Apache® DataSketches™

A Production Quality Sketching Library for the Analysis of Big Data

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Outline

Problematic Queries of Big Data

Where traditional analysis methods don’t work well

Big Data Analysis Using Sketches

How using stochastic processes and probabilistic analysis wins in a systems architecture context

Our Mission, Sketch Design, Research

The sketch design process

Our collaboration with scientists around the world

The Open Source Apache DataSketches Library

A quick overview of this unique library dedicated to production systems that process big data.

Big Data is…big…and growing

IDC Global Datasphere Whitepaper, published Nov 2018,

(new data created each year)

- 2018**: 33 Zetabytes***
- 2025**: 175 Zetabytes,** CAGR = 27%
- **479 Exebytes*** created daily.
- **150B** connected devices, most of which are creating data

Fortune Business Insights (2024):

- In 2023, the global big data & business analytics market was **$307.5B** and is projected to reach **$924.4B** by 2032. CAGR = 13.0%.

* Zeta =10^{21}; Exe = 10^{18}; Peta = 10^{15}; Tera = 10^{12}; Giga = B = 10^{9}; Mega = 10^{6}; Kilo = 10^{3}

The Data Analysis Challenge ...

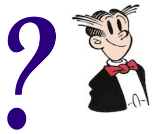
Example: Web Site Logs

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 or *K,V* Pairs …					

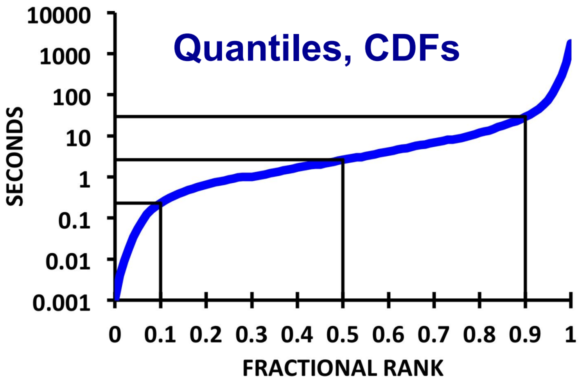
… Analyze This Data In Near-Real Time.

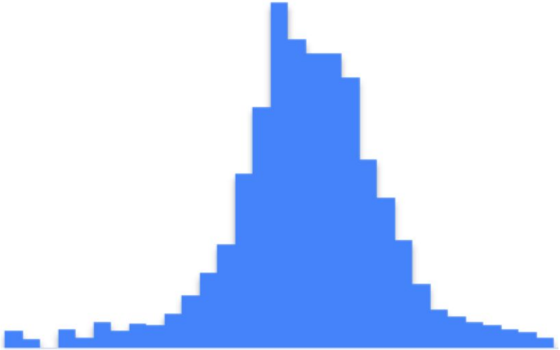
Some Very Common, but Problematic, Queries …

Unique Identifiers
with Set Expressions:
(A∪B)∩(C∪D) \ E

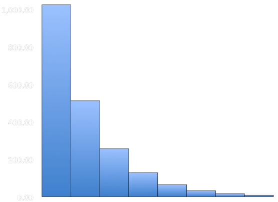


Set
Membership





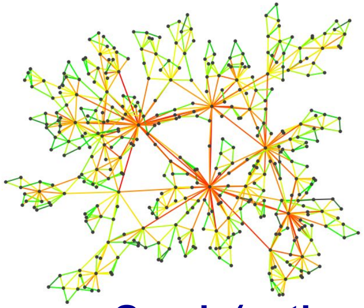
Histograms, PMFs



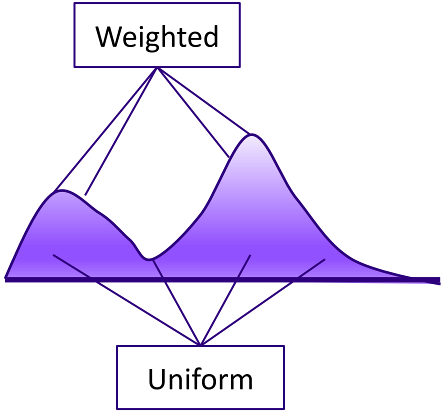
Frequent Items /
Heavy Hitters /
"Top-N"

$$\begin{Bmatrix}5 & \cdots & 2\\ \vdots & \ddots & \vdots\\ 4 & \cdots & 3\end{Bmatrix}$$

Vector & Matrix
Operations:
SVD, Density,
etc.



