KHyperLogLog

Estimating Reidentifiability and Joinability of Large Data at Scale

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Is data reidentifying?

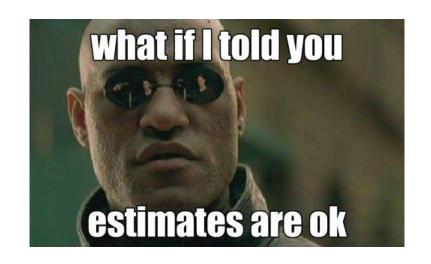
Are data sets joinable?



Problem: Data is LARGE









Background on Approximate Counting



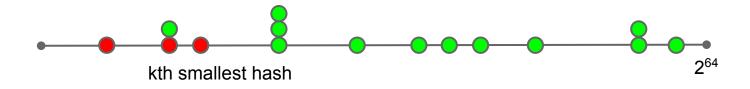


Approximate Counting

- sublinear memory
 - compact data structures (sketches)
 - often bounded size (KBs)
- streaming algorithm
- easily parallelizable
- bounded error rate

K Min Values

- Use a uniform hash function
- Hash input values, keep K smallest hashes
- Extrapolate from the density of K smallest hashes

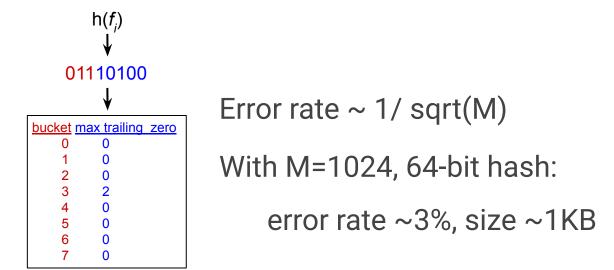


Error rate $\sim 1/ \text{sqrt}(K)$

With K=1024, 64-bit hash: error rate ~3%, size ~8KB

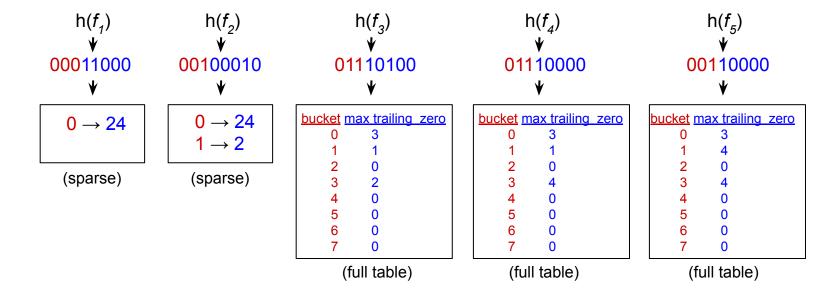
HyperLogLog_[2]

- Hash input values ⇒ keep max count of trailing 0's
- High number of trailing 0's \Rightarrow has seen a lot of unique values
- High variance ⇒ average over M counts



HyperLogLog++[3]

- Sparse representation for low cardinalities
 - ⇒ better estimates + less memory



But cardinality estimate is not enough

Introducing KHyperLogLog

to estimate reidentifiability and joinability





KHyperLogLog (KHLL)

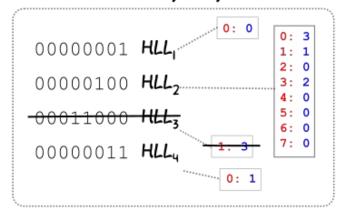
Two level counting

- 1st level → K Min Values
- $\bullet \quad 2^{nd} \; level \rightarrow HyperLogLog++_{HalfByte} \\$

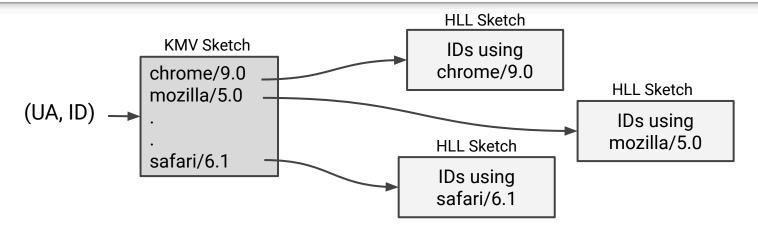
Ex: estimate uniqueness of User Agent (UA) strings

h (UA)	h(ID)
0000001	00000011
00000100	00011000
00000100	00100010
00000100	01110100
00011000	00101000
00000011	00011010

