Enabling Micro-Synchrophasor Data Analytics

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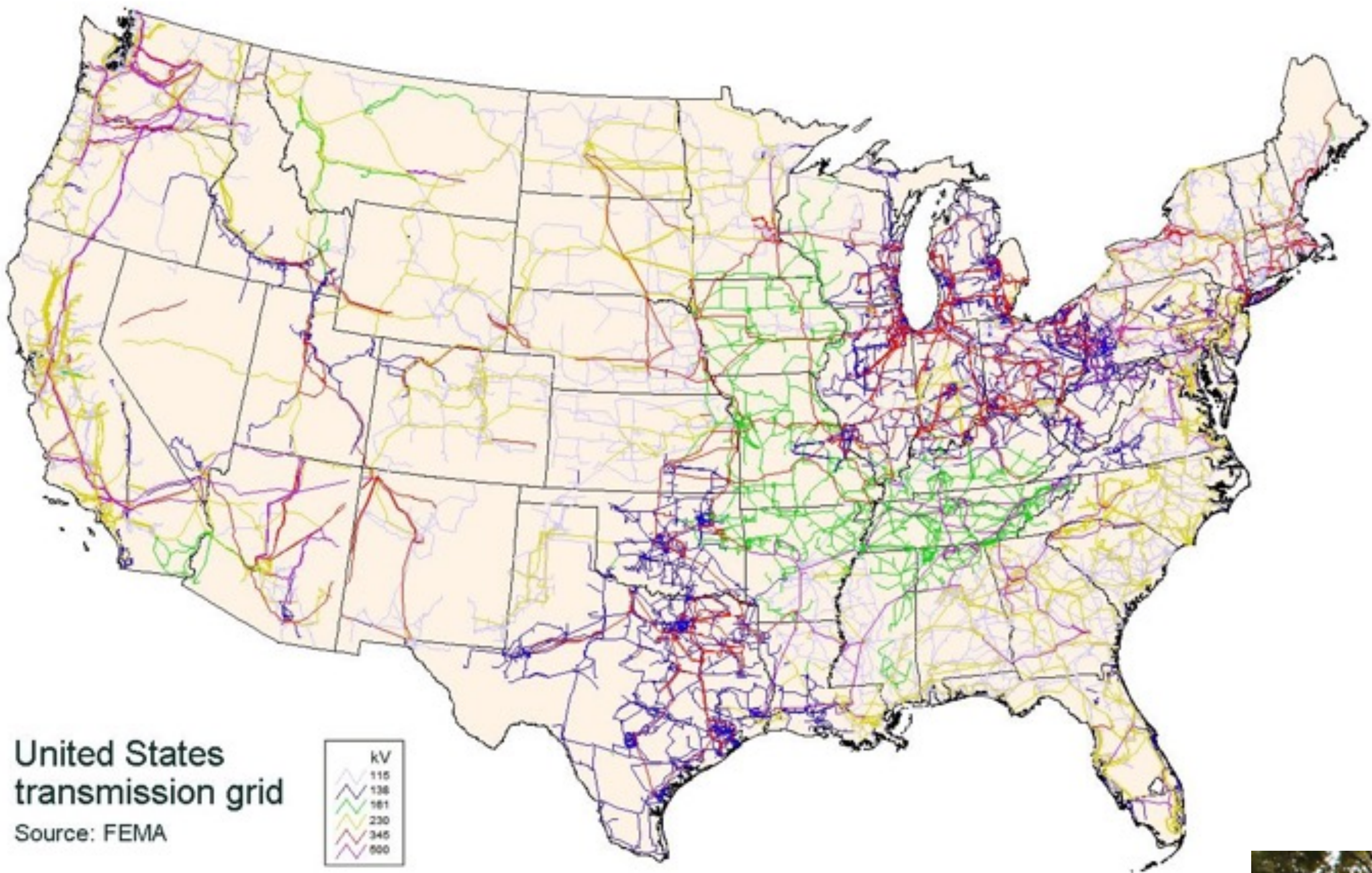
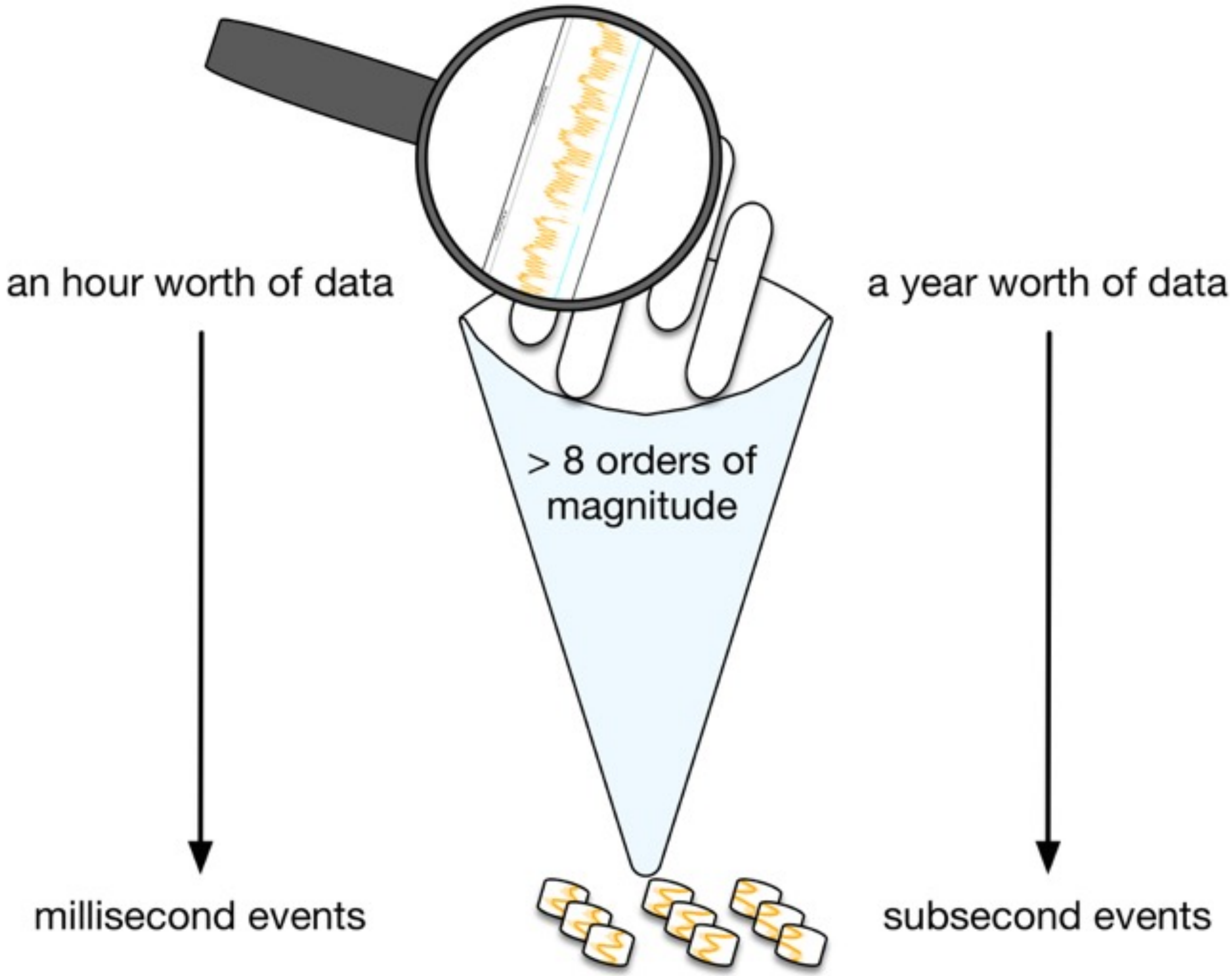