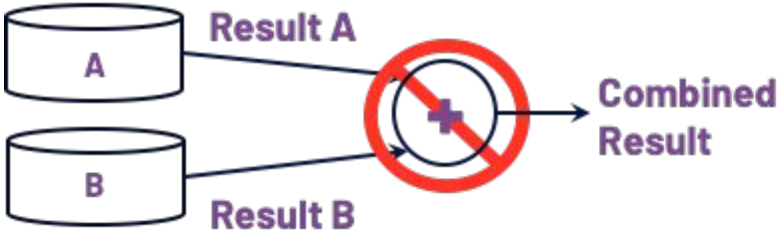
Graph (path,
funnel) Analysis



Reservoir Sampling

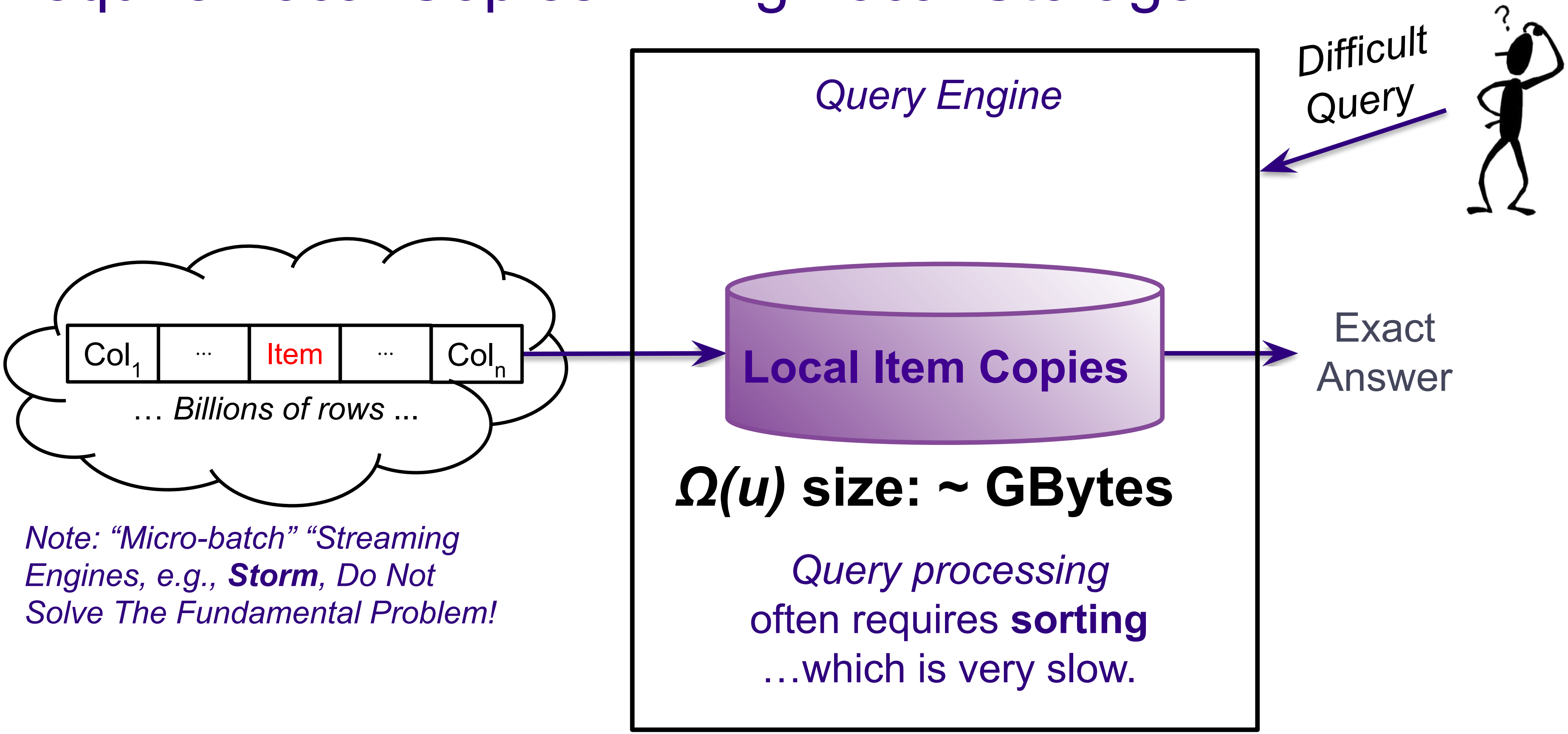
All Of These Queries Are Problematic:

- The Analysis Operations are *Non-Additive* or *Non-Linear*



- Addressing these queries with traditional methods requires multiple touches of the data.
- Time to process and resources required gets worse as the

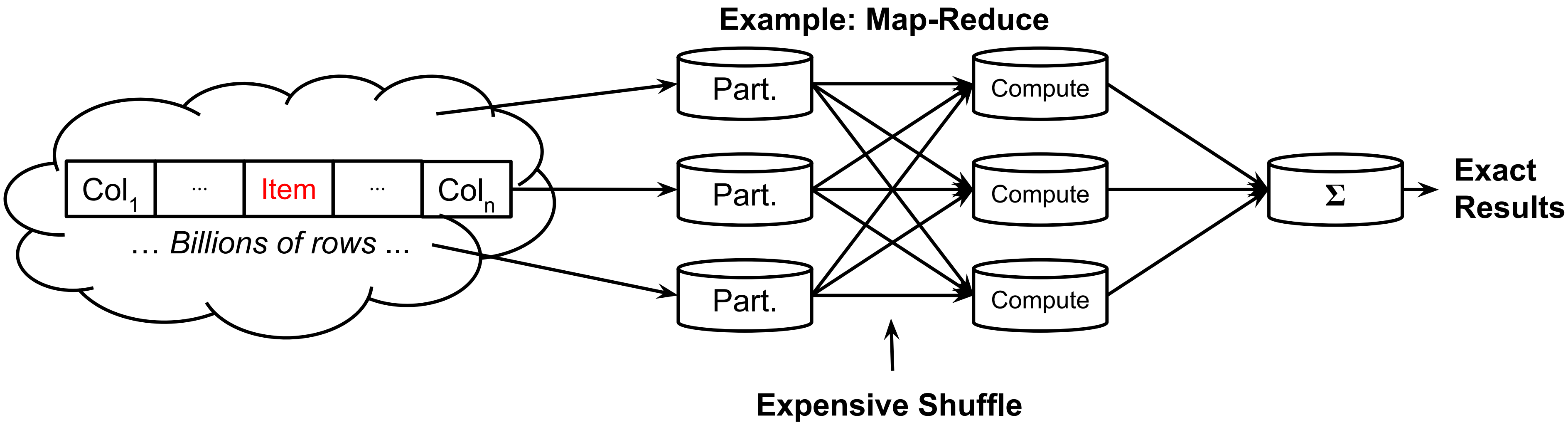
Traditional Exact Analysis Methods Require Local Copies → Big Local Storage



