

Probabilistic Data Structures

(Wow that's hard to spell)

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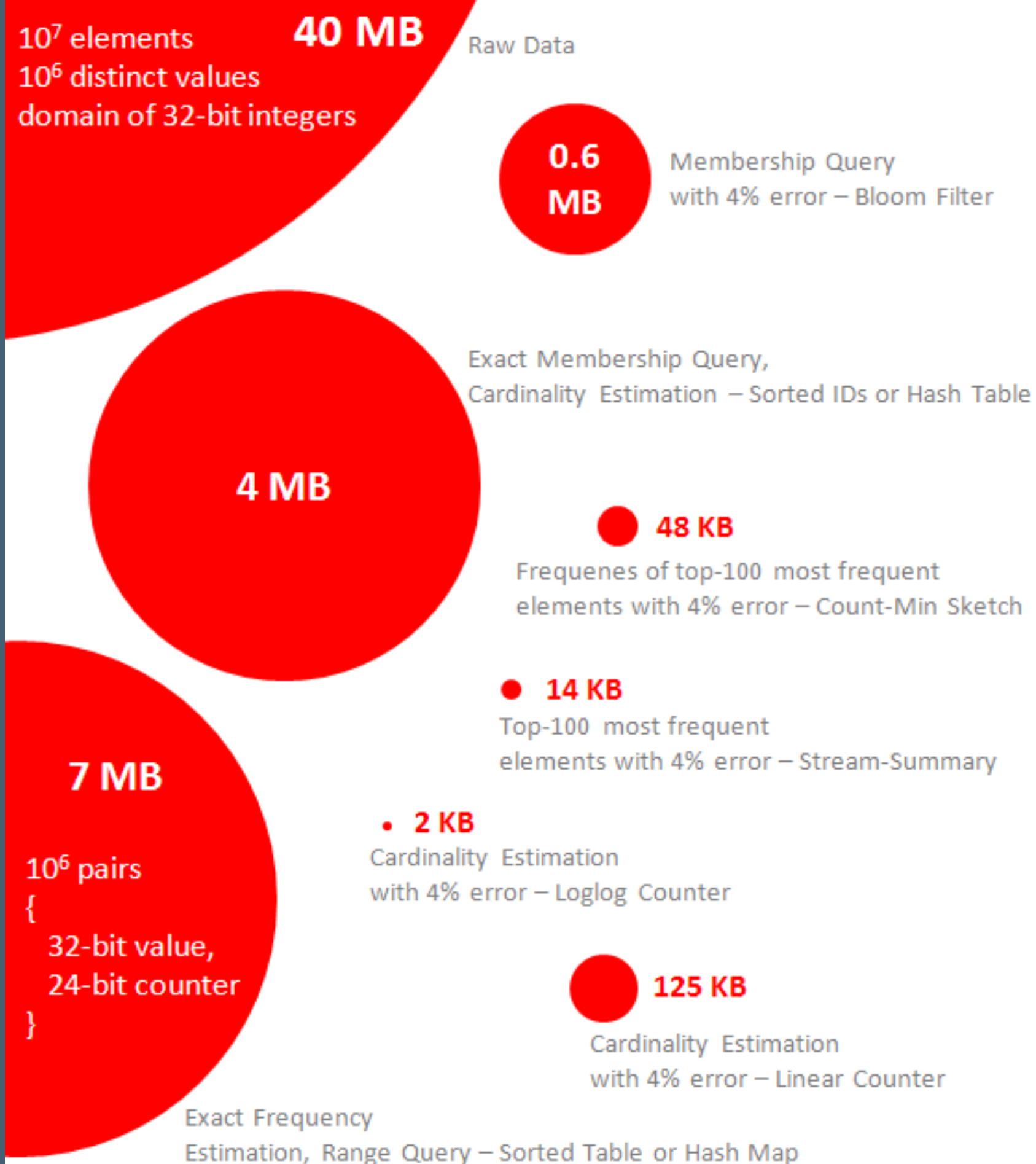
Highlights

- >> Why this topic?
- >> Bloom Filter
- >> Count-min sketch
- >> HyperLogLog

Why this topic ¹?

