Data Stream Processing (Part III)

•Gibbons. "Distinct sampling for highly accurate answers to distinct values queries and event reports", VLDB'2001.

•Ganguly, Garofalakis, Rastogi. "Tracking Set Expressions over Continuous Update Streams", ACM SIGMOD'2003.

•*SURVEY-1:* S. Muthukrishnan. "Data Streams: Algorithms and Applications"

•*SURVEY-2:* Babcock et al. "Models and Issues in Data Stream Systems", ACM PODS'2002.

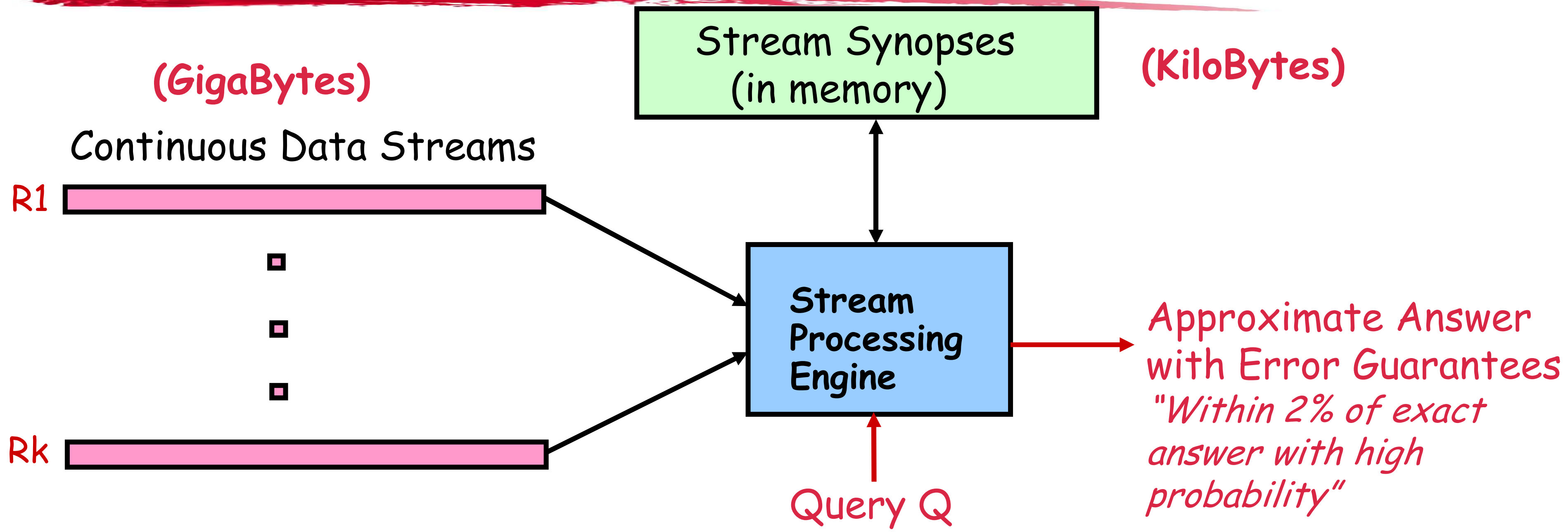
The Streaming Model

- Underlying signal: One-dimensional array A[1…N] with values A[i] all initially zero
  - Multi-dimensional arrays as well (e.g., row-major)
- Signal is implicitly represented via a stream of updates
  - j-th update is <k, c[j]> implying
    - A[k] := A[k] + c[j]   (c[j] can be >0, <0)
- Goal: Compute functions on A[] subject to
  - Small space
  - Fast processing of updates
  - Fast function computation
  - …

Streaming Model: Special Cases

- Time-Series Model
  - Only j-th update updates A[j] (i.e., A[j] := c[j])
- Cash-Register Model
  - c[j] is always >= 0 (i.e., increment-only)
  - Typically, c[j]=1, so we see a multi-set of items in one pass
- Turnstile Model
  - Most general streaming model
  - c[j] can be >0 or <0 (i.e., increment or decrement)
- *Problem difficulty varies depending on the model*
  - E.g., MIN/MAX in Time-Series vs. Turnstile!

