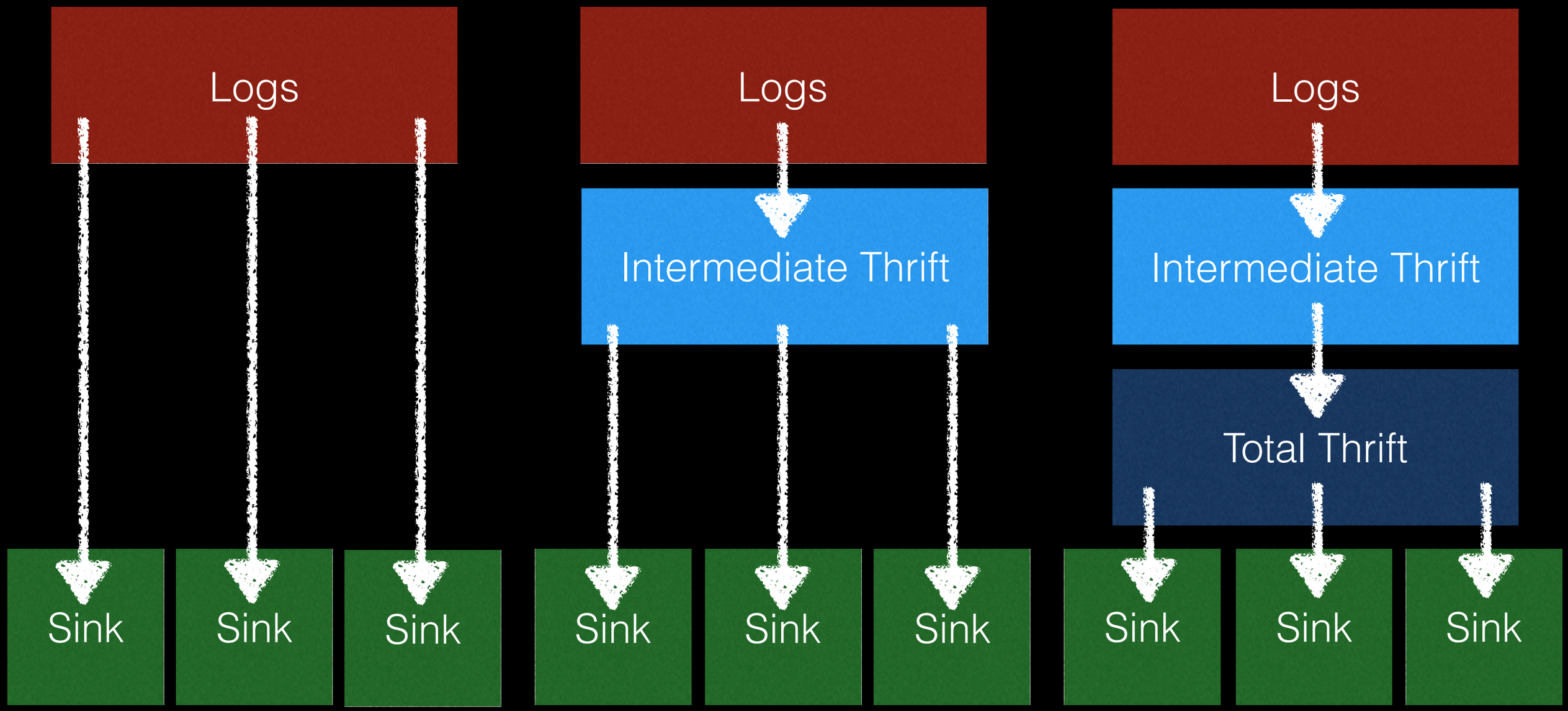
```
aggregate {

  onKeys (
    (TweetIdField),
    (ClientApplicationIdField),
    (TweetIdField, ClientApplicationIdField)  // Covering Template
  ) produce (
    ...
  ) sinkTo (
    ...
  )
```

