DataSketches

A Required Toolkit for the Analysis of Big Data

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YAHOO!

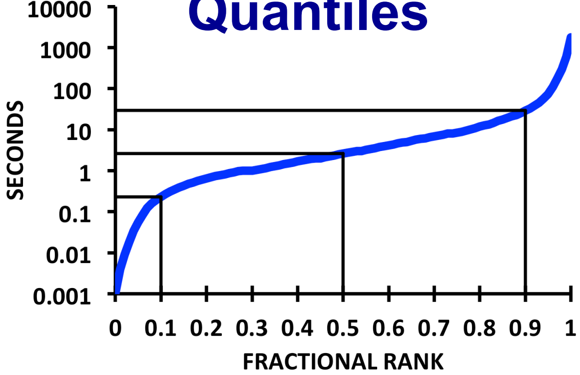
The Challenge

Web Site Logs

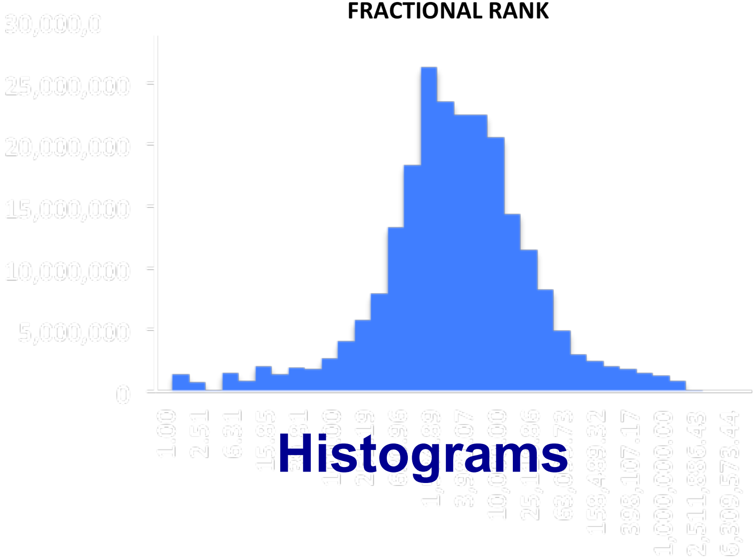
Time Stamp	User ID	Device ID	Site	Time Spent Sec	Items Viewed
9:00 AM	U1	D1	Apps	59	5
9:30 AM	U2	D2	Apps	179	15
10:00 AM	U3	D3	Music	29	3
1:00 PM	U1	D4	Music	89	10
Billions of rows …					

Some Very Common Queries …

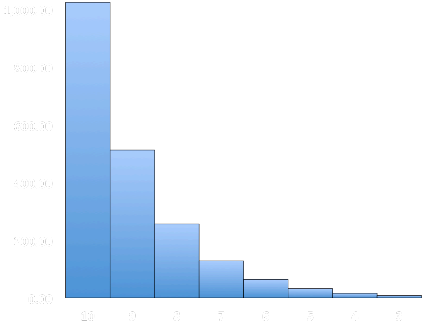
Unique Users



Quantiles



Histograms



Most Frequent Occurrences

Why are ***these*** operations so difficult with Big Data?

Mathematically Proven Lower Space Bound = $\Omega(u)$:

With no prior knowledge of the data …
There does not exist an algorithm that can produce an exact result with