*Note: "Micro-batch" "Streaming Engines, e.g., **Storm**, Do Not Solve The Fundamental Problem!*

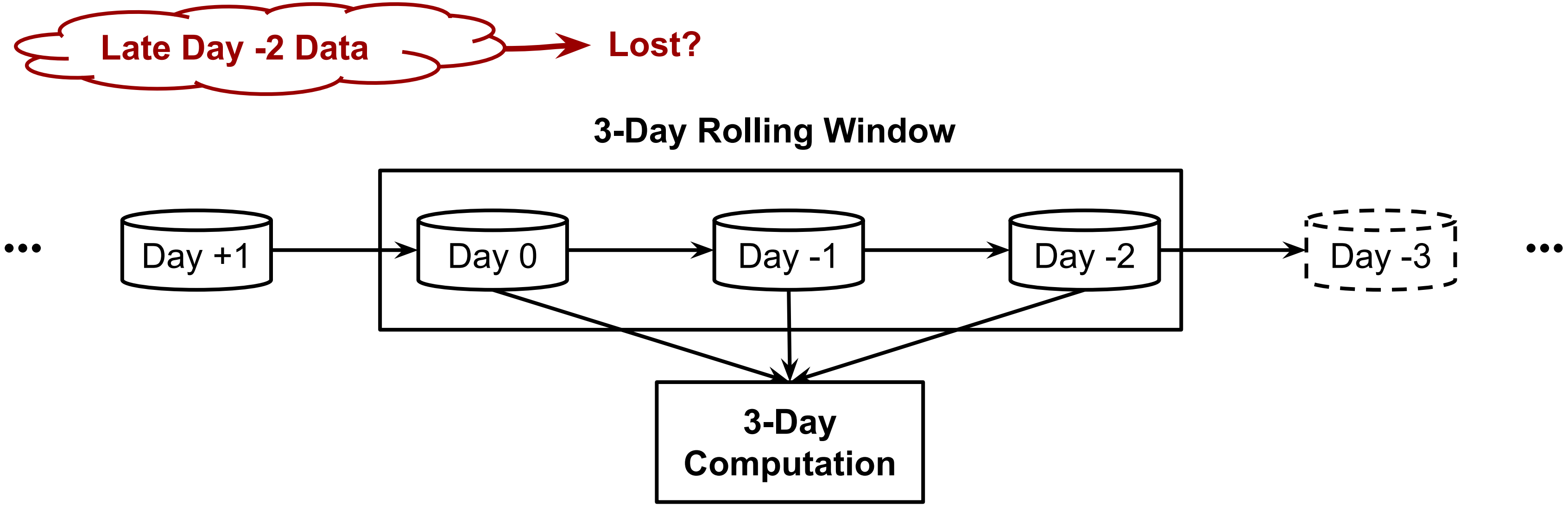
Parallelization is Not A Solution

- Because of Non-Additivity.
- Multiple touches means all the data must be available;
- And/or lots of data movement & lots of hardware



Traditional Time Windowing

Requires Multiple Touches of Every Item in Every Dataset



Every daily dataset is processed N times for a rolling N-day window!

Late Data Processing is not feasible.

Let’s Challenge the Fundamental Premise

… that our results must be exact!

If we can allow for some approximation,
along with some accuracy guarantees;

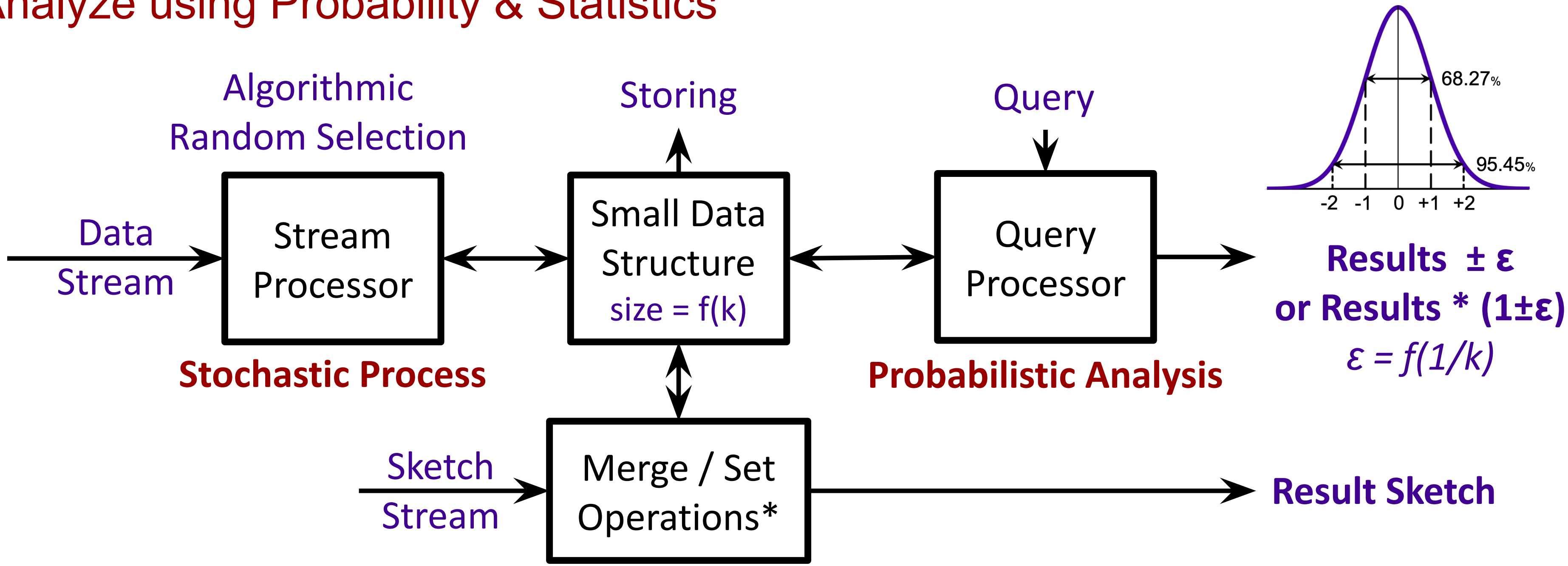
We can often achieve orders-of-magnitude improvement in