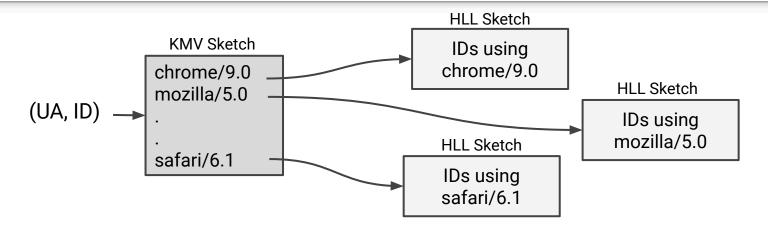
KHYPERLOGLOG, K=3, M=8



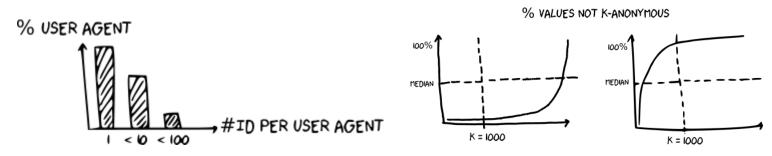
Uniqueness Distribution



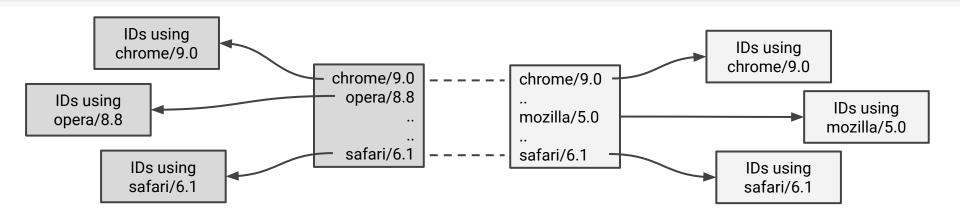
Uniqueness Distribution



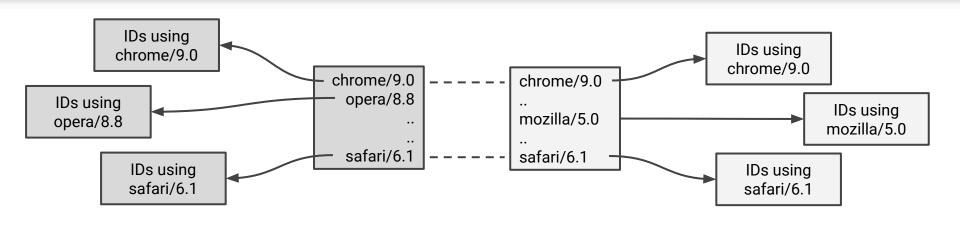
From a KHLL sketch, we can estimate



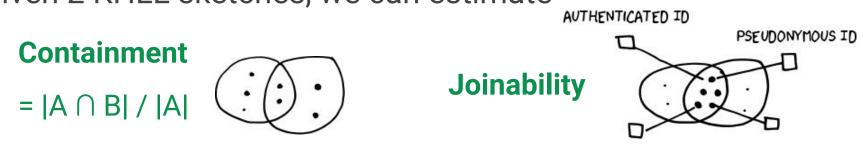
Containment & Joinability



Containment & Joinability



Given 2 KHLL sketches, we can estimate



How does KHyperLogLog perform?