$$\text{Space} < C * \#\mathit{Unique\ Items}$$

C = A constant factor ≥ 1

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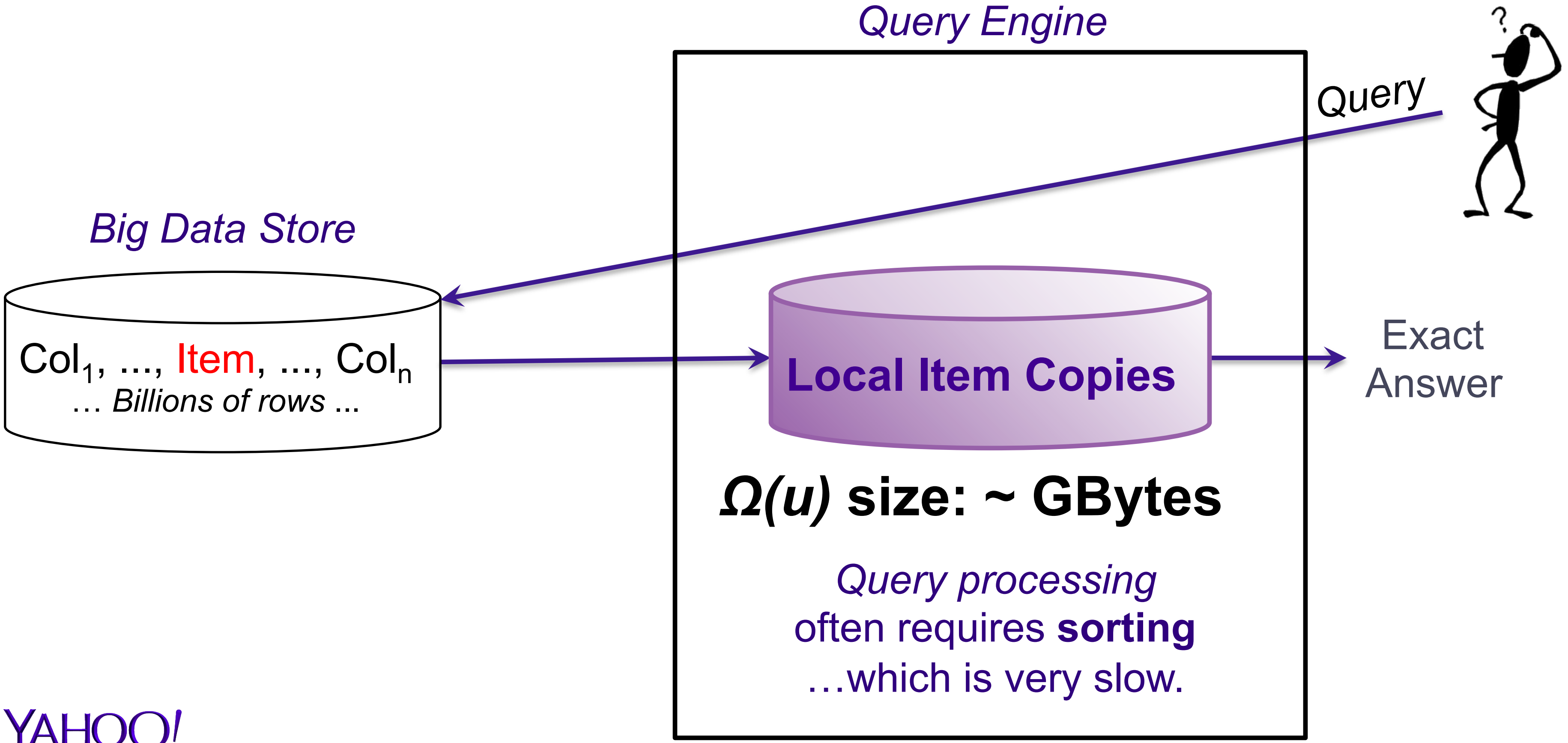
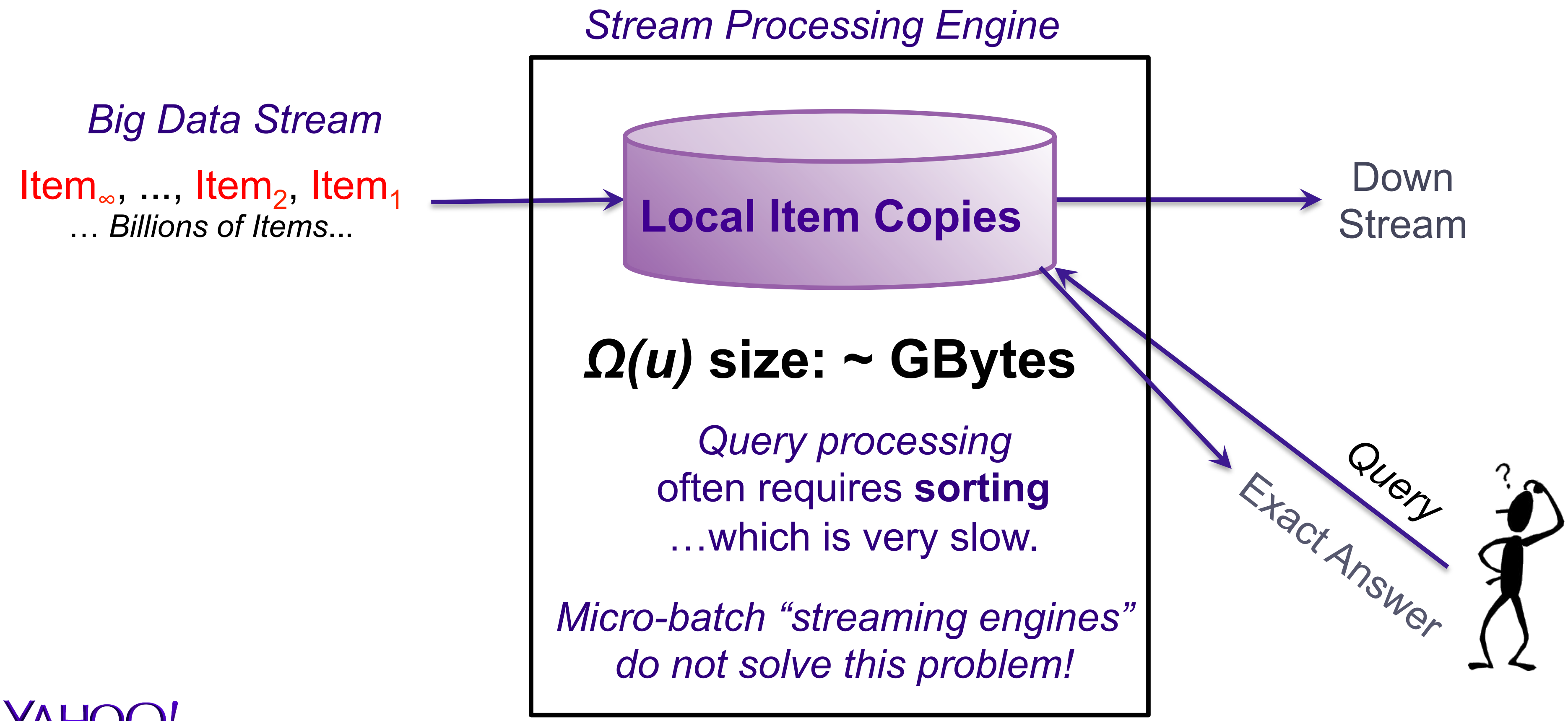
Exact Approach From Stored Data