- Speed
- Storage
- Reduction of compute resources (CPU cycles)
  => Less Energy, Space, Heat, $$$

Introducing the ***Sketch*** (a.k.a, Stochastic Streaming Algorithm)

Model the Problem as a Stochastic Process with a Dynamic Data Structure.

Analyze using Probability & Statistics

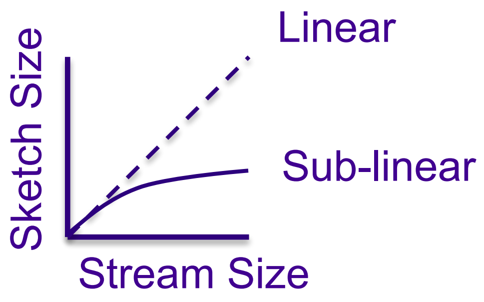


A Single Sketch Contains Many Algorithms

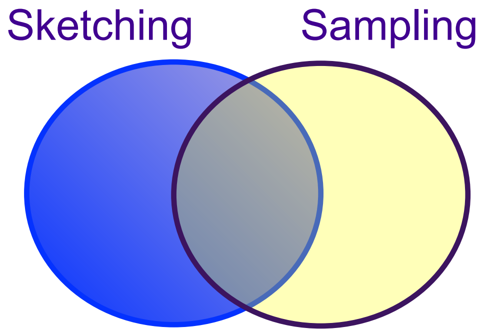
Key Sketch Properties

- Small Stored Size
- Sub-linear in Space
- Single-pass, “One-Touch”
- Data Insensitive
    - By distribution, order or value
- Mergeable
- **Mathematically Proven Error Bounds**
- Easy to use:

Sketch s = new Sketch();
while (data-exists) { s.update(datum); }
Result R = s.getResult();



Some Sketches Overlap with Sampling



Big Data Analysis Using Sketches

How & Why Sketches Achieve Superior Performance

For Systems Processing Massive Data

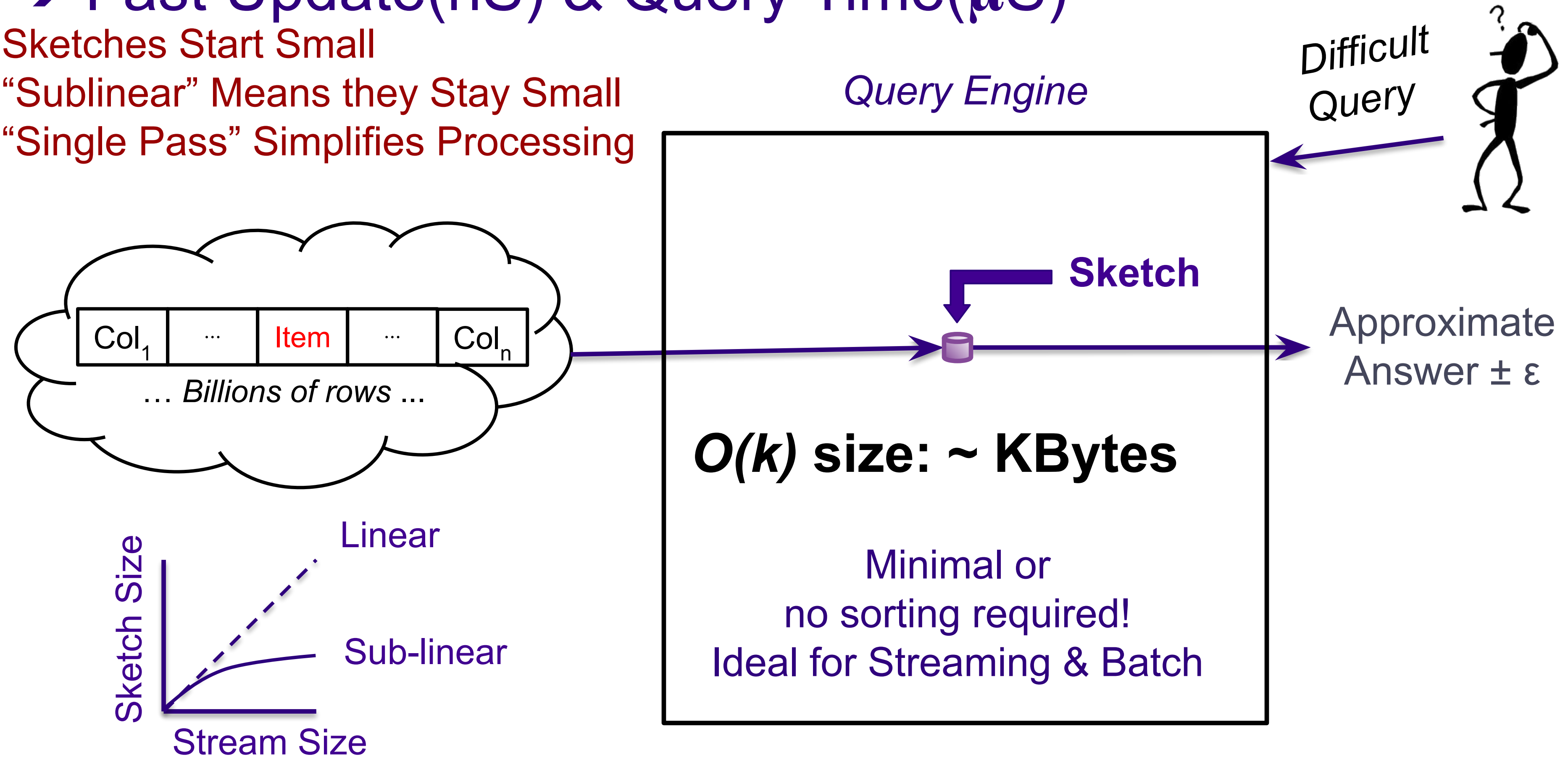
Win #1: Small Sketch Size = Small Query Space