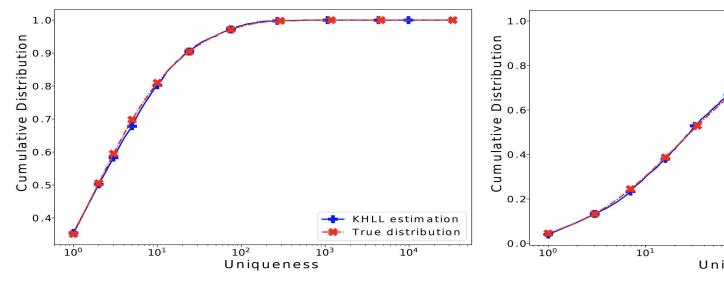


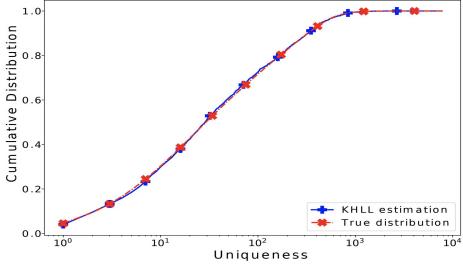
Efficiency

- KHLL vs exact counting
 - CPU performance 1 or 2 orders of magnitude faster
 - Bounded memory usage
 - With K=1024, M=512, size ~256KB
 - Scale to large data sets

Accuracy: Uniqueness Distribution

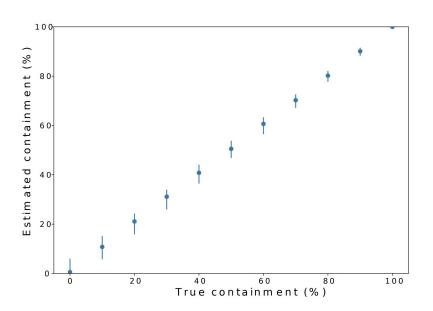
- Prepared test distributions using Netflix & US census data
- Validated accuracy of estimated distributions

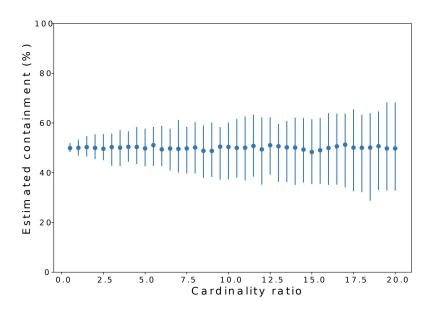


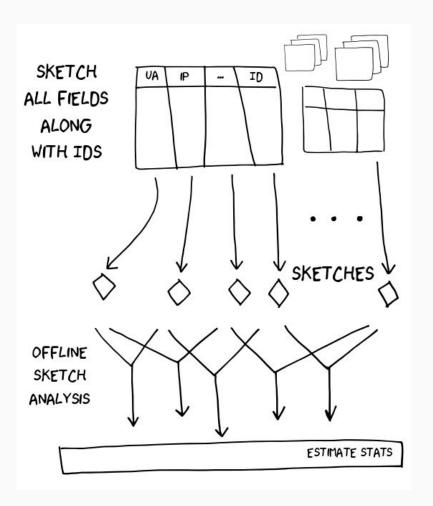


Accuracy: Containment

- Sets of equal size: ±5% error 90% of time
- But, problematic for sets of highly unequal sizes







Practical Use of KHLL

- Read data once (petabytes)
- Produce sketches
- Offline
 - Estimate reidentifiability
 - Estimate joinability

Summary

- KHLL for estimating reidentiability & joinability at scale
- Approximation errors possible, but great for
 - Understanding data e.g., for evaluating data strategies
 - Regression testing esp. detecting data joinability

Summary

- KHLL for estimating reidentiability & joinability at scale
- Approximation errors possible, but great for
 - Understanding data e.g., for evaluating data strategies
 - Regression testing esp. detecting data joinability
- Future work
 - Memory efficient but still CPU intensive
 - Applications in privacy enhancing techniques?

Thanks! Questions about KHyperLogLog?





References

- 1. On Synopses for Distinct-Value Estimation Under Multiset Operations.
 - K. Beyer, P. J. Haas, B. Reinwald, Y. Sismanis, and R. Gemulla.
- 2. **HyperLogLog: the analysis of a near-optimal cardinality estimation algorithm.** P. Flajolet, E. Fusy, O. Gandouet and F. Meunier.
- 3. HyperLogLog in Practice: Algorithmic Engineering of a State of The Art Cardinality Estimation Algorithm. S. Heule, M. Nunkesser, A. Hall.

HLL++ half-byte VS HLL++

- Compressed sparse list
- Bias correction (between linear and HLL counting)

HLL++_{half-byte} -- readability | cpu efficiency | accuracy

- Sparse list
- Half-byte counters

Half-byte Counters in HLL++

Observation: counters tend to clump together