Exact Approach From Streamed Data



If Approximate Results are Acceptable … We Can Reduce the Query Size Substantially … by *Sketching*!

Sketch Type	Sketch K	Sketch Size	Sketch Error
Distinct Count	k = 4096	32 KB (or 2 KB HLL)	1.6% Relative
Frequent Items	k = 256	4 KB	(1.4% * W) Absolute
Quantiles	k = 128, N = 1B	25 KB	1.7% Absolute Rank

k = A configuration parameter that affects size and accuracy

W = Sum of all count weights

N = Stream size

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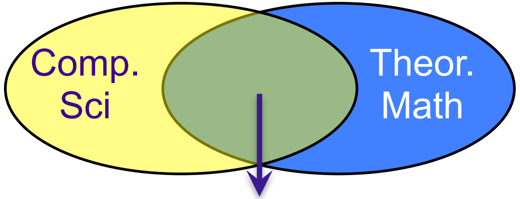
Sketch Origins



Research Disciplines

- Stochastic Streaming Algorithms
- Sub-linear Algorithms

"Sketch"

- The Common Term for a Broad Range of Algorithms

Relatively Recent Papers

- Unique Counts:
  - Flajolet, et al, HLL: 2007
  - Lang, Rhodes, et al, 2016
  - Lang, 2017
- Frequent Items:
  - Cormode, et al, 2009
  - Anderson, Bevan, Lang, Liberty, Rhodes, Thaler, 2017
- Quantiles:
  - Cormode, et al, 2013,
  - Lang, Liberty, et al, 2016