image source: power standards lab

Big Data Analytics



120 samples per second -> **3.8 billion samples** per stream per year -> **30 billion bytes** per stream per year

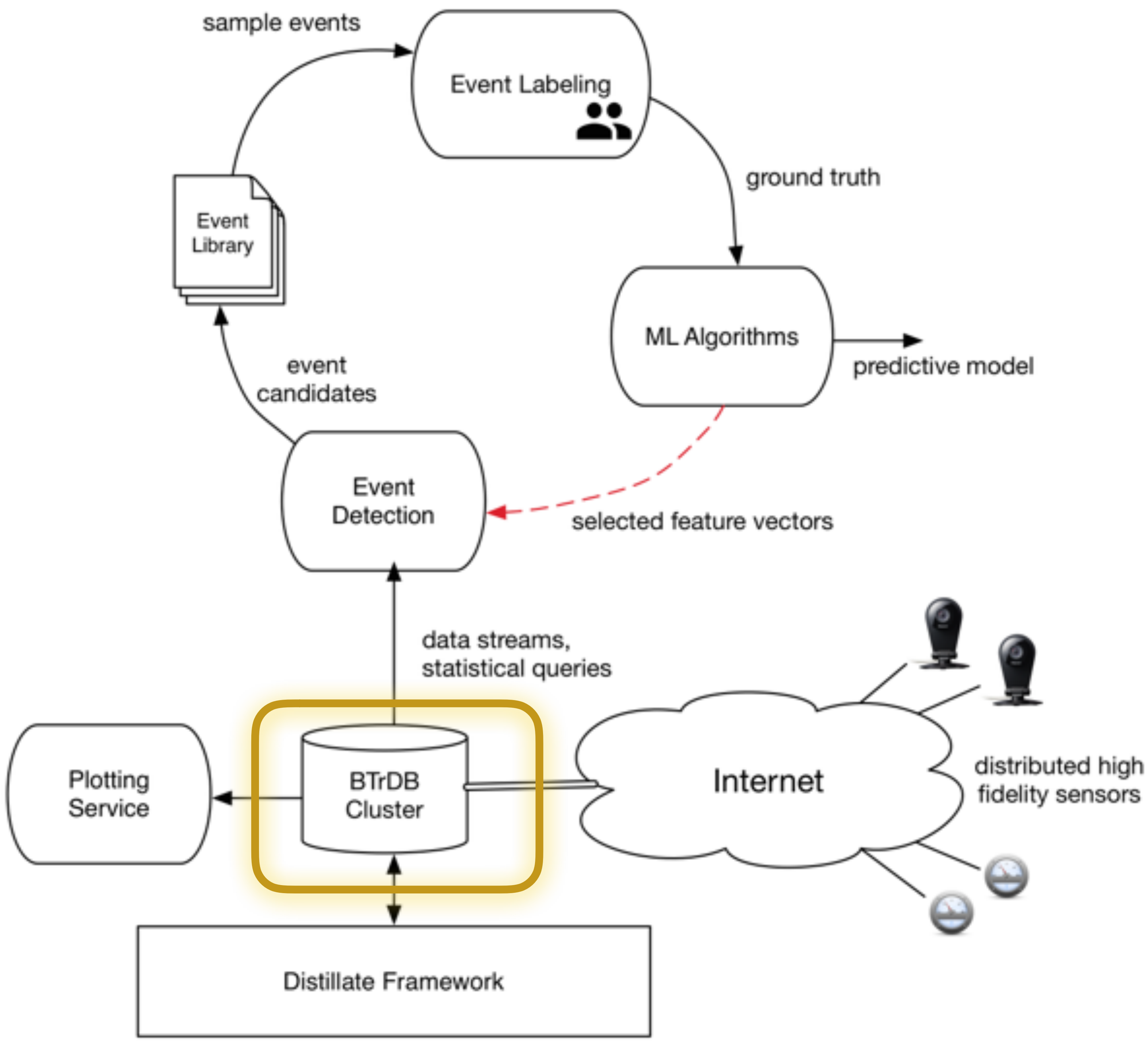
Introduction

- High-precision high-sample-rate data from distributed high fidelity sensors
  - ✴ many sensors, a wide range of temporal scales, *rare* events
- Finding anomalies in these systems is the holy grail
  - ✴ failing to identify and react to critical events in a timely manner may cost millions of dollars
- Energy data analytics (both real-time and historical) is critical yet computationally expensive
  - ✴ the ability to detect, analyze, and control with a limited time budget

Goals

- Detect: identify rare events
  - using an efficient search algorithm that is logarithmic in the size of the data set and linear in the number of events that are found