Data-Stream Processing Model



- Approximate answers often suffice, e.g., trend analysis, anomaly detection
- Requirements for stream synopses
  - *Single Pass:* Each record is examined at most once, in (fixed) arrival order
  - *Small Space:* Log or polylog in data stream size
  - *Real-time:* Per-record processing time (to maintain synopses) must be low
  - *Delete-Proof:* Can handle record deletions as well as insertions
  - *Composable:* Built in a *distributed fashion* and combined later

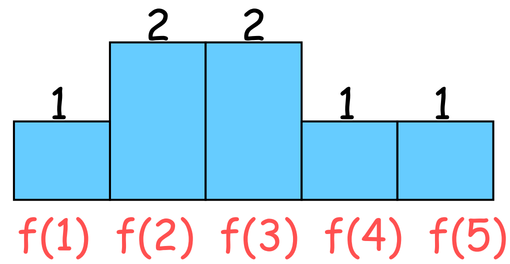
Probabilistic Guarantees

- Example: Actual answer is within 5 ± 1 with prob ≥ 0.9
- Randomized algorithms: Answer returned is a specially-built random variable
- User-tunable (ε,δ)–**approximations**
  - Estimate is within a relative error of ε with probability >= $1-\delta$
- Use Tail Inequalities to give probabilistic bounds on returned answer
  - Markov Inequality
  - Chebyshev's Inequality
  - Chernoff Bound
  - Hoeffding Bound

Linear-Projection (aka AMS) Sketch Synopses

- *Goal:* Build small-space summary for distribution vector f(i) (i=1,..., N) seen as a stream of i-values

Data stream: 3, 1, 2, 4, 2, 3, 5, . . . →



- *Basic Construct: Randomized Linear Projection of f()* = project onto inner/dot product of f-vector

$$< f, \xi > = \sum f(i)\xi_i$$ where ξ = vector of random values from an appropriate distribution

  - Simple to compute over the stream: Add ξ_i whenever the i-th value is seen

Data stream: 3, 1, 2, 4, 2, 3, 5, . . . → $\xi_1 + 2\xi_2 + 2\xi_3 + \xi_4 + \xi_5$

  - Generate ξ_i 's in small (logN) space using pseudo-random generators
  - *Tunable probabilistic guarantees* on approximation error
  - *Delete-Proof:* Just subtract ξ_i to delete an i-th value occurrence
  - *Composable:* Simply *add* independently-built projections

Overview

- Introduction & Motivation
- Data Streaming Models & Basic Mathematical Tools
- Summarization/Sketching Tools for Streams
  - Sampling
  - Linear-Projection (aka AMS) Sketches
    - *Applications:* Join/Multi-Join Queries, Wavelets
  - Hash (aka FM) Sketches
    - *Applications:* Distinct Values, Distinct sampling, Set Expressions

Distinct Value Estimation

- Problem: Find the *number of distinct values* in a stream of values with domain [0,...,N-1]
  - Zeroth frequency moment F_0 , L0 (Hamming) stream norm
  - Statistics: number of *species or classes* in a population
  - Important for query optimizers
  - *Network monitoring:* distinct destination IP addresses, source/destination pairs, requested URLs, etc.
- Example (N=64)