- » Big data is about taking different approaches to data problems due to your dataset size
- » Just because you *can* compute the **exact** number of distinct customers in 1PB of logs doesn't mean you *should*
- » Let's use really old, un-hip, proven techniques like sampling and hashing!

¹ Notice how it's "*this topic*" so I don't have to spell probabilistic again?



Size saving approximations²

² <https://highlyscalable.wordpress.com/2012/05/01/probabilistic-structures-web-analytics-data-mining/>

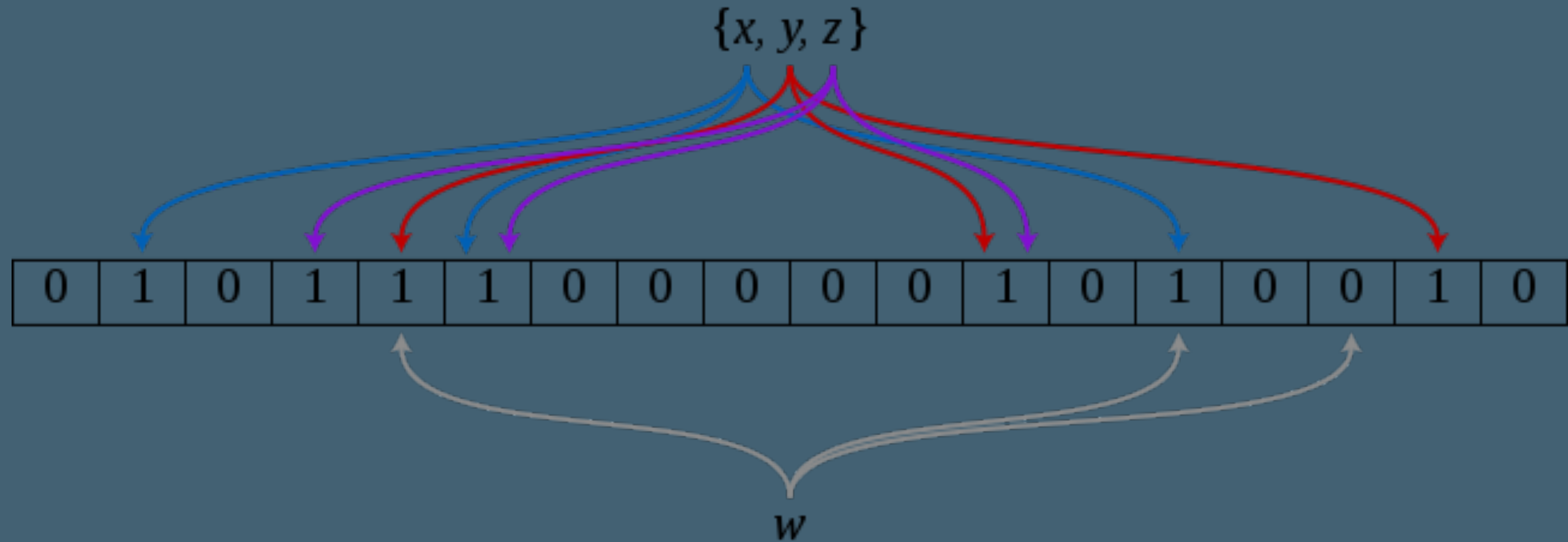
Problem:

Have we seen this item before?