→ Fast Update(nS) & Query Time(μS)

Sketches Start Small

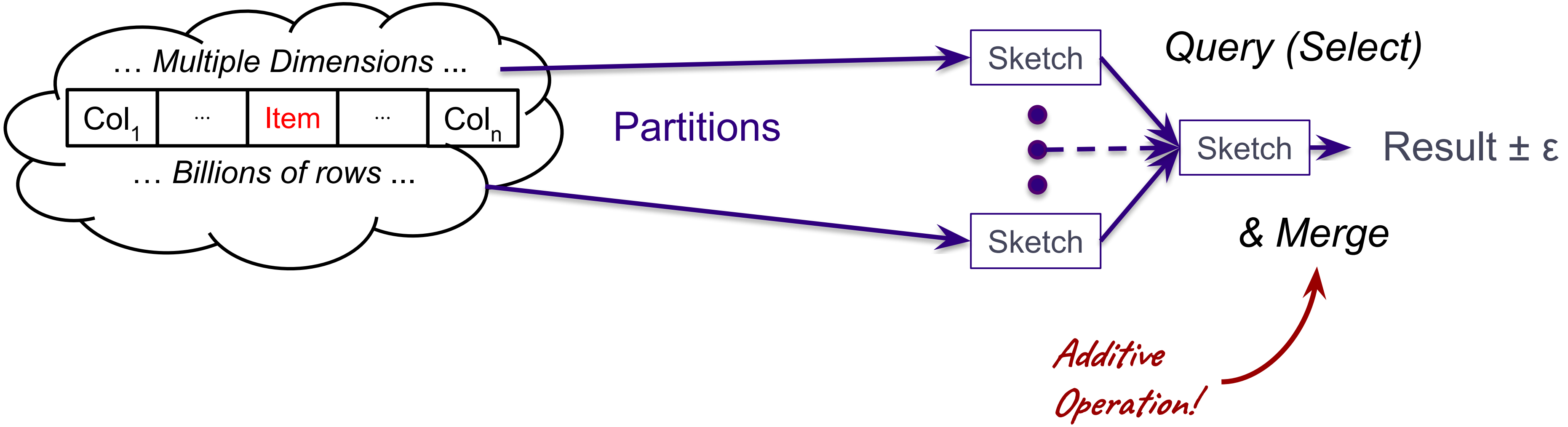
“Sublinear” Means they Stay Small

“Single Pass” Simplifies Processing



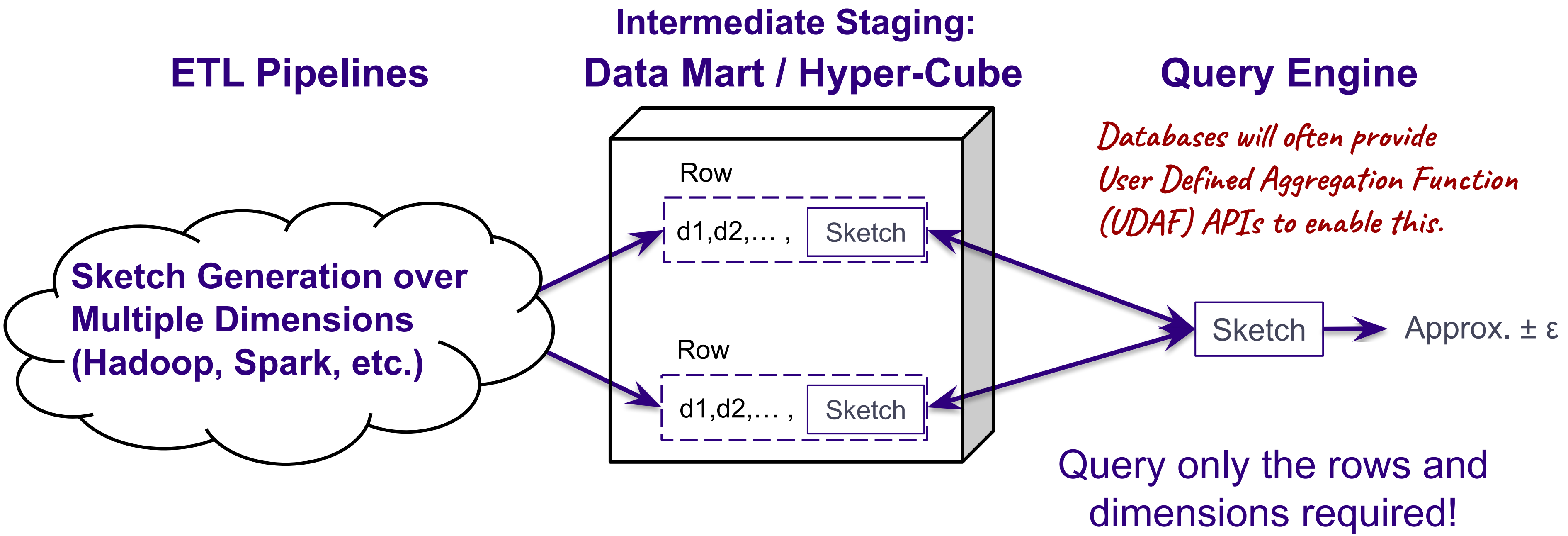
Win #2: Sketch Mergeability ➔ Parallelism ➔ Win #3: Near Real Time Performance

- Sketches transform **Non-Additive** operations into **Additive** operations
- With No Additional Loss of Accuracy!
- The Result of a Sketch Merge is Another Sketch
