
Developers
Business
CUSTOMERS
Info Sec
Operations
Research
Management
Agenda
Data Size/Frequency
Data Quality
VERACITY
ENTROPY
METRICS
LOGS
FUNCTIONAL ARCHITECTURE
OLAP
HADOOP
HBASE
BIG INSIGHTS
Data at eBay is BIG and getting BIGGER
Data is becoming more and more valuable
Big data needs Big Architecture
- Remove Entropy as early as possible
- Data Distribution needs to be elastic
- Storage Optimized for Access Patterns
ebay is HIRING!!
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Big Data Problems In Monitoring At eBay
Yuri Finkelstein
Bhaven Avalani
Problem 4: Scalable Time Series Data Store
Problem 1: Logs - A Data Entropy Problem
Logs
- Unstructured, schema-free
- Not Typed
- Not Governed
Challenges:
requires high processing power
requires parsing rules
difficult to track sequence of events
difficult to track concurrent activities
Problem 2: Large Scale Data Distribution
Problem 3: Metric Extraction


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Monitoring And Big Data: The Problem Domain

4 Problems

- Reduction of Data Entropy
- Robust Data Distribution
- Metric Extraction
- Efficient Storage

Monitoring: The Problem Domain

Operational Management
- Performance
- Errors
- Anomaly Detection

Triaging
- Root Cause Analysis

Business Monitoring
- Customer Behaviors
- Click Stream Analytics

Developers

Business

CUSTOMERS

Info Sec

Operations

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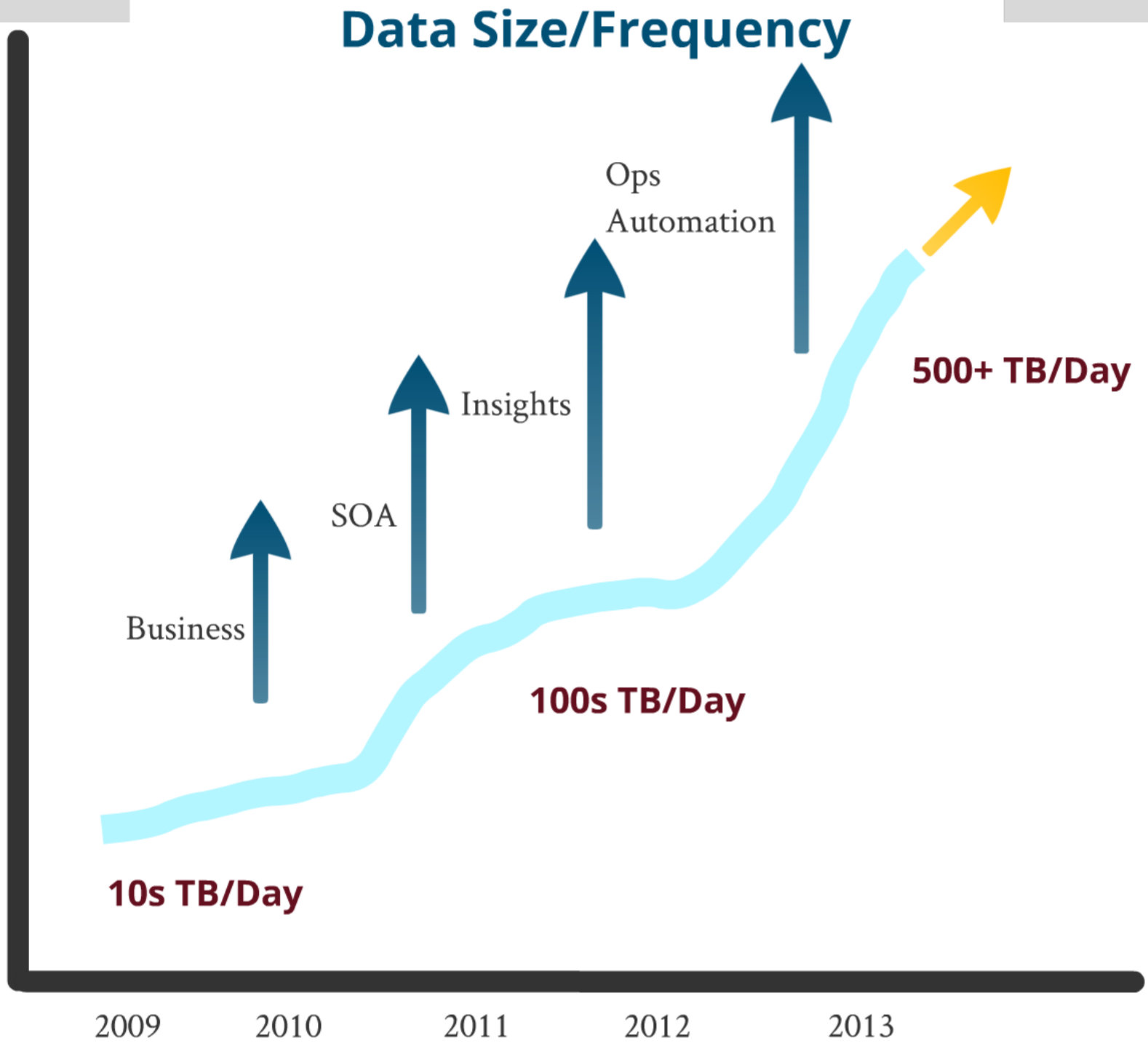
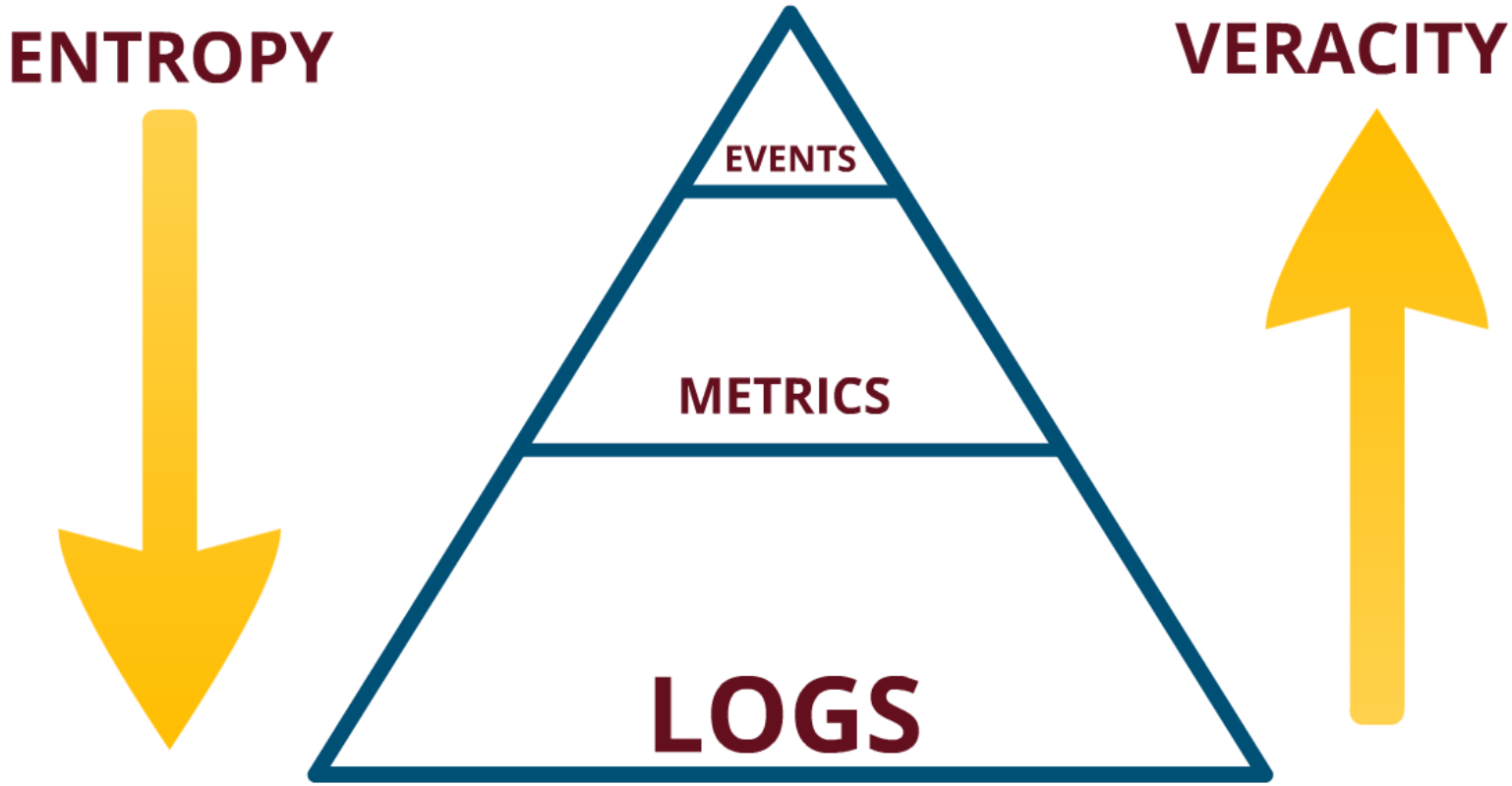
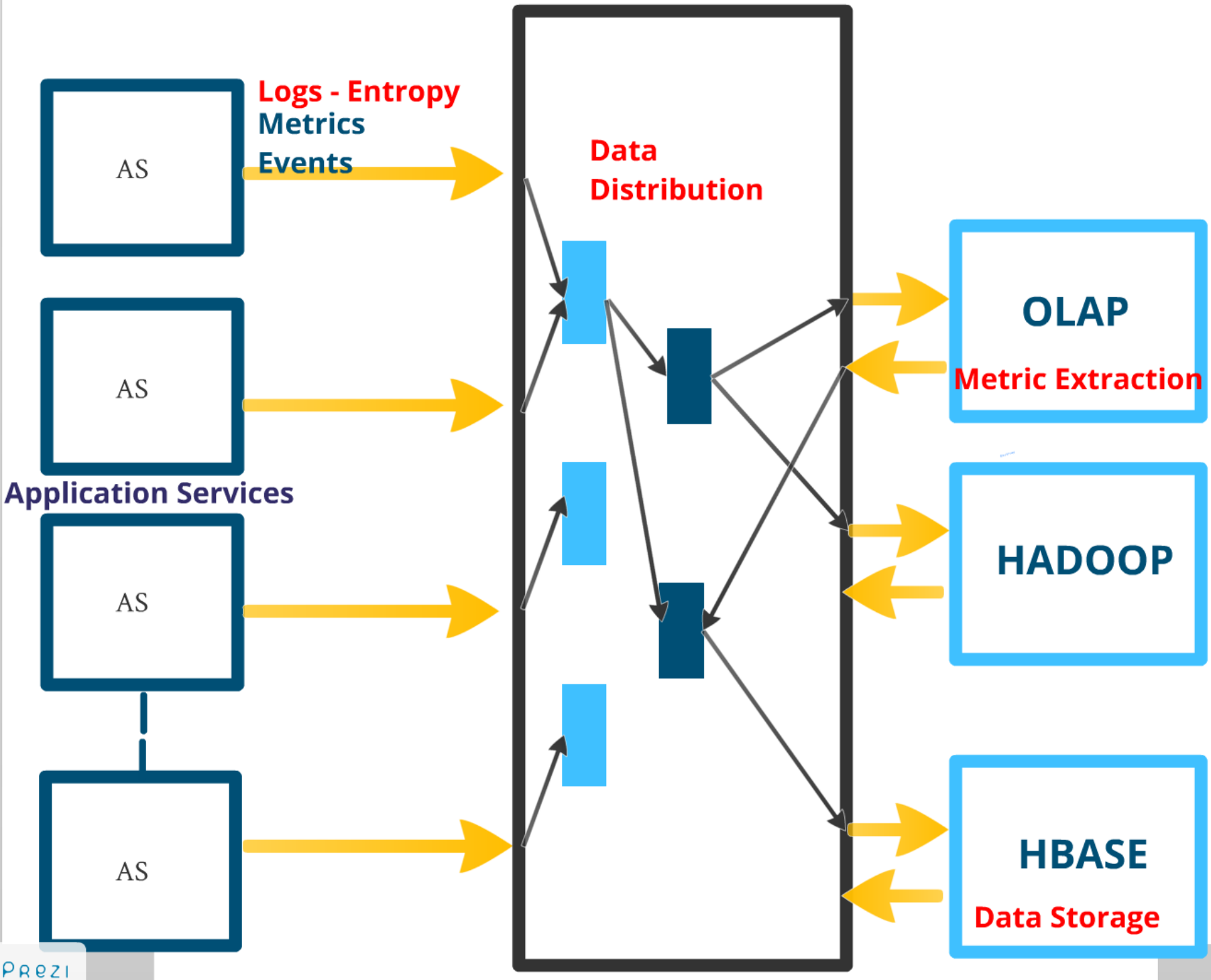
Management