# Intermediate Sinks

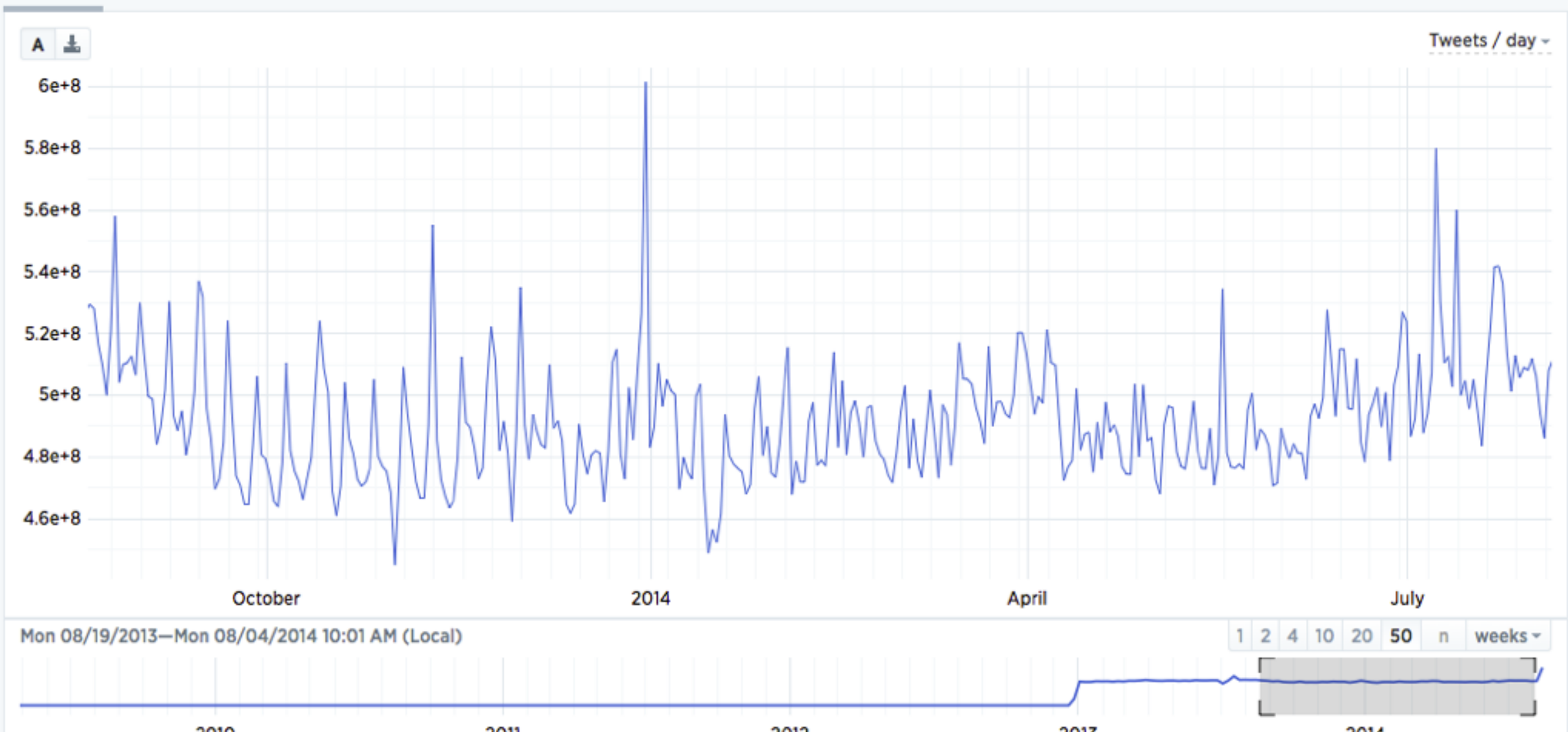
```
Config(
 base = Base(
    namespace            = 'tsar-examples',
    name                 = 'tweets',
    user                 = 'tsar-shared',
    thriftAttributesName = 'TweetAttributes',
    origin               = '2014-05-15 00:00:00 UTC',
    jobclass             = 'com.twitter.platform.analytics.examples.TweetJob',
    outputs              =  [
        Output(sink = Sink.IntermediateThrift, width = 1 * Day),
        Output(sink = Sink.TotalThrift, width = 1 * Day),
        Output(sink = Sink.Manhattan1, width = 1 * Day),
        Output(sink = Sink.Vertica, width = 1 * Day)
      ],
    …
```