  - ➔ For Storage, Transport, or Set Expressions (Tuple Sketch)



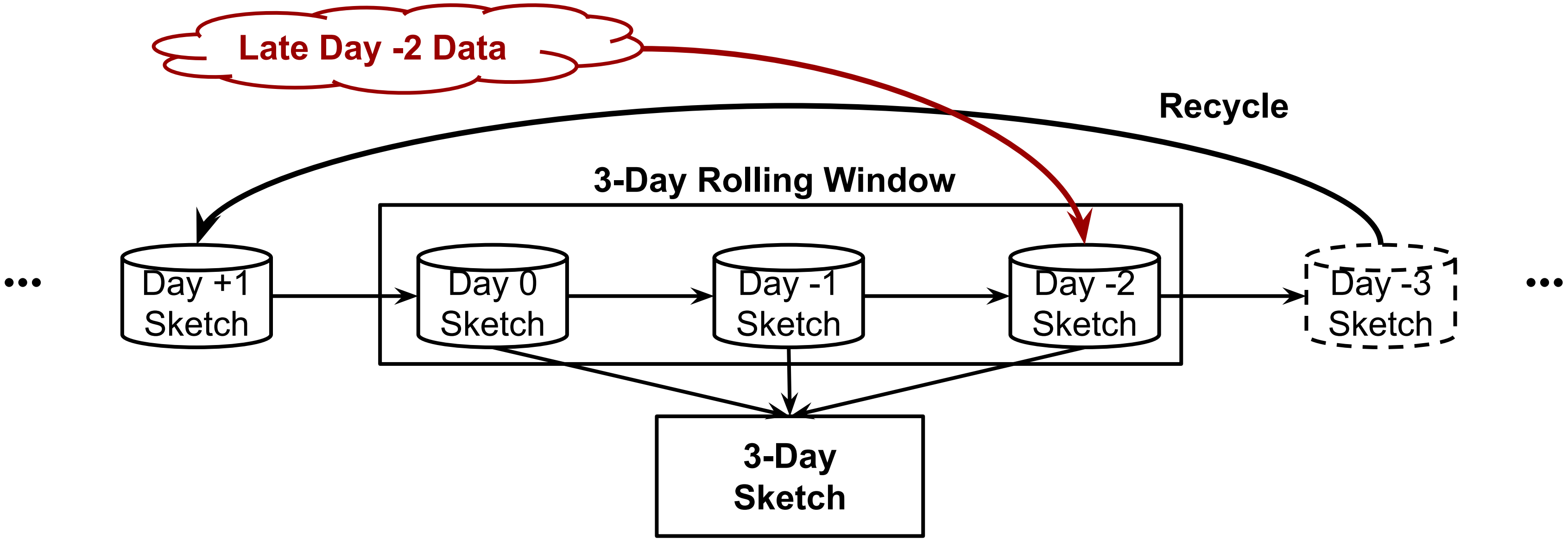
Win #4: Simpler Architecture

- Sketches are small enough to store in each row along with dimension & other data!
- Intermediate Hyper-Cube Staging Enables Fast, Multiple-Dimensional Predicate Queries



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

Win #5: Simplified Time Windowing & Late Data Processing



Every daily dataset is processed only **once** for a rolling N-day window!