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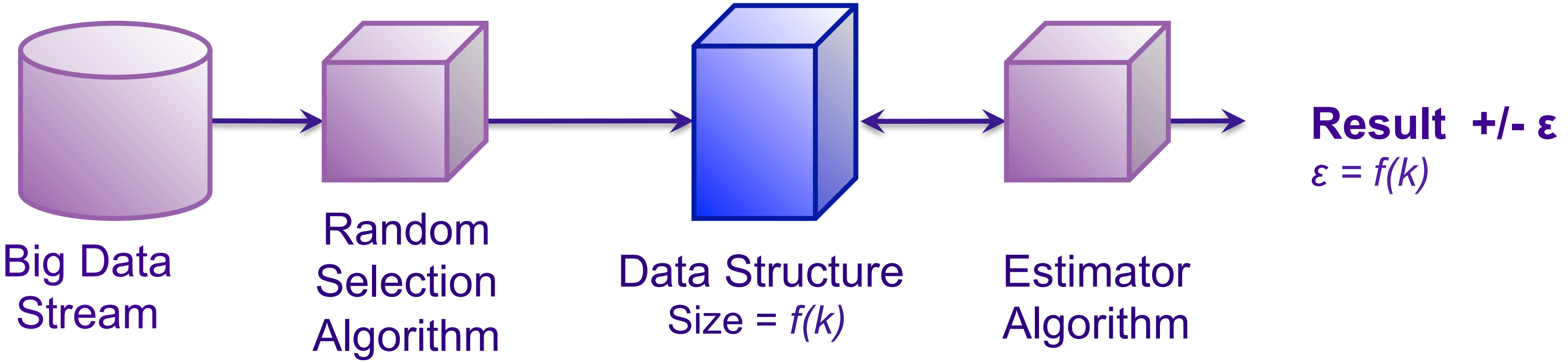
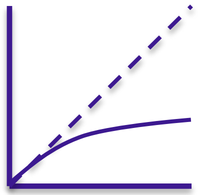
Sketch: Common Elements & Properties



- Single-pass
- **Sub-linear space**
- Mergeable
- Mathematically proven error bounds


Sub-Linear

First Big Win: Query Space

Query Engine

Sub-linear Space Significantly Reduces Query Space

Query

Big Data Store

Col_1, ..., Item, ..., Col_n

… Billions of rows ...

Sketch

Approximate Answer ± ε

***O(k)* size: ~ KBytes**

Minimal or no sorting required!

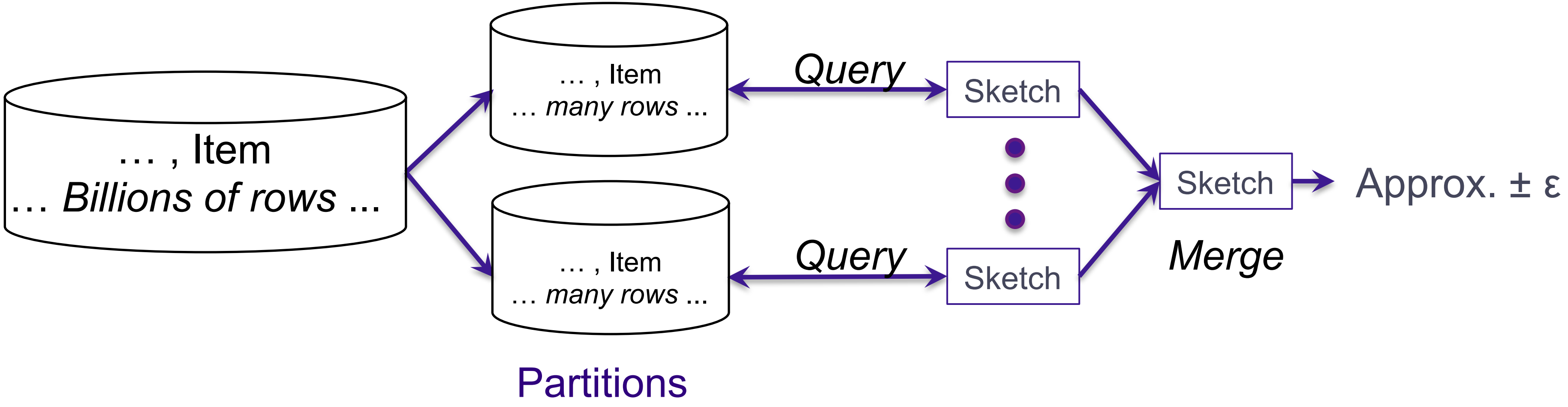
Ideal for Streaming & Suitable for Batch

Single Pass Simplifies Processing But Processing All The Data Still Takes Time.