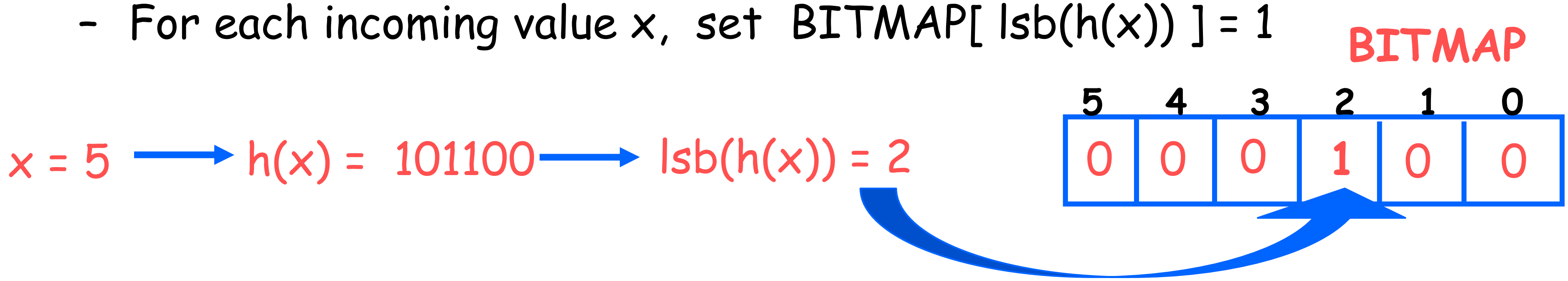
Data stream: 3 0 5 3 0 1 7 5 1 0 3 7

Number of distinct values: 5

- Hard problem for random sampling! [CCMN00]
  - Must sample almost the entire table to guarantee the estimate is within a factor of 10 with probability > 1/2, regardless of the estimator used!

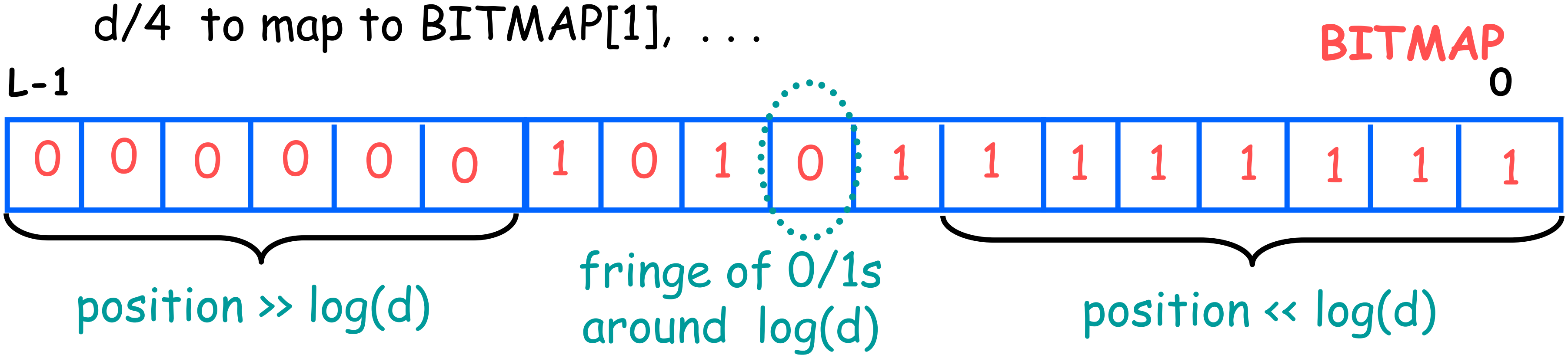
Hash (aka FM) Sketches for Distinct Value Estimation [FM85]

- Assume a hash function h(x) that maps incoming values x in [0,…, N-1] *uniformly* across [0,…, 2^L-1], where L = O(logN)
- Let lsb(y) denote the position of the least-significant 1 bit in the binary representation of y
  - A value x is mapped to lsb(h(x))
- Maintain *Hash Sketch* = BITMAP array of L bits, initialized to 0
  - For each incoming value x, set BITMAP[lsb(h(x))] = 1



Hash (aka FM) Sketches for Distinct Value Estimation [FM85]

- By uniformity through h(x): Prob[BITMAP[k]=1] = Prob[10^k] = $\frac{1}{2^{k+1}}$
  - Assuming d distinct values: expect d/2 to map to BITMAP[0] , d/4 to map to BITMAP[1], . . .