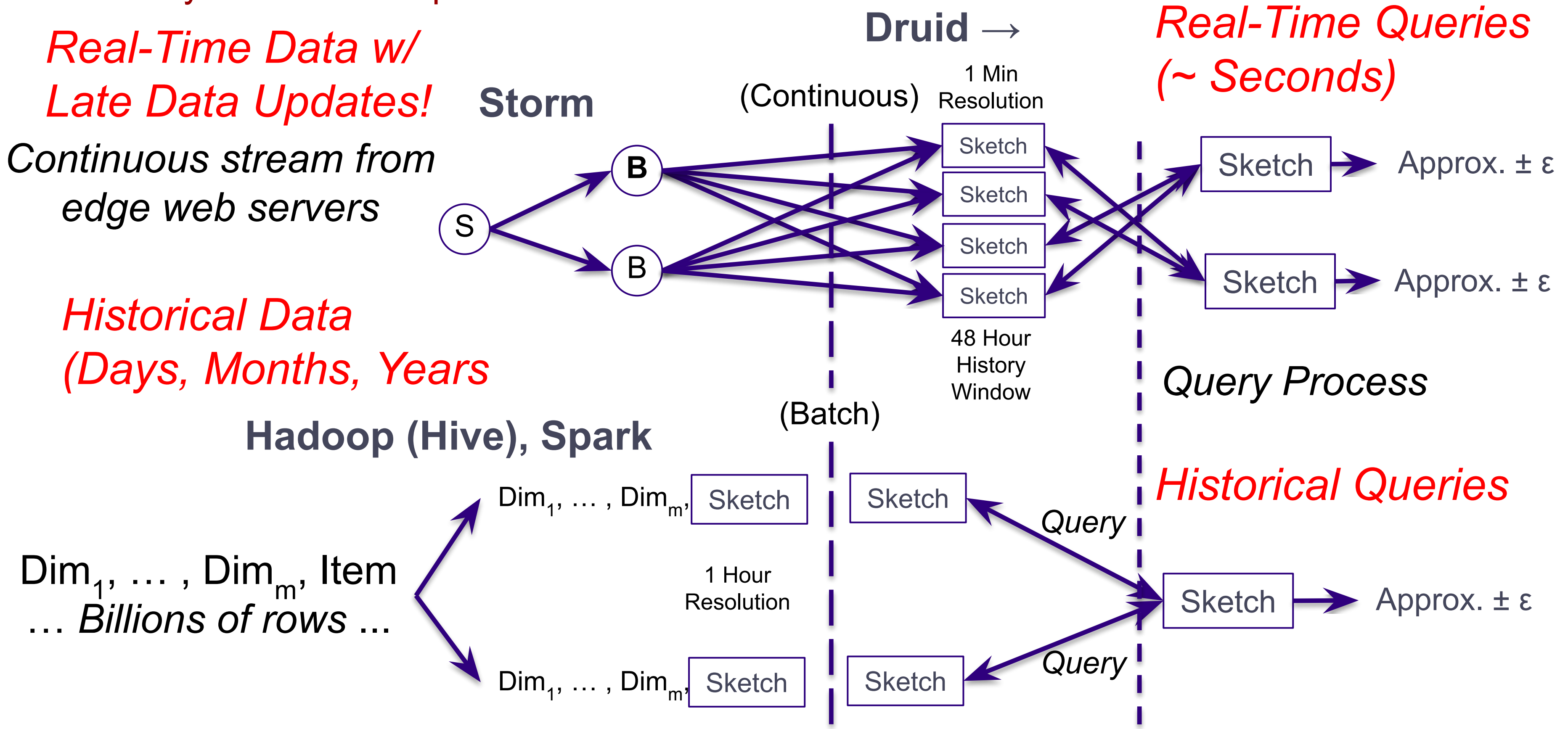
Late-data processing is now possible.

Sketches can be recycled.

Win #6: Near-Real Time Results, with History

Combine Off-Line, On-Line for Real-Time + History

Case Study: Storm/Hadoop/Druid Sketch Flow Architecture



Win #7: Lower System Cost ($)

Case Study : Before: Not Real-time; After: Near Real-time

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

Big Wins!
Near-Real Time,
Lower System $

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

* VCS: Virtual Core Seconds

Our Mission…

Combine Deep Science with Exceptional Engineering

To Develop **Production Quality** Sketches

That Address These Difficult Queries

The Sketch Design Process

1. The Art:
   Model a problem as a stochastic process and a data structure …

2. The Science:
   Analyze the data structure & algorithms using probability, statistics to extract the desired result with well understood error properties.
   Mathematically Prove that it works! Publish to Scientific Venues.
   https://datasketches.apache.org/docs/Community/Research.html

3. The Engineering:
   Transform the Art and the Science Theory into a Product!
   - Create useful APIs for use in production systems
   - Document with code examples for system engineers
   - Exhaustively test & characterize to ensure robustness
   - Publish to Open Source

World-Wide Science / Research Contacts

- ✯ Edith Cohen, Google Scientist, Israel & Bay Area
- ✯ Graham Cormode, Professor, University of Warwick, UK
- ✯ Charlie Dickens, (ex-Yahoo), Scientist, Entrepreneur, San Francisco
- ✯ Kevin Lang, (ex-Yahoo, deceased), Chief Scientist, DataSketches Project
- ✯ Edo Liberty, (ex-Yahoo), Chief Scientist, Founder, Pinecone Technologies, NY, Israel
- ✯ Justin Thaler, (ex-Yahoo), Professor, Georgetown University, Washington D.C.
- ✯ Daniel Ting, Scientist, Facebook/Meta, Seattle
- ✯ Pavel Vesely, Professor, Charles University, Prague
- ✯ …more…

The **Apache DataSketches** Library

Cardinality, 4 Families

- **HLL (on/off Heap)** A very high performance implementation of this well-known sketch
- **CPC** The best accuracy per space
- **Theta Sketches**: Set Expressions (e.g., Union, Intersection, Difference), on/off Heap
- **Tuple Sketches**: Generic, Associative Theta Sketches, multiple derived sketches:

Quantiles Sketches, 4 Families

- **Quantiles**, Histograms, PMF's and CDF's of streams of comparable objects, on/off Heap.
- **KLL**, highly optimized for accuracy-space.
- **Relative Error Quantiles(REQ),** Extremely accurate at the ends of the rank domain
- **T-Digest**, Empirical, yet very small and accurate for most data.