Data Size/Frequency
Ops
Automation
Insights
SOA
Business
500+ TB/Day
100s TB/Day
10s TB/Day
2009
2010
2011
2012
2013

Data Quality



FUNCTIONAL ARCHITECTURE



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Traditional Logging

[Wed Oct 11 14:32:52 2000] [error] [client 127.0.0.1] client denied by server configuration: /export/home/live/ap/htdocs/test
127.0.0.1 - frank [10/Oct/2000:13:55:36 -0700] "GET /apache_pb.gif HTTP/1.0" 200 2326

Structured Logging

```
-----------------------------------------------------
0 t21:48:14.01  URL     Ginger.m.1.GET
1    E21:48:14.01       URL     Request 0       /m/1/pictures/getObjectIdForMd5?md5=mGcMs8xhD_j8SBgAq2Bx2AQ&widt
1    E21:48:14.01       URL     ClientInfo      0       ClientIP=10.91.119.29&
1    E21:48:14.01       URL     Headers 0       accept=application/json&cache-control=no-cache&pragma=no-cache&u
connection=keep-alive&x-ebay-client-ip=10.94.110.91&x-ebay-web-tier-ip=10.91.119.65&
1    A21:48:14.01       SEC     Ginger.m.1.Security     0       0       SecurityEnabled=false&InternalIP=false
1    t21:48:14.03       Metadata GET Request    com.ebay.zoom.eps.Image
2       t21:48:14.03    MetadataFind    com.ebay.zoom.eps.dao.ImageDo
3          t21:48:14.03 PictureFailover Process GET Request
4             A21:48:14.03      EXEC    40305040        0       16      image05host
3          T21:48:14.04 PictureFailover Process GET Request     0       17      Got request for Oracle lookup&Su
-----------------------------------------------------
2       T21:48:14.04    MetadataFind    com.ebay.zoom.eps.dao.ImageDo   0       17      key=mGcMs8xhD_j8SBgAq2Bx
-----------------------------------------------------
1    T21:48:14.04       Metadata GET Request    com.ebay.zoom.eps.Image 0       17
-----------------------------------------------------
0 T21:48:14.04  URL     Ginger.m.1.GET  0       18      REQUEST-ID=13ac9bf6-2be0-a5ac-4594-42a4ffffd96d!m.1!10.9
```

t - open transaction (time, type, name)
T - close transaction (time, type, name, status_code, duration, data (name=value&name=value&...)
A - atomic transaction (like t and T in one line)
E – event (time, class, name, status_code, data)
H – heartbeat (time, class, name, data)
Transactions can be nested,

Problem 2: Large Scale Data Distribution

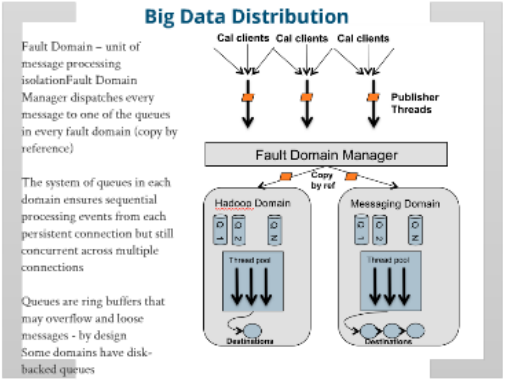
Source: ~10K of Service Instances

Data Volume: 100s of Terabytes per Day

Destination: Data Processing Services with different QoS

Challenges:

- limit scope of fault domains
- absorb temporary pressure
- maintain visibility of pressure points

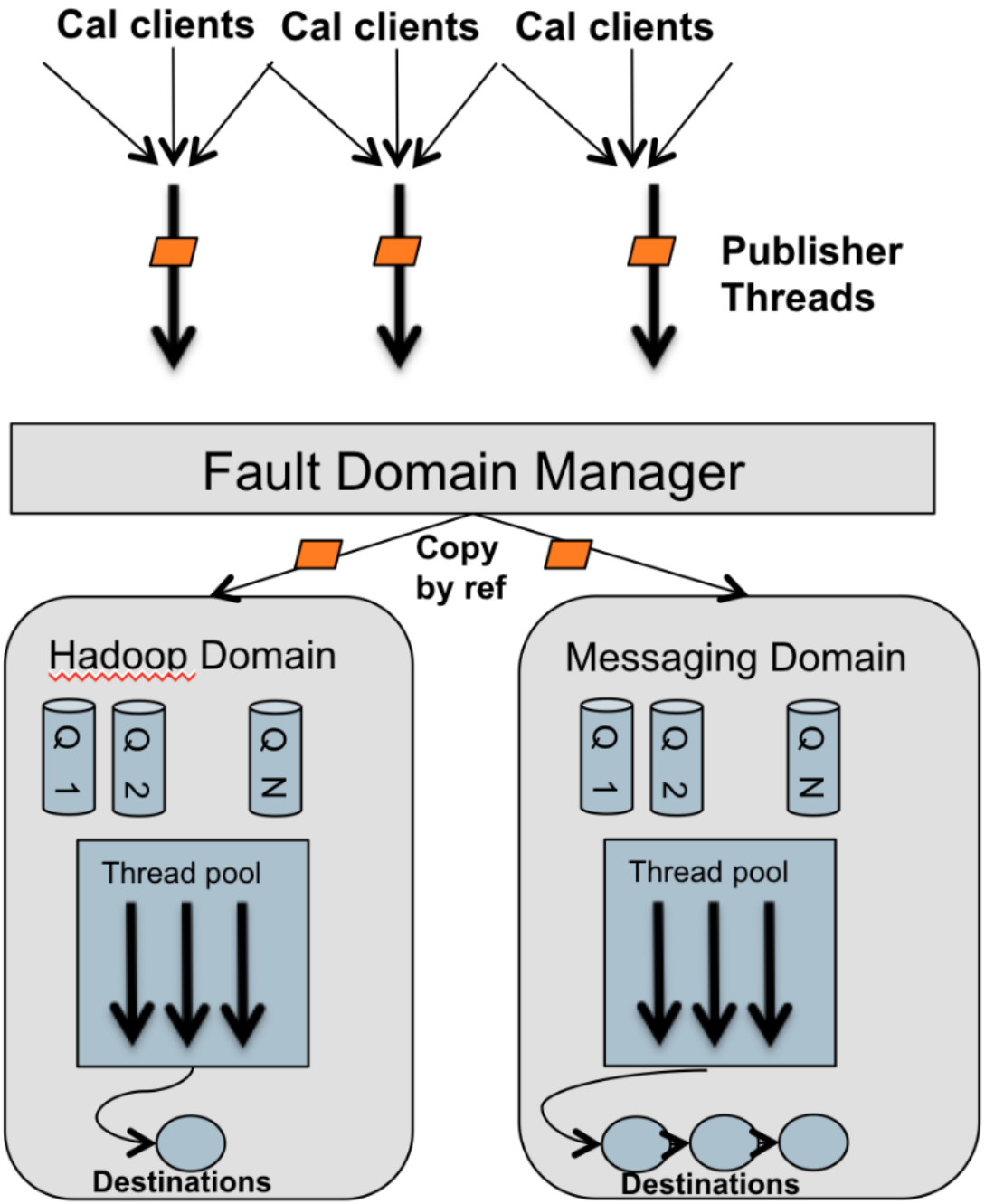


Big Data Distribution

Fault Domain – unit of message processing isolationFault Domain Manager dispatches every message to one of the queues in every fault domain (copy by reference)