- Analyze: run compute intensive tasks on smaller chunks of data
- Control: take corrective/preventive actions (in real-time applications)

System Architecture



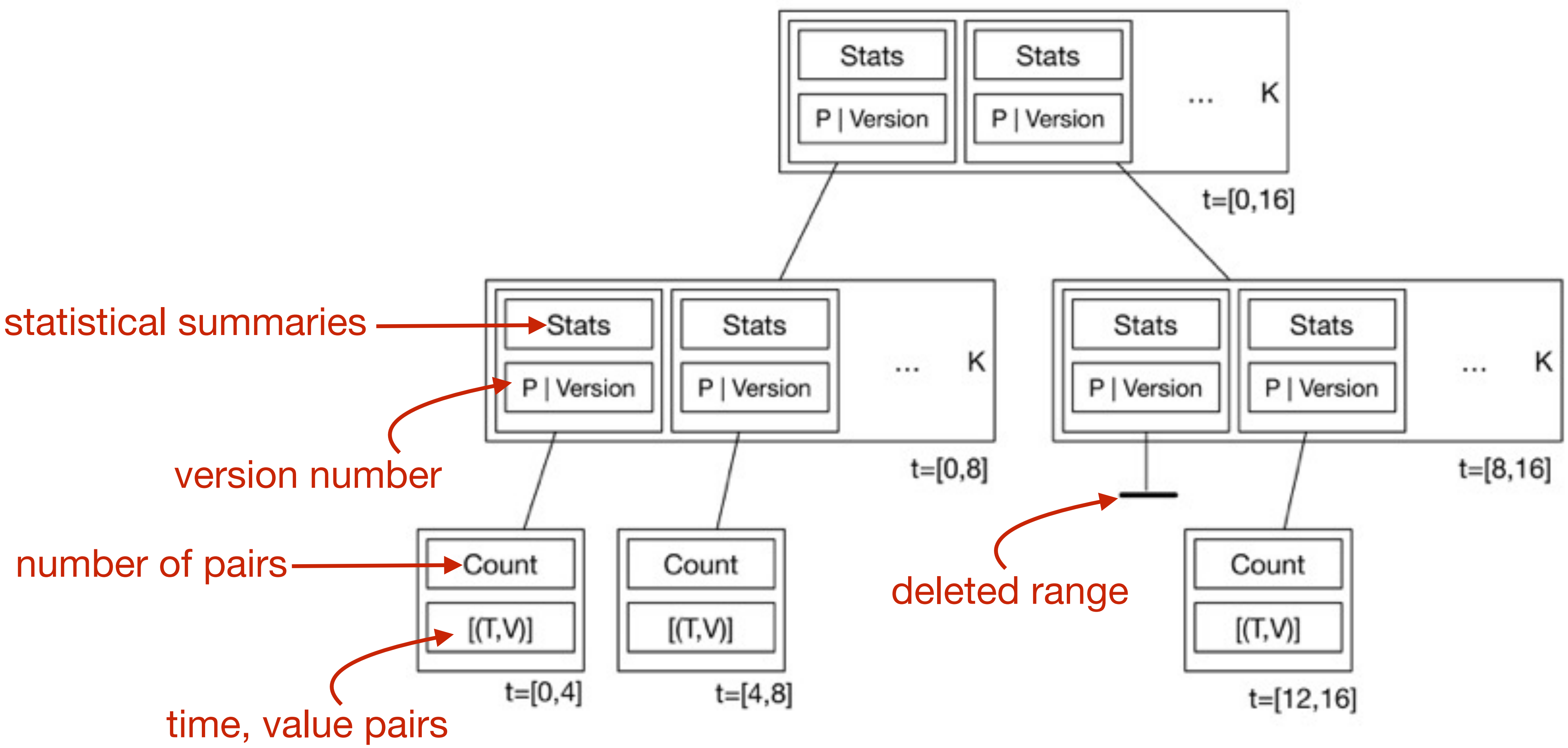
BTrDB Timeseries Database

- High throughput, fixed response-time timeseries store running on a four-node cluster
  - 53 million inserted values per second
  - 119 million queried values per second
- Provides nanosecond timestamp precision
- Supports out-of-order arrivals

References:
[1] Michael Andersen, Sam Kumar, Connor Brooks, Alexandra von Meier, David Culler, “DISTIL: Design and Implementation of a Scalable Synchrophasor Data Processing System”, IEEE SmartGridComm, 2015.
[2] Michael P Andersen and David E. Culler, “BTrDB: Optimizing Storage System Design for Timeseries Processing”, USENIX Conference on File and Storage Technologies, 2016.