- Let R = position of rightmost zero in BITMAP
  - Use as indicator of log(d)
- [FM85] prove that E[R] = $\log(\phi d)$, where $\phi = .7735$
  - Estimate d = $2^R / \phi$
  - Average several iid instances (different hash functions) to reduce estimator variance

Hash Sketches for Distinct Value Estimation

- [FM85] assume "ideal" hash functions h(x) (N-wise independence)
  - [AMS96]: pairwise independence is sufficient
    - h(x) = $(a \cdot x + b) \bmod N$, where a, b are random binary vectors in [0,…,2^L-1]
  - Small-space (ε, δ) estimates for distinct values proposed based on FM ideas
- *Delete-Proof:* Just use counters instead of bits in the sketch locations
  - +1 for inserts, -1 for deletes
- *Composable:* Component-wise OR/add distributed sketches together
  - Estimate |S1 ∪ S2 ∪ … ∪ Sk| = *set-union cardinality*

Generalization: Distinct Values Queries

- SELECT COUNT(DISTINCT target-attr)
- FROM relation
- WHERE predicate

Template

- SELECT COUNT(DISTINCT o_custkey)
- FROM orders
- WHERE o_orderdate >= '2002-01-01'
  - "How many distinct customers have placed orders this year?"
  - Predicate not necessarily only on the DISTINCT target attribute

TPC-H example

- *Approximate answers with error guarantees over a stream of tuples?*

Distinct Sampling [Gib01]

Key Ideas

- Use FM-like technique to collect a specially-tailored sample over the *distinct values in the stream*
  - ***Use hash function mapping to sample values from the data domain!!***
  - Uniform random sample of the distinct values
  - Very different from traditional random sample: each distinct value is chosen uniformly regardless of its frequency
  - DISTINCT query answers: simply scale up sample answer by sampling rate
- To handle additional predicates
  - *Reservoir sampling* of tuples for each distinct value in the sample
  - Use reservoir sample to evaluate predicates

Building a Distinct Sample [Gib01]

- Use FM-like hash function h() for each streaming value x
  - Prob[h(x) = k] = $\frac{1}{2^{k+1}}$
- *Key Invariant: "All values with h(x) >= level (and only these) are in the distinct sample"*

```
DistinctSampling( B , r )
// B = space bound, r = tuple-reservoir size for each distinct value
level = 0; S = ∅
for each new tuple t do
    let x = value of DISTINCT target attribute in t
    if  h(x) >= level  then    // x belongs in the distinct sample
            use  t  to update the reservoir sample of tuples for x
    if  |S| >= B then   // out of space
            evict from S all  tuples with  h(target-attribute-value) = level
            set  level = level + 1
```

Using the Distinct Sample [Gib01]

- If level = l for our sample, then we have selected all distinct values x such that $h(x) >= l$
  - Prob[h(x) >= l] = $\frac{1}{2^l}$
  - By h()'s randomizing properties, we have uniformly sampled a 2^{-l} fraction of the distinct values in our stream

Our sampling rate!

- *Query Answering:* Run distinct-values query on the distinct sample and scale the result up by 2^l

- *Distinct-value estimation:* Guarantee ε relative error with probability $1 - \delta$ using $O(\log(1/\delta)/\varepsilon^2)$ space
  - For q% selectivity predicates the space goes up inversely with q

- *Experimental results:* 0-10% error vs. 50-250% error for previous best approaches, using 0.2% to 10% synopses

Distinct Sampling Example

- B=3, N=8 (r = 0 to simplify example)

Data stream: 3 0 5 3 0 1 7 5 1 0 3 7

hash:

0	1	3	5	7
0	1	0	1	0

Data stream: 1 7 5 1 0 3 7

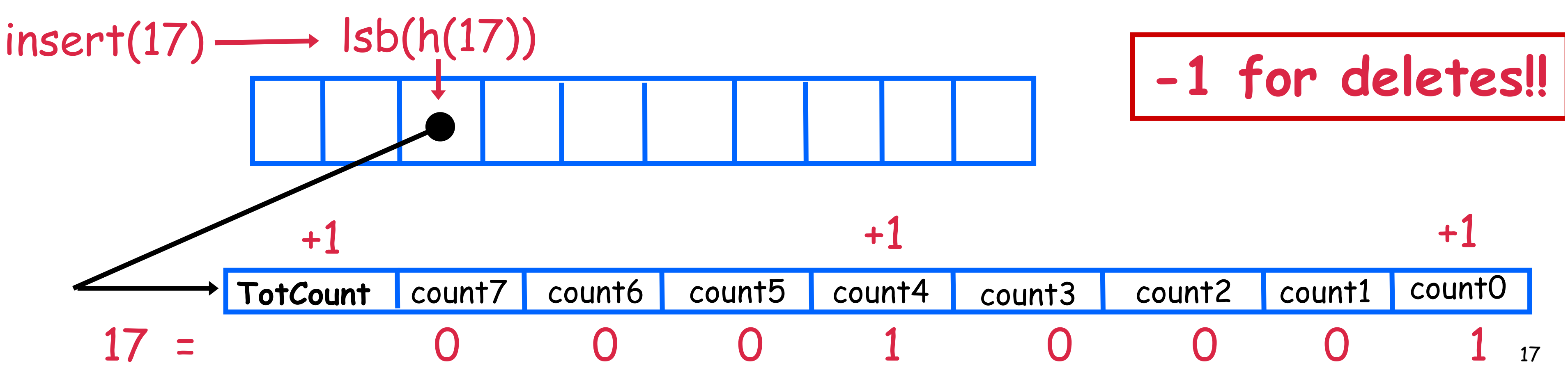
S={3,0,5}, level = 0

S={1,5}, level = 1

- Computed value: 4

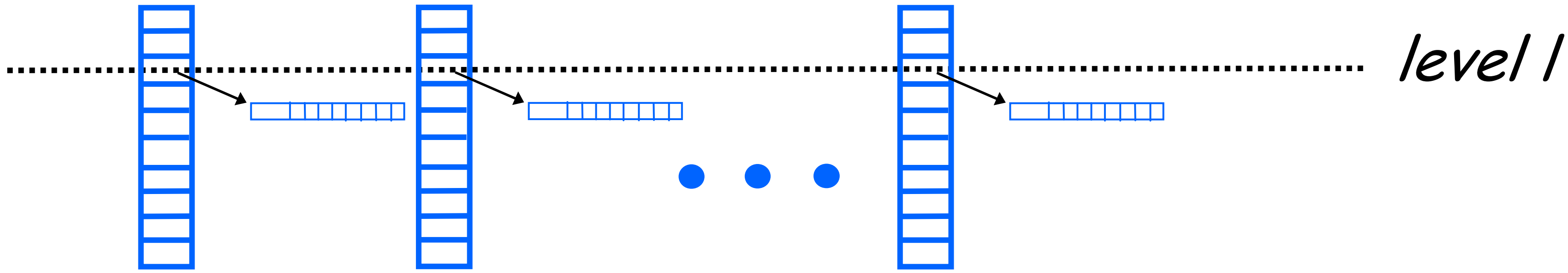
Processing Set Expressions over Update Streams [GGR03]

- Estimate cardinality of *general set expressions* over streams of updates
  - E.g., number of distinct (source,dest) pairs seen at both R1 and R2 but not R3? $|(R1 \cap R2) - R3|$
- *2-Level Hash-Sketch (2LHS) stream synopsis:* Generalizes FM sketch
  - *First level:* $\Theta(\log N)$ buckets with exponentially-decreasing probabilities (using lsb(h(x)), as in FM)
  - *Second level:* Count-signature array (logN+1 counters)
    - One "total count" for elements in first-level bucket
    - logN "bit-location counts" for 1-bits of incoming elements