Bloom filter

- >> Conceived by Burton Howard Bloom back in 1970; probably most well-known probabilistic data structure
- >> Used to estimate set membership
- >> False positives are possible (thought we had something we don't), false negatives are not; recall therefore 100%
- >> Technique involves maintaining a bitset where each bit is mapped to some number of fixed bits by independent hash functions

Bloom filter³



³ https://en.wikipedia.org/wiki/Bloom_filter

Bloom filter

- >> Lots of work done around tuning for space & error rates
- >> Able to estimate set membership of **10^9** items, with false positive rate of **1%**, using **1.12g** space⁴
- >> Typical use cases include pre-checks for expensive API lookups and distributed system coordination
- >> **LOTS** of OSS implementations exist; Google Guava ships w/ serializable version (no guaranteed backward compatibility)

⁴ <http://hur.st/bloomfilter>

Problem:

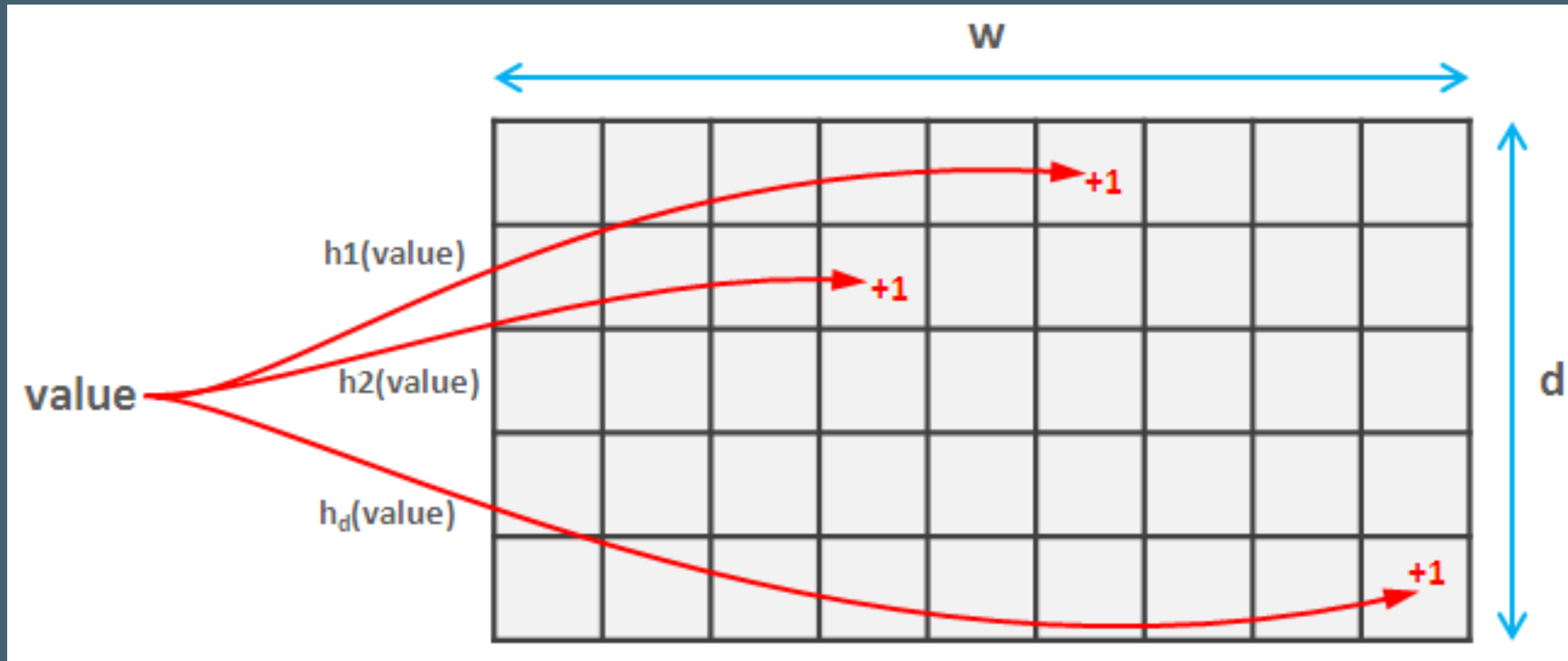
What are the 100 most popular items in our dataset (and what is the measure of their popularity)?