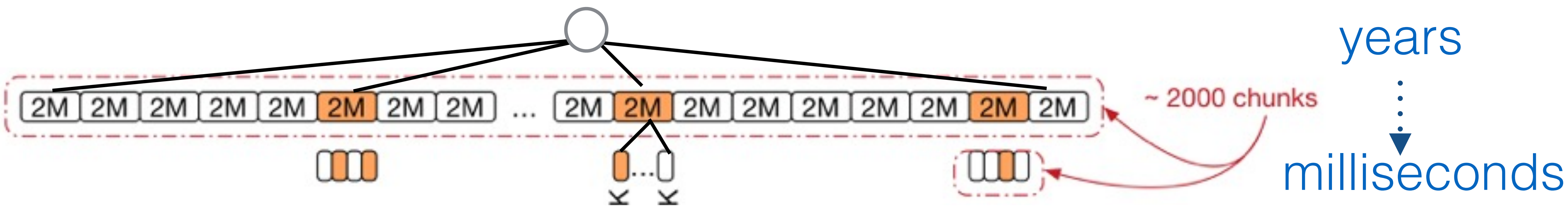
Abstraction for Timeseries Data

- Time-partitioning version-annotated copy-on-write K-ary tree

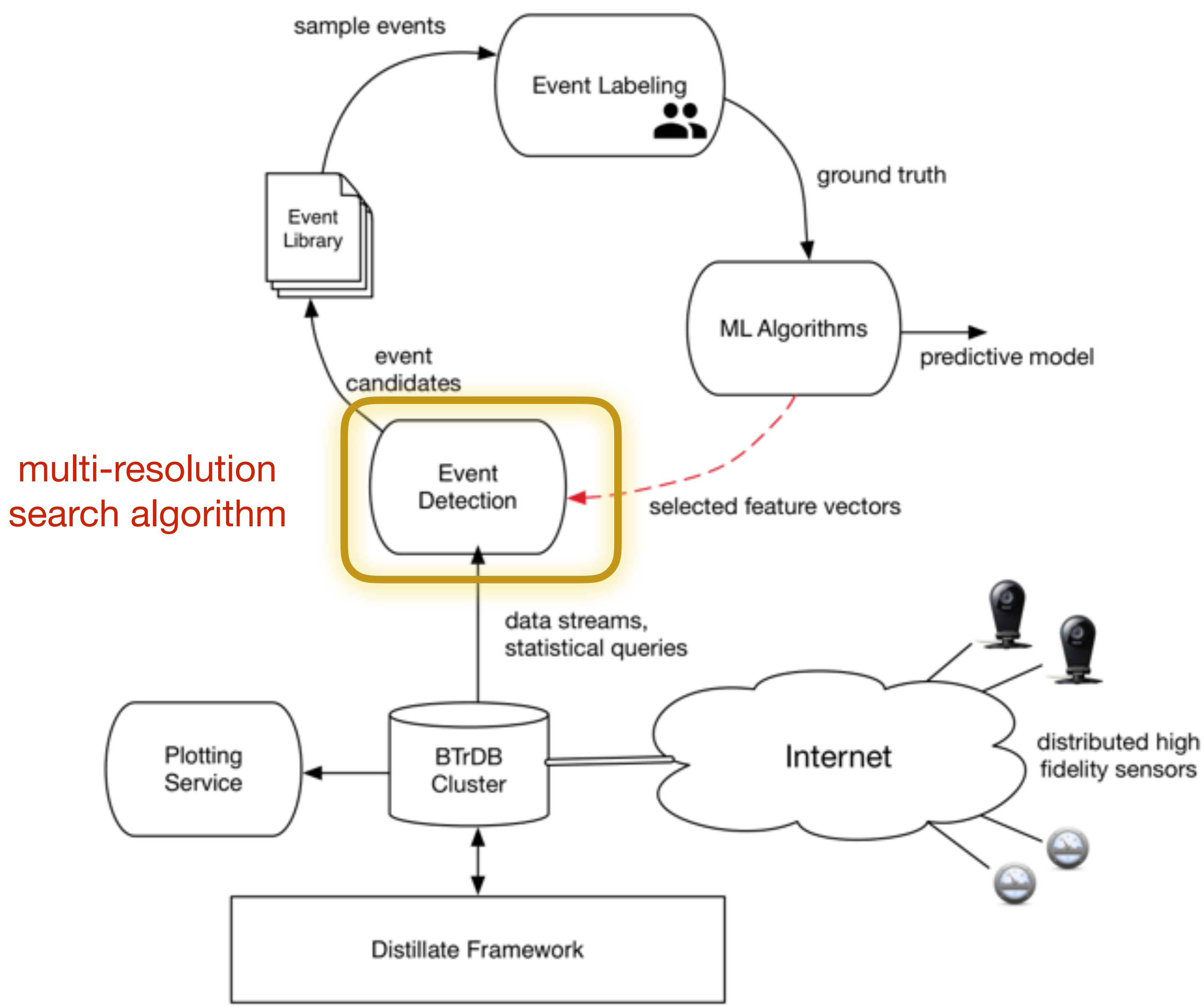


Statistical Summaries

- statistical summaries (max, min, average, and count) are stored at different temporal resolutions



System Architecture



Example Query

Find 5-second intervals that contain at least one value greater than a threshold

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Find 5-second intervals that contain a value greater than a threshold

- Query **max** at the given temporal resolution
- Dive down if $max_{resolution}$ > threshold
- Repeat for the next temporal resolution until the desired resolution is reached