Processing Set Expressions over Update Streams: Key Ideas

- Build several independent 2LHS, fix a level l, and look for *singleton first-level buckets* at that level l



- Singleton buckets and singleton element (in the bucket) are easily identified using the *count signature*

Singleton bucket count signature

Total=11	0	0	0	0	11	0	11	0

→ Singleton element = $1010_2 = 10$

- Singletons discovered form a *distinct-value sample* from the union of the streams
  - Frequency-independent, each value sampled with probability $\frac{1}{2^{l+1}}$
- Determine the fraction of *"witnesses"* for the set expression E in the sample, and scale-up to find the estimate for |E|

Example: Set Difference, |A-B|

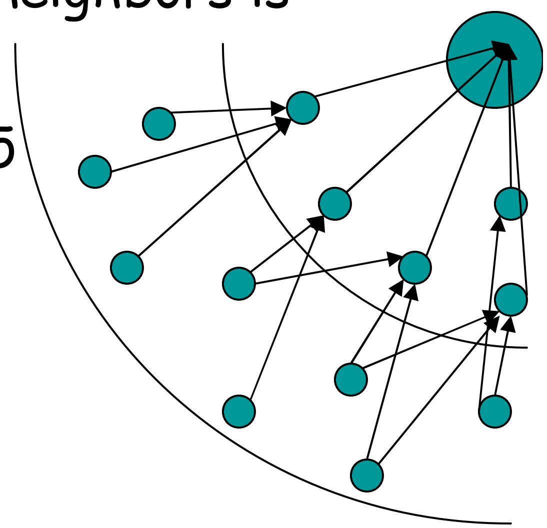
- Parallel (same hash function), independent 2LHS synopses for input streams A, B
- Assume robust estimate $\hat{u}$ for $|A \cup B|$ (using known FM techniques)
- Look for buckets that are *singletons for* $A \cup B$ at level $l \approx \lceil \log \hat{u} \rceil$
  - Prob[singleton at level l] > constant (e.g., 1/4)
  - Number of singletons (i.e., *size of distinct sample*) is at least a constant fraction (e.g., > 1/6) of the number of 2LHS (w.h.p.)
- *"Witness" for set difference A-B:* Bucket is singleton for stream A and empty for stream B
  - Prob[witness | singleton] = $|A-B| \,/\, |A \cup B|$
- Estimate for |A-B| = $\frac{\#\,\text{witnesses for } A-B}{\#\,\text{singleton buckets}} \times \hat{u}$

Estimation Guarantees

- Our set-difference cardinality estimate is within a relative error of ε with probability $\geq 1-\delta$ when the number of 2LHS is $O(\frac{|A \cup B| \log(1/\delta)}{|A-B|\varepsilon^2})$
- *Lower bound* of $\Omega(\frac{|A \cup B|}{|A-B|\varepsilon})$ space, using communication-complexity arguments
- Natural generalization to arbitrary set expressions E = f(S1,…,Sn)
  - Build parallel, independent 2LHS for each S1,…, Sn
  - Generalize "witness" condition (inductively) based on E's structure
  - (ε, δ) estimate for |E| using $O(\frac{|S1 \cup \ldots \cup Sn| \log(1/\delta)}{|E|\varepsilon^2})$ 2LHS synopses
- *Worst-case bounds!* Performance in practice is much better [GGR03]

Extensions

- Key property of FM-based sketch structures: ***Duplicate-insensitive!!***
  - Multiple insertions of the same value don't affect the sketch or the final estimate
  - Makes them ideal for use in broadcast-based environments
  - E.g., wireless sensor networks (broadcast to many neighbors is critical for robust data transfer)
  - Considine et al. ICDE'04; Manjhi et al. SIGMOD'05



- Main deficiency of *traditional random sampling*: Does not work in a Turnstile Model (inserts+deletes)
  - "Adversarial" deletion stream can deplete the sample
- Exercise: Can you make use of the ideas discussed today to build a "delete-proof" method of maintaining a random sample over a stream??