YAHOO!

The Second Big Win: Mergeability

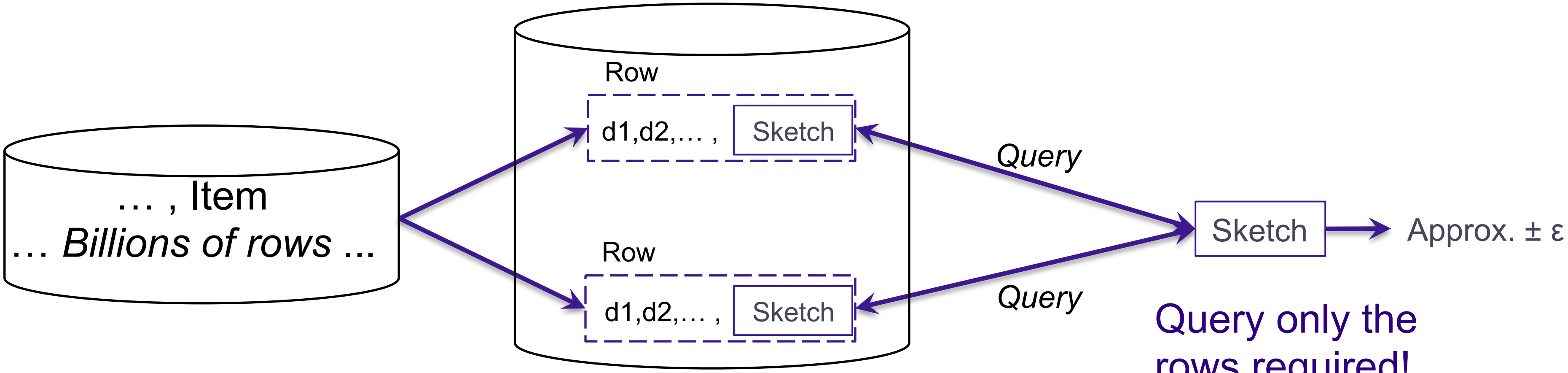
- Mergeability Enables Parallelism
- With No Additional Loss of Accuracy!
- But Data Skew Across Partitions Can Still Be A Challenge



Big Wins 3, 4: Speed, Simpler Architecture

Intermediate Sketch Staging Enables Query Speed & Simpler Architecture

Data Mart (Cube)



Intermediate Staging

Query only the rows required!

Stored Sketches Can Be Merged
By Any Dimensions, Including Time!

Advantages of Sketch-based System Design

- Architectural simplicity
  - Fewer processing steps: Multiple sketches in parallel in one pass
  - Fewer intermediate tables: Store sketches vs. reprocessing raw data
  - Results stored in “additive” data cube instead of non-leverageable reports
- Enables reporting on arbitrary dimension combinations
  - Fast merging: Recombine sketches as needed
    - Exact counting is not “additive”: Lots of tables, not a data cube
  - Rolling day, week or month
  - Simple time zone adjustments
- Set operations are cheap
  - Intersections, e.g. for user retention
  - Set differences, e.g. for filtering

Case Study 1: Simple Batch Distinct Counting

- **Web Logs:** *Dim1*: PageID, *Dim2*: Time-Stamp,
  Id1: Browser Cookie, *Id2*: UserID
  (+ many other fields)
- **Data Size**: ~245GB daily; ~7.6TB monthly
- **Task**: Report: *Count Distinct Id1* and *Id2* by PageID,
  and by hour, day, week, and month
- **Note**: This case study was run on Pig, Hive and Spark. The results below are from Pig. Hive and Spark showed similar results.