Multi-Resolution Search

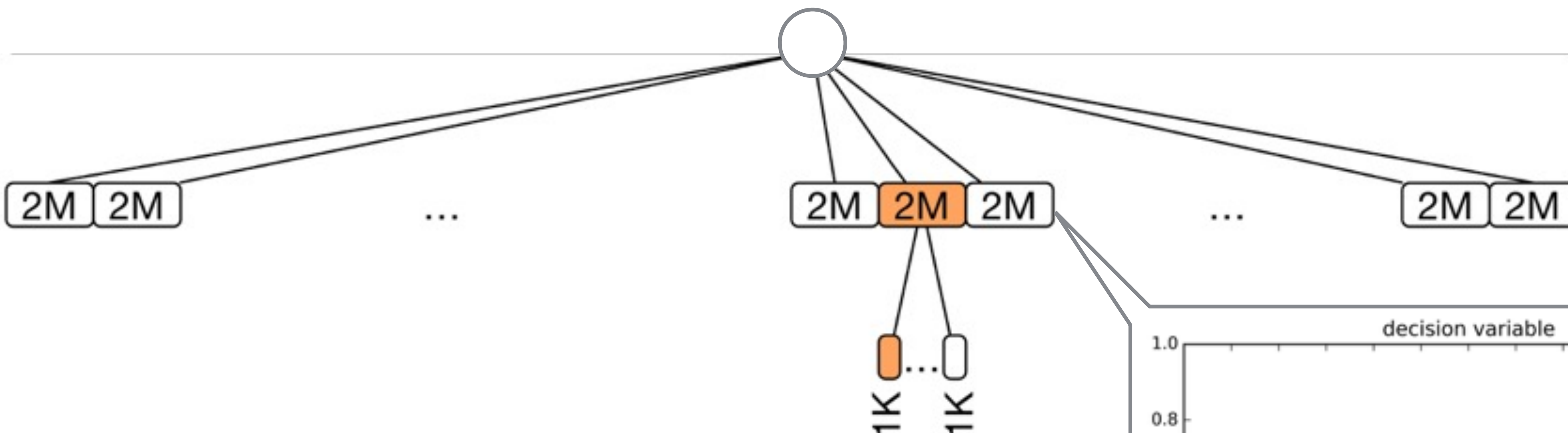
- Start with a definition of the event (search criteria)
- Query statistical summaries of data at a given temporal resolution
- Compare a function of these statistical summaries against a threshold
- Dive down if the condition is satisfied
- Query raw data when the desired resolution is reached and run your algorithm on a small chunk of data

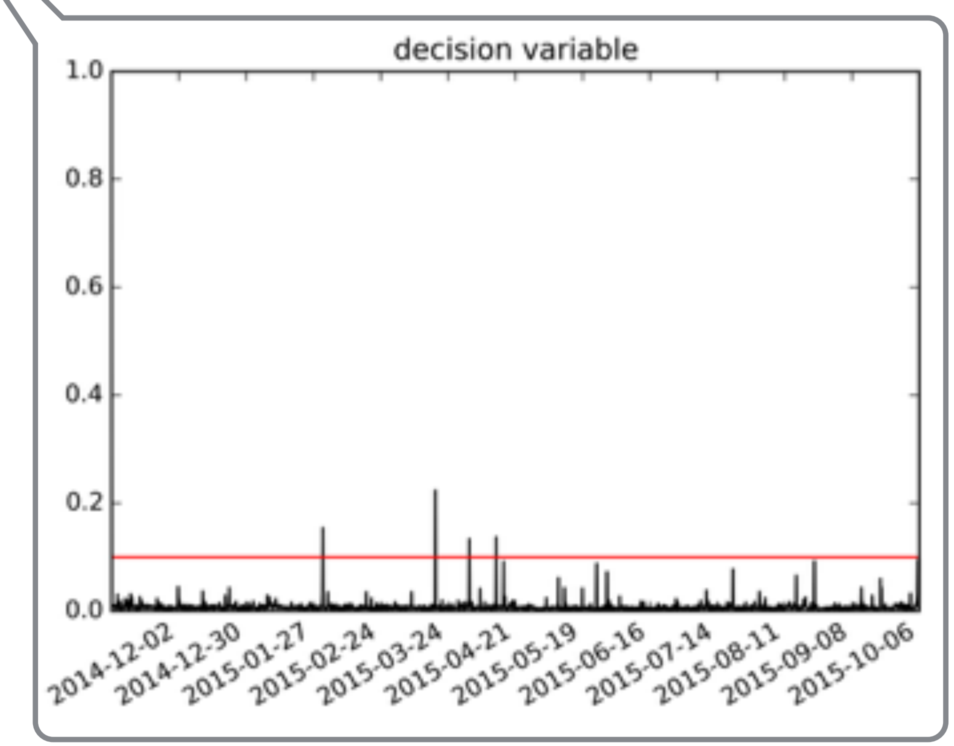
Interesting Events

- voltage sags
    - voltage magnitude stream
- tap changing events
    - angle difference stream
- reverse flows
    - real power or power factor stream
- switching events
- …