The system of queues in each domain ensures sequential processing events from each persistent connection but still concurrent across multiple connections

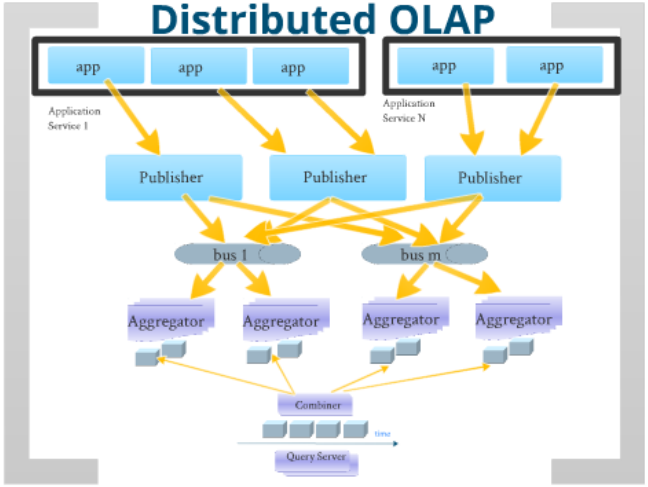
Queues are ring buffers that may overflow and loose messages - by design
Some domains have disk-backed queues



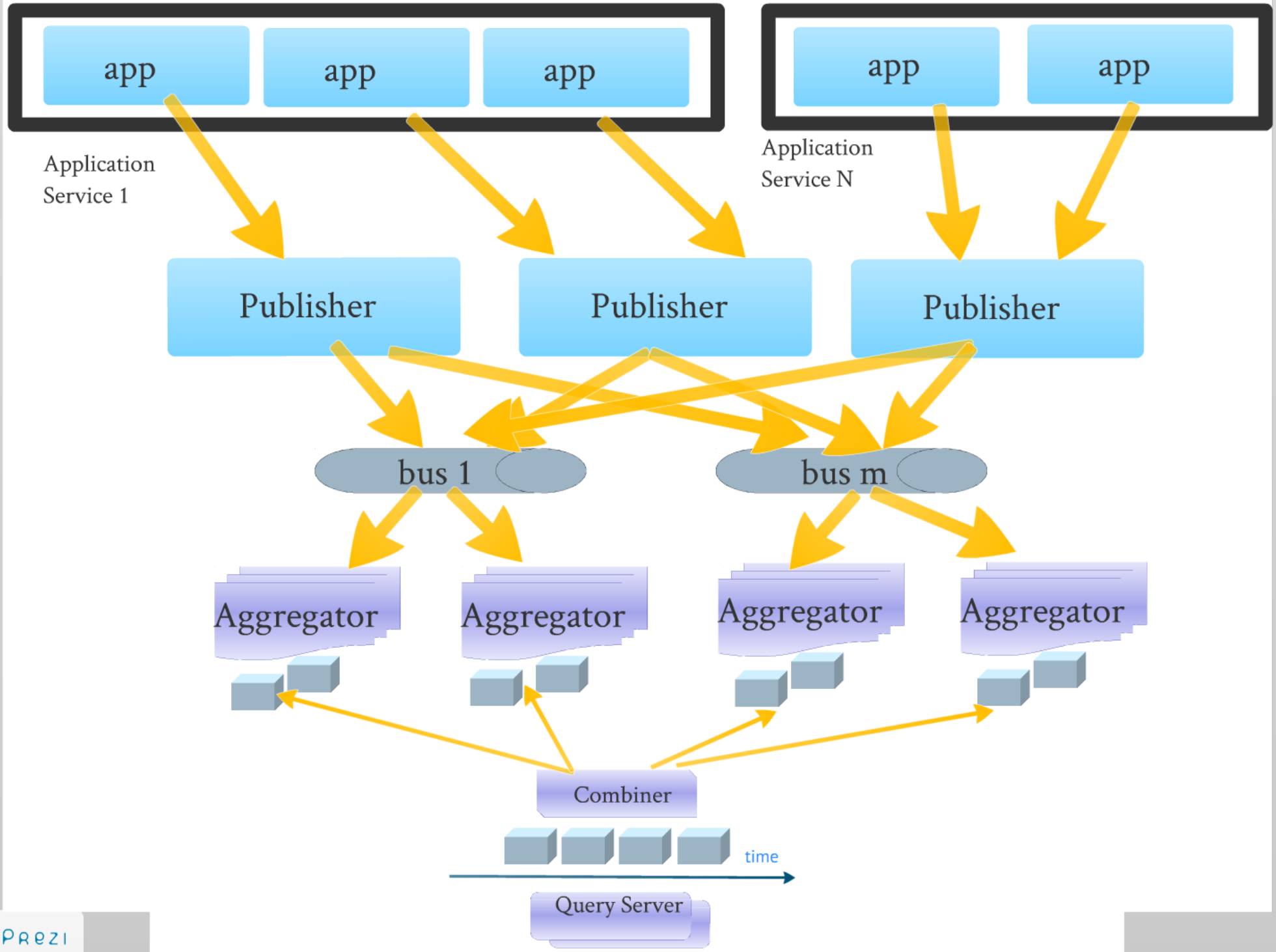
Problem 3: Metric Extraction

Semi-Structured Logs need to be processed for metric and event extraction

Logs -> Metrics + Events (In Real-time)



Distributed OLAP



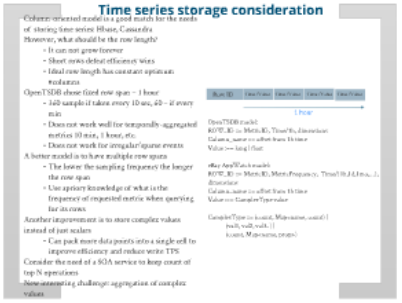
Problem 4: Scalable Time Series Data Store

Millions Inserts Per Second

Data is multi-dimensional time series

Challenges:

- **How scale writes and reads**
- **How to find time series given dimensional constraints**
- **How to down-sample metrics**
- **How to purge stale data**



Time series storage consideration

Column-oriented model is a good match for the needs of storing time series: Hbase, Cassandra

However, what should be the row length?

- It can not grow forever
- Short rows defeat efficiency wins
- Ideal row length has constant optimum #columns

OpenTSDB chose fixed row span – 1 hour