Frequency (Heavy-Hitters) Sketches, 3 Families

- **Frequent Items**: Weighted or Unweighted
- **Frequent Directions** (Approximate SVD) (a Vector Sketch)
- **Frequent Distinct Tuples**: Multi-dimensional Frequency & Distinct Analysis
- **CountMin:** Approx frequency for any item, enables deletions

Reservoir and Weighted-Sampling Sketches, 3 Families

- **Reservoir:** Uniform random to fixed-k sized buckets. Mergeable with different size k.
- **VarOpt:** Optimal variance weighted sampling for subset sums.
- **EBPPS Sampling**: Exact and Bounded Probability Proportional to Size

Specialty Sketches

- **Customer Engagement, Sketch Maps**, etc.
- **Differential Privacy,** (experimental)
- **Density Estimation**
- **Filters, e.g. BloomFilter, QuotientFilter (under development)**

Languages Supported:

- Java, C++, Python, Go*
- Binary Compatibility across languages and history (12+ years)

* In development

Who Uses DataSketches?…That we know of!

We only find out about users if they contact us.

● **Public Database Integrations:** Hive, Pig, PostgreSQL, Druid, Spark, Presto, GCHQ / Gaffer, Netflix / Atlas Database, Pinot, Iceberg, Vertica, Greenplum, ClickHouse, Impala, Quix.io, GoogleCloudPlatform/BigQuery, (AWS via *lift & shift*)…

● **Major users:** Microsoft Gray Labs, GCHQ, Canadian Communications Security Establishment (CSE), GameAnalytics, Visa, Nielsen, DataDog, Criteo, Imply, Permutive, Expedia …

● **Library Integrations:** TechAscent/tech.ml.dataset (TMD), WhyLabs (ML)

Bright Future for Sketching Technology & Solutions ...

Items (words, IDs, events, clicks, …)
- Count Distinct
- Frequent Items, Heavy-Hitters, etc
- Quantiles, Ranks, PMFs, CDFs, Histograms
- Set Operations
- Sampling: Uniform, Weighted, Proportional
- Mobile (IoT)
- Moment and Entropy Estimation
- Turnstyle Sketches
- Filters: Bloom, Quotient, Infinifilter, etc.

Graphs (Social Networks, Communications, …)
- Connectivity
- Cut Sparsification
- Weighted Matching
- Path & Funnel Analysis

Vectors (text docs, images, features, …) And Matrices (text corpora, recommendations, …)
- Dimensionality Reduction (SVD)
- Ridge Regression
- Covariance Estimation
- Low Rank Approximation
- Sparsification
- Clustering (k-means, k-median, …)
- Linear Regression
- Machine Learning (in some areas)
- Density Estimation

Differential Privacy (experimental)
- Reach, Frequency

Areas where we have sketch implementations / solutions
In Development
Areas of research (World-wide)

THANK YOU!

Learn more about Apache DataSketches
Visit Us and become a Contributor!
https://datasketches.apache.org

Apache DataSketches

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.

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 = 16 d, 2hr

Ratio: 30.4 : 1

Ratio: 1.31 : 1

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 = 12d, 6hr

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: • -> Hourly Report	Join: {site, day, count(id1), count(id2)}
Total CPU Time	96,300 sec =26.75 hrs

Ratio: 135.8 : 1

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 = 11.8 min

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 (12 hrs) Month: 46,500 sec (13h, via daily) Month: 70,900 sec (20h, via hourly)

Ratios:
Week: 102.6 : 1
Mo.: 99.79 : 1
Mo.: 152 : 1

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, and as the input size grows, the benefit of using sketches becomes even more dramatic

Recently Added Sketches

CountMin Sketch

- Approximate Frequency Estimation for any queried item in contrast to our Frequent Items Sketch for Heavy Hitters.
- Basic building block for numerous types of analysis
- Can be configured to enable deletions as well as insertions

Density Sketch

- Builds a coreset from the given set of input points
- Provides a density estimate at any given point
- Provides for a user defined Kernel Function as well as built-in ones for computing distance between two vectors.
- Handles multi-dimensional vectors

EB-PPS Sampling

- **E**xact and **B**ounded, **P**robability **P**roportional to **S**ize
- Produces a random sample of data from a stream of weighted items, ensuring that the probability of including an item is always exactly equal to the item's weight.
- This is in contrast to our VarOpt sketch, which provides optimal variance in the computation of subset sums given a random sample of weighted inputs.

T-Digest

- An empirical quantiles sketch that has excellent size and error properties.
- This sketch does not have mathematically proved error properties, in contrast with our other quantile sketches that do.

BloomFilter, QuotientFilter

Recently Added Sketch Enhancements

KLL & Classic Quantiles Items Sketches

- Added highly scalable Partitioning Feature for partitioning very large data sets into equally sized partitions.
- Added integer-weighted input capability
- Added data type “long”

Theta Sketch

- Added a new compression capability that provides for superior size reduction of serialized sketch images compared to standard compression tools