# Trade space for time

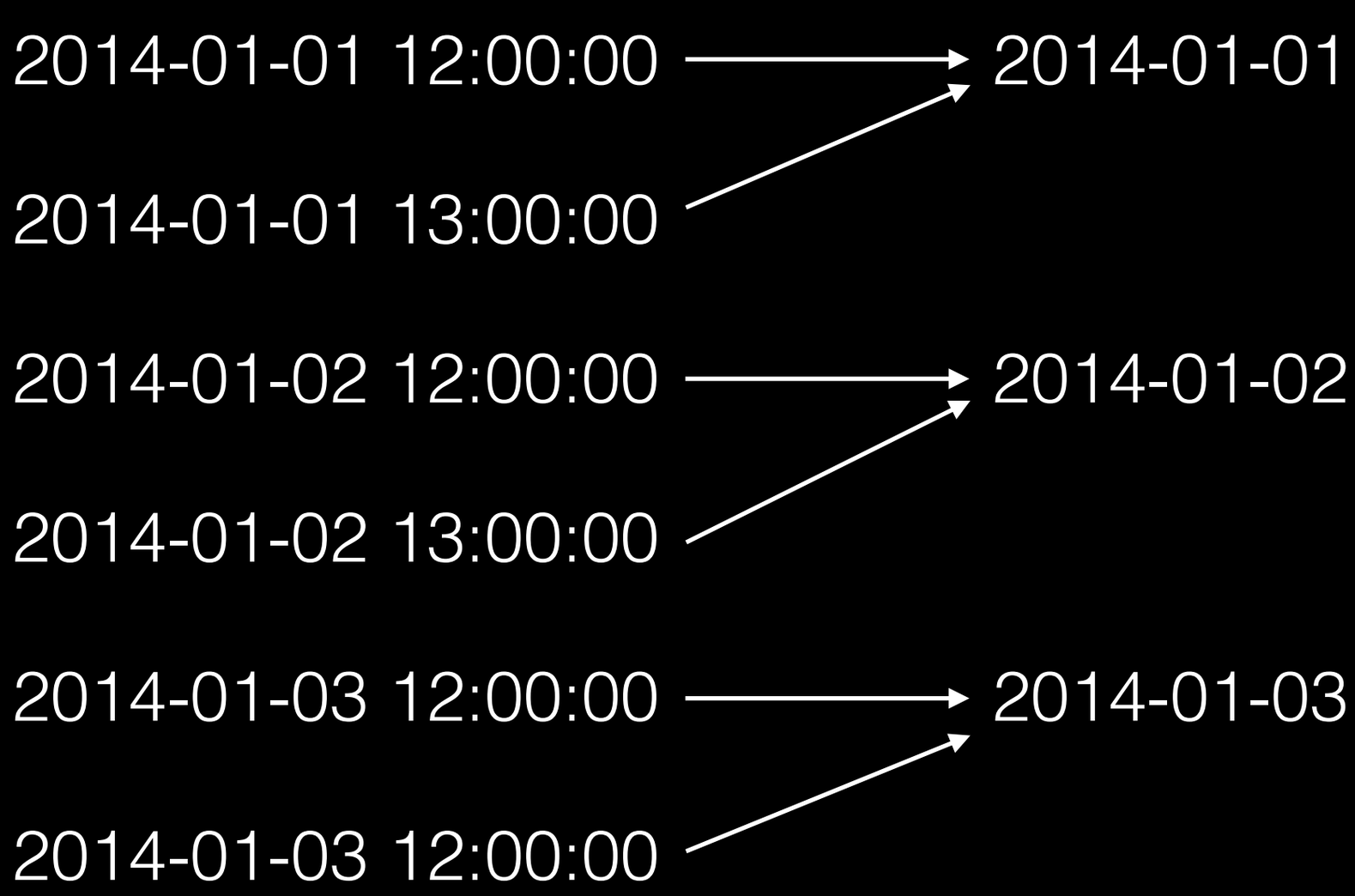


# Manhattan - Key Clustering

## Reduces Manhattan queries for large time ranges

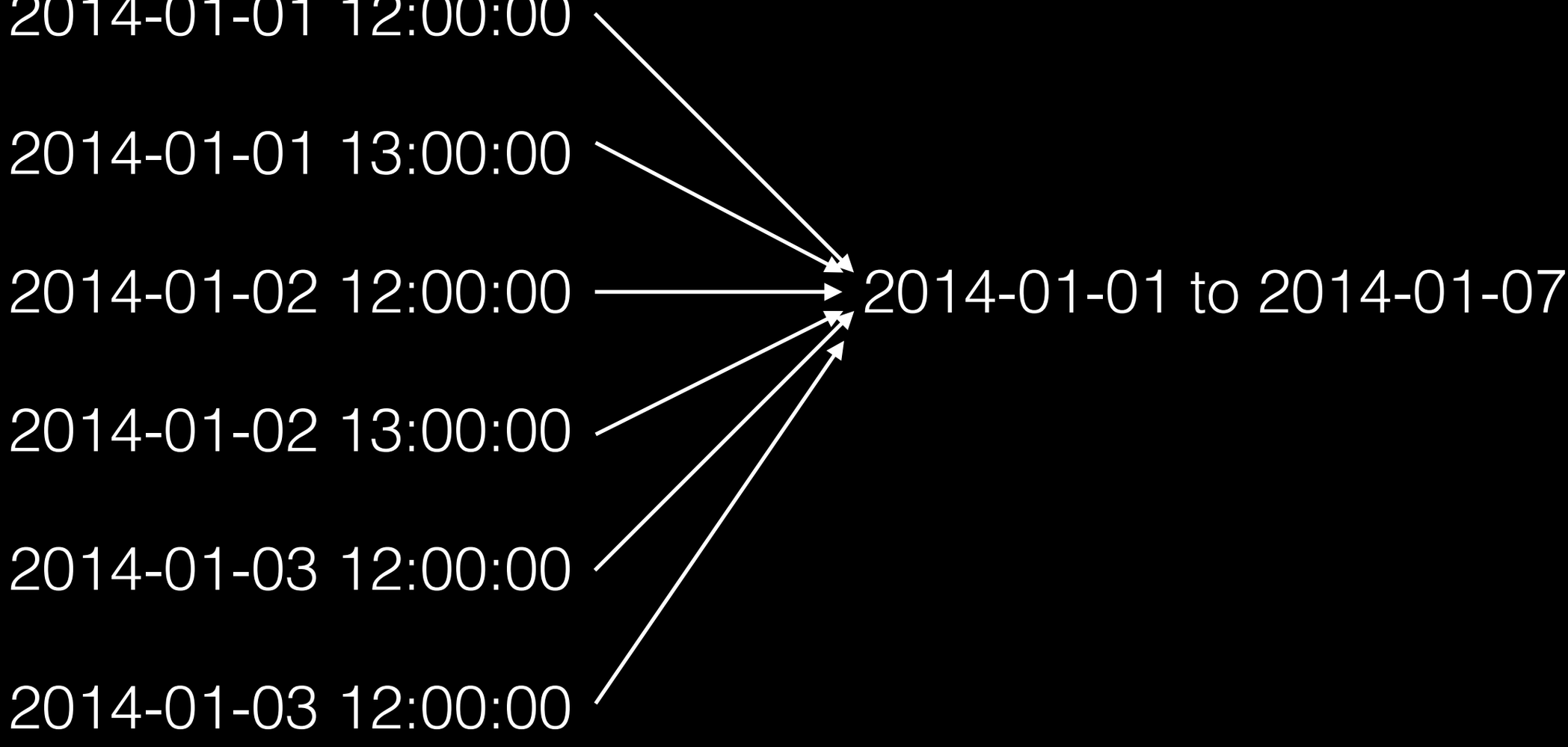


# Manhattan - Key Clustering




1 Day Clustering

# Manhattan - Key Clustering




7 Day Clustering

# Value Packing - Key Indexer

Some keys are always queried together

| Location | Impressions |
|---|---|
| **All campaigns** | **1,177,780** |
| United States | 610,968 |
| United Kingdom | 186,313 |
| Canada | 127,818 |
| Spain | 69,910 |
| France | 58,335 |
| Netherlands | 49,483 |
| Germany | 41,632 |
| Belgium | 23,610 |
| Ireland | 8,676 |

# Value Packing - Key Indexer

Naive approach:

```
 (CampaignIdField, CountryField) --> Impressions
```

Would have to query:

```
 (CampaignIdField, USA) --> Impressions_USA
 (CampaignIdField, UK)  --> Impressions_UK
 …
```

Better approach:

```
 (CampaignIdField) -> Map[CountryField -> Impressions]
```

Would have to query:

```
 (CampaignIdField) -> Map[USA -> Impressions_USA,
                          UK  -> Impressions_UK,…]
```

- Limits key fanout
- Implicit index on CountryField - don’t need to know which countries to query for

# TSAR Visualization

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# Conclusion: Three basic problems

# Conclusion: Three basic problems

- Computation management
  - Describe and execute computational logic
  - Specify aggregation dimensions, metrics and time granularities
- Dataset management
  - Define, deploy and evolve data schemas
  - Coordinate data migration, backfill and recovery
- Service management
  - Define query services, observability, alerting, regression checks, coordinate deployment across all underlying services

TSAR gives you all of the above

# Key Takeaway

# Key Takeaway

"The end-to-end management of the data pipeline is TSAR's key feature. The user concentrates on the business logic."

Thank you!

Questions?

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