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Case Study 1: Hourly Process

Exact: For Hourly Reports and Basis for Daily Reports

Sub-Task	Data Stored
Stage 1: • Read Raw Data • -> Hourly Tables	Create Table1: Group By {site, hour, id1} Create Table2: Group by {site, hour, id2}
Intermediate Size	33.4 GB 1 Month of Hourly
Stage 2a: • Read Hourly Tables • Count Uniques	Group By {site, hour}, Count Id1 Group By {site, hour), Count Id2
Stage 2b: • -> Hourly Report	Join: {site, hour, count(id1), count(id2)}
Total CPU Time	1.39M Sec

Sketches Cube: For All Reports

Sub-Task	Data Stored
Stage 1: • Read Raw Data • -> Data Cube	Create Sketches Cube: By Dim Combination {site, hour, sketch(id1), sketch(id2)}
Intermediate Size	1.1 GB
Stage 2 • Read Data Cube • Produce Hourly Report	Merge Sketches across Chosen Dimensions
Total CPU Time	1.06M Sec

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Case Study 1: Daily Rollups

Exact: For Daily Reports and Basis for Weekly and Monthly

Sub-Task	Data Stored
Stage 1: • Read Hourly Intermediates • -> Daily Tables	Create Table1: Group By {site, day, id1} Create Table2: Group by {site, day, id2}
Intermediate Size	16.0 GB just for Daily
Stage 2a: • Read Daily Intermediates • Count Uniques	Group By {site, day}, Count Id1 Group By {site, day), Count Id2
Stage 2b: • Produce Hourly Report	Join: {site, day, count(id1), count(id2)}
Total CPU Time	96,300 sec

Sketches Cube: For All Reports

Sub-Task	Data Stored
Stage 1: • Read Data Cube • -> Produce Daily Report	N/A
Intermediate Size	N/A
Total CPU Time	709 Sec

YAHOO!

Case Study 1: Weekly, Monthly Rollups

Exact: For Wk/Mo Reports

Sub-Task	Data Stored
Stage 1: • Read Daily Tables	Create Temp Table1: Group By {site, wk/mo, id1} Create Temp Table2: Group by {site, wk/mo, id2}
Stage 2a: • Read Temp Tables • Count Uniques	Group By {site, wk/mo}, Count Id1 Group By {site, wk/mo), Count Id2
Stage 2b: • Produce Report	Join: {site, wk/mo, count(id1), count(id2)}
Total CPU Time	Week: 43,500 sec Month: 46,500 sec (via daily) Month: 70,900 sec (via hourly)

Sketches Cube: For All Reports

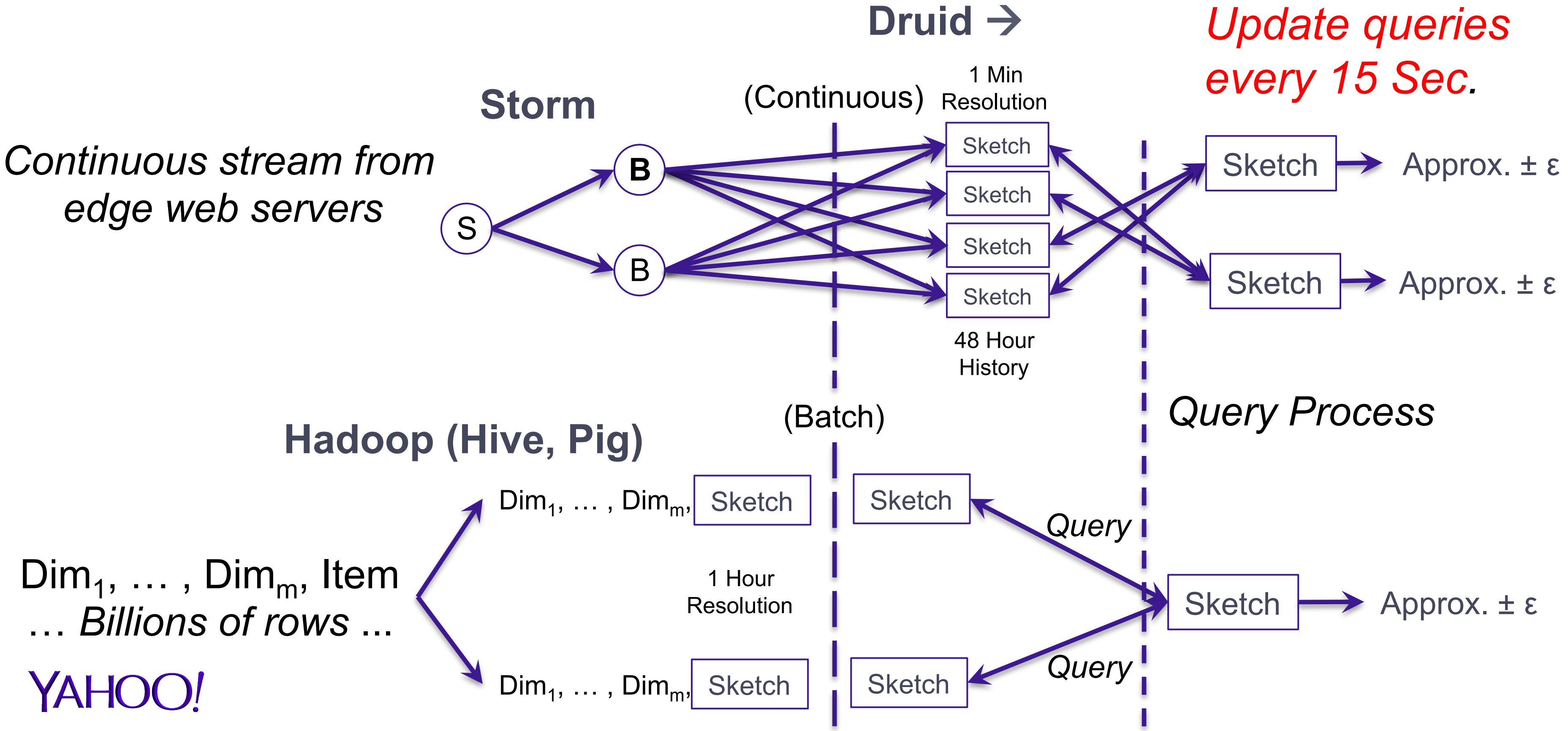
Sub-Task	Data Stored
Stage 1: • Read Data Cube • -> Produce Weekly or Monthly Reports	N/A
Total CPU Time	Week: 424 Sec Month: 466 Sec