- 360 sample if taken every 10 sec, 60 – if every min
- Does not work well for temporally-aggregated metrics 10 min, 1 hour, etc.
- Does not work for irregular/sparse events

A better model is to have multiple row spans

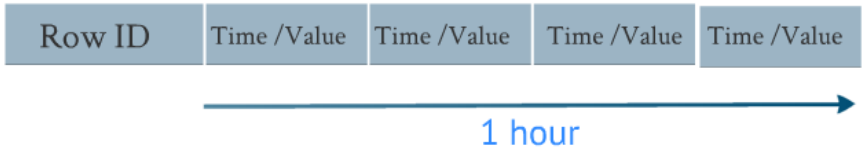
- The lower the sampling frequency the longer the row span
- Use apriory knowledge of what is the frequency of requested metric when querying for its rows

Another improvement is to store complex values instead of just scalars

- Can pack more data points into a single cell to improve efficiency and reduce write TPS

Consider the need of a SOA service to keep count of top N operations

New interesting challenge: aggregation of complex values



OpenTSDB model:
ROW_ID ::= MetricID, Time/1h, dimensions
Column_name ::= offset from 1h time
Value :== long | float

eBay AppWatch model:
ROW_ID ::= MetricID, MetricFrequency, Time/{1h,1d,1mo,…}, dimensions
Column_name ::= offset from 1h time
Value :== ComplexType value

ComplexType ::= (count, Map<name, count) |
(val1, val2, val3..) |
(count, Map<name, prop>)

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