Case Study: Voltage Sag Detection

Step 1: Querying Statistical Summaries at a Given Temporal Resolution

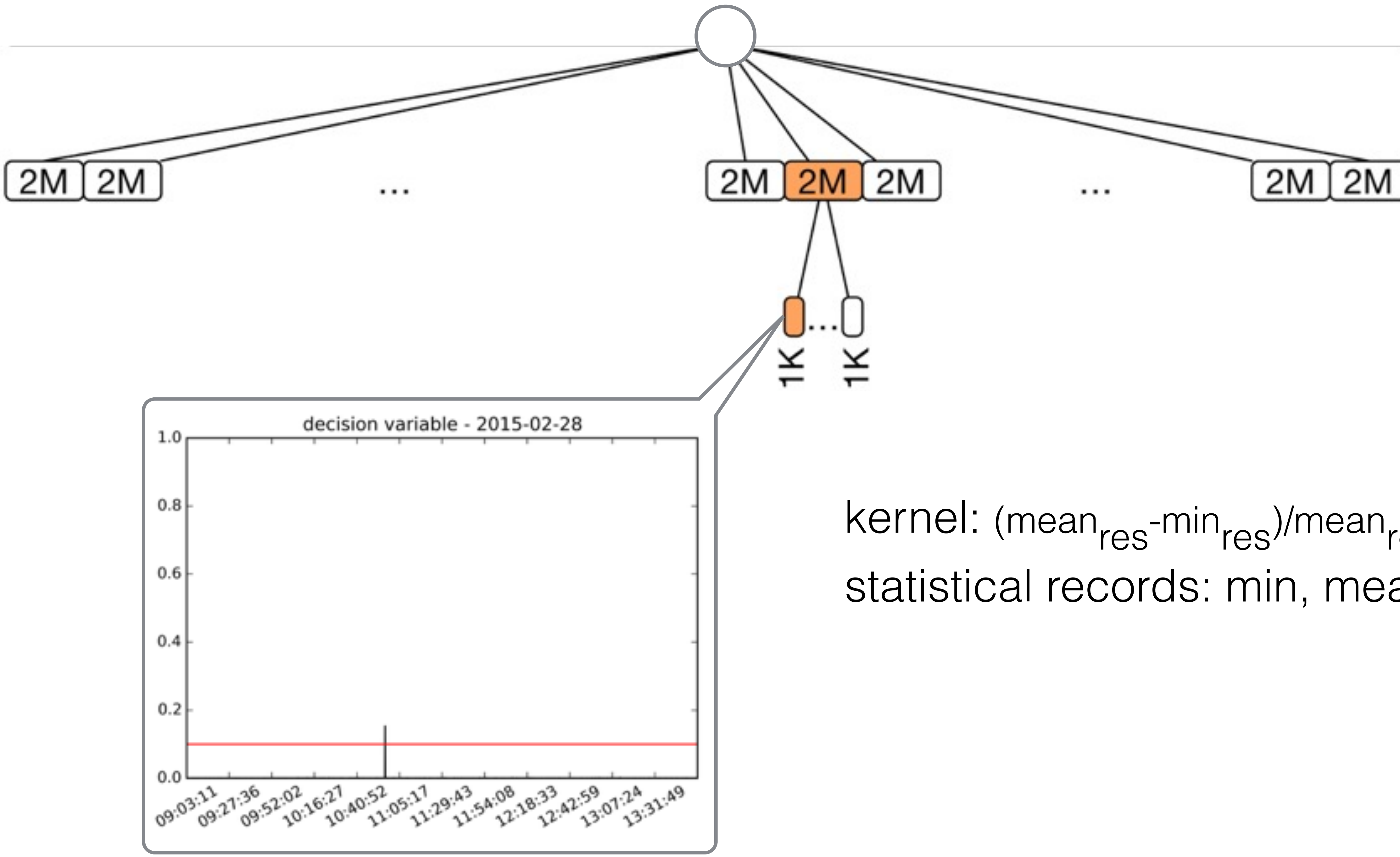




kernel: $(\text{mean}_{\text{res}}-\text{min}_{\text{res}})/\text{mean}_{\text{res}}$