Case Study 1: Perspectives

- Only a few dimensions and metrics, moderate data size
  - Manageable with exact counting
  - However, sketching can still show substantial benefits, especially in real-time streaming
- Batch process (e.g. Pig, Hive)
  - Substantial job overhead penalizes the relative sketch compute time.
  - Contrast this to real-time reporting engines (e.g. Druid), where rollups can be computed in seconds.
- As the number of dimensions grows, the benefit of using sketches becomes even more dramatic

Big Wins 5, 6: Real-time, Late Data Updates

Case Study 2: Flurry/Druid Sketch Flow Architecture



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Case Study 2: Real-time Flurry, Before and After

- Customers: >250K Mobile App Developers
- Data: 40-50 TB per day
- Platform: 2 clusters X 80 Nodes = 160 Nodes
  - Node: 24 CPUs, 250GB RAM

Big Win 7:
Lower System $

	Before Sketches	After Sketches
VCS* / Mo.	~80B	~20B
Result Freshness	Daily: 2 to 8 hours; Weekly: ~3 days Real-time Unique Counts Not Feasible	15 seconds!

* VCS: Virtual Core Seconds

YAHOO!

Major Sketch Families in DataSketches Library

Cardinality: Theta & HyperLogLog (HLL) Sketches

- Theta: Includes Set Expressions (e.g., Union, Intersection, Difference)
- HLL & HLL Map: Highly compact
- Sample code for Java, Hive, Pig, Druid, Spark
- Adaptors for Hive, Pig, Druid
- Can Operate Off-Heap

Quantiles Sketches

- Quantiles, PMF’s and CDF’s of streams of comparable values.
- Sample code for Java, Hive, Pig
- Adaptors for Hive, Pig, Druid
- Can Operate Off-Heap

Major Sketch Families in DataSketches Library

Frequent Items Sketches

- Heavy Hitters of arbitrary objects from a stream of objects
- Sample code for Java, Hive, Pig
- Adaptors for Hive, Pig

Associative: Tuple Sketches

- Theta Sketches with attributes
- Sample code for Java, Hive, Pig
- Adaptors for Hive, Pig

Sampling: Reservoir Sketches, Weighted and Unweighted.

- Uniform sampling to fixed-*k* sized buckets
- Sample code for Java, Pig
- Adaptors for Pig

Thank You!

Please Visit:

DataSketches.GitHub.io

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