statistical records: min, mean

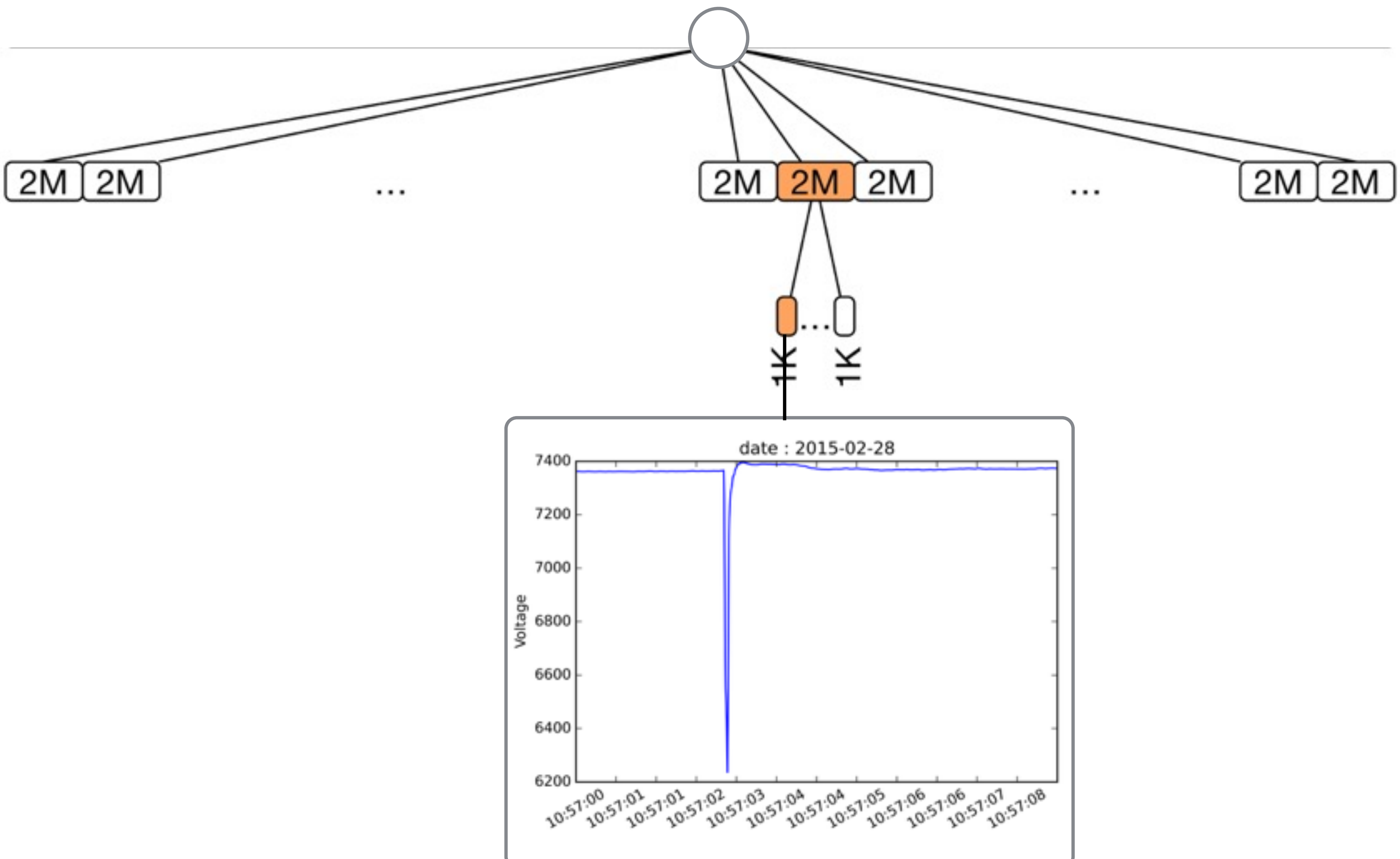
Step 2: Diving Down



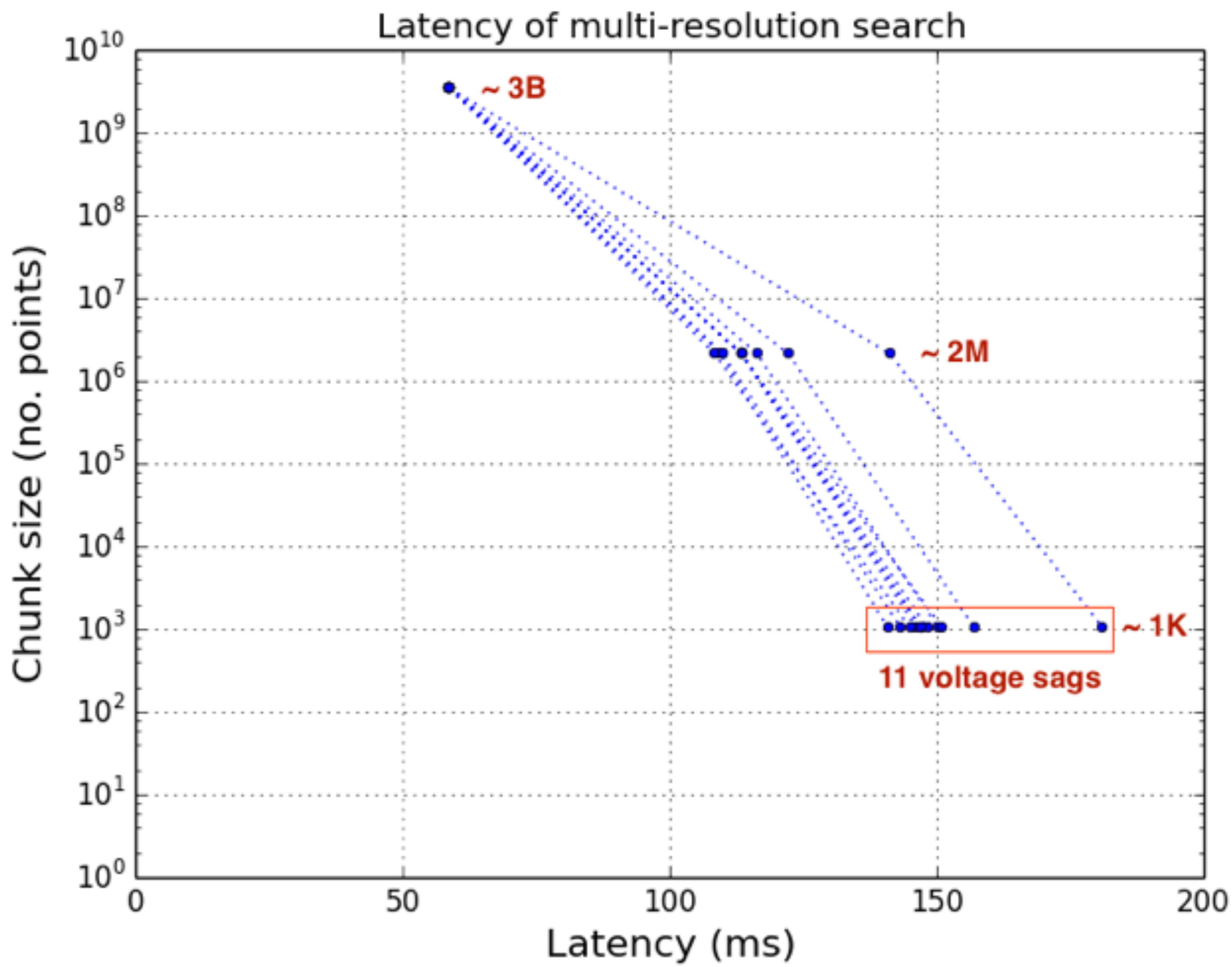
kernel: $(mean_{res} - min_{res})/mean_{res}$

statistical records: min, mean

Step 3: Querying Raw Data



Evaluation



Latency of multi-resolution search
10^{10}
10^9
10^8
10^7
10^6
10^5
10^4
10^3
10^2
10^1
10^0
Chunk size (no. points)
0
50
100
150
200
Latency (ms)
~ 3B
~ 2M
~ 1K
11 voltage sags

Example Result

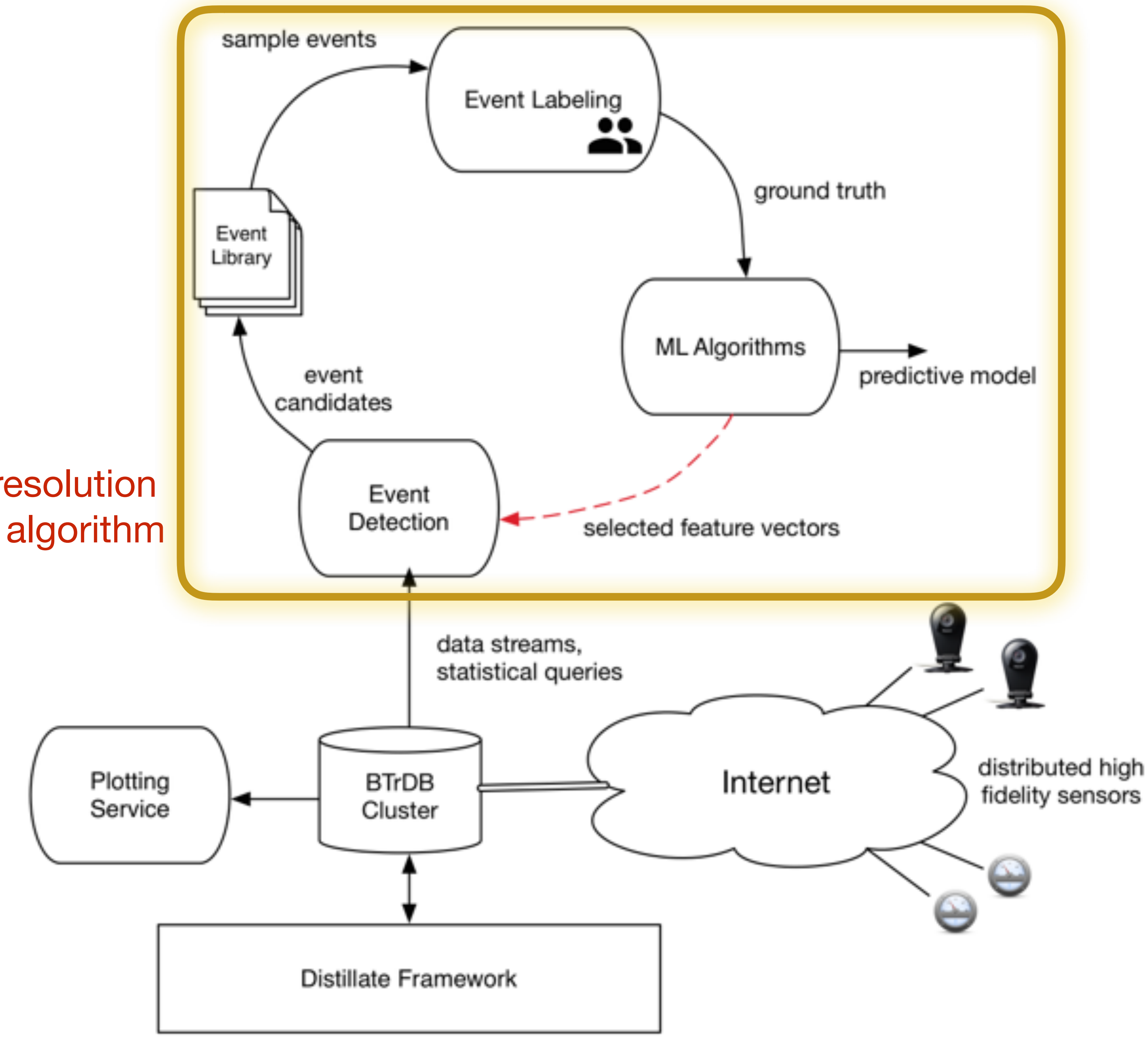
	no. events (0.05)	runtime (ms)	no. events (0.1)	runtime (ms)	no. events (0.15)	runtime (ms)	no. events (0.2)	runtime (ms)	days
/clean/GP_BUS1/L1MAG	9	431.77	4	237.13	0	76.78	0	88.41	135
/clean/GP_BUS1/L2MAG	10	394.39	4	226.85	1	115.30	0	70.55	135
/clean/GP_BUS1/L3MAG	5	309.07	2	163.25	1	118.95	0	77.08	135
/clean/switch_a6/L1MAG	14	666.59	6	273.01	3	194.95	1	132.75	330
/clean/switch_a6/L2MAG	21	947.24	11	523.78	4	235.44	3	190.83	330
/clean/switch_a6/L3MAG	11	608.94	4	318.44	2	213.57	0	90.06	330
/clean/RPU/CE_CERT_Bld_1200/L1MAG	8	312.53	2	68.41	1	64.93	1	66.55	86
/clean/RPU/CE_CERT_Bld_1200/L2MAG	12	379.19	4	163.71	3	119.51	2	112.95	86
/clean/RPU/CE_CERT_Bld_1200/L3MAG	12	627.72	4	228.18	2	111.41	2	133.00	86

10% drop

logarithmic in the size of the data set and linear in the number of events that are found

Event Detection: A Data Driven Approach

multi-resolution
search algorithm



Takeaways

- Complexity of the search algorithm is O(nLog(L))
  - Locating and analyzing rare events among billions of time-value pairs is possible in a fraction of a second
- Defining a kernel function can be quite challenging for some detectors
- Machine learning techniques can be used to develop sophisticated detectors