Count-min sketch⁵

- » Serves as a frequency table of events from a stream of data
- » Technique involves hashing events to frequencies, using multiple hash functions (*recognize a pattern here?*), using minimum hashed value (w/ potential collisions)
- » Similar to bloom filters, approximate count will never be more than estimate but could be less

⁵ <http://sites.google.com/site/countminsketch/cm-latin.pdf>

Count-min sketch²



² <https://highlyscalable.wordpress.com/2012/05/01/probabilistic-structures-web-analytics-data-mining/>

Count-min sketch

- >> Hard to generalize results due to sketch size, error rate, & distribution; analysis against different real-world data sets has been done⁶
- >> First example: Top-100 w/ **4%** error on **10^7** values using **48kb**²
- >> CMS can perform poorly on non-Zipfian distributions; *Count-mean-min sketch* estimates noise for each hash & subtracts

⁶ <http://www.cs.rutgers.edu/~muthu/cmz-sdm.pdf>

² <https://highlyscalable.wordpress.com/2012/05/01/probabilistic-structures-web-analytics-data-mining/>

Problem:

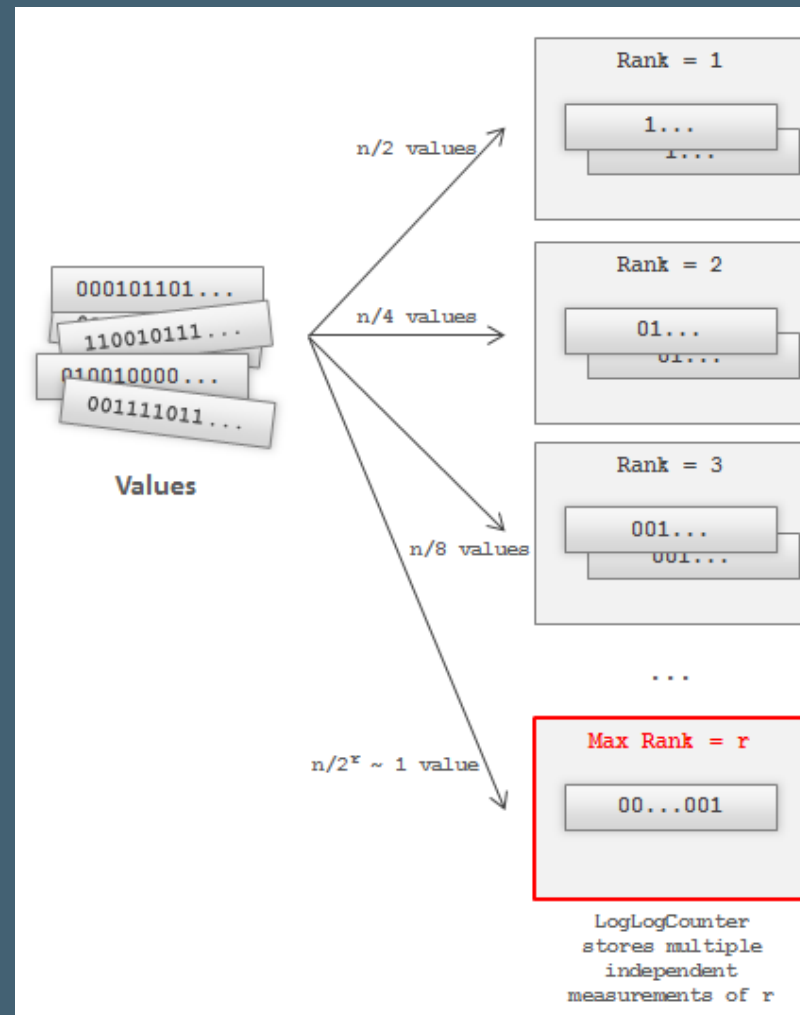
How many distinct items are in
this set?

HyperLogLog⁷

- » Extension of prior LogLog algorithm
- » Approximates number of unique elements in a set using very little memory
- » Technique involves hashing original set elements, then estimating cardinality by calculating maximum number of leading zeros in binary string version of hashed elements

⁷ <http://algo.inria.fr/flajolet/Publications/FlFuGaMeo7.pdf>

HyperLogLog²



² <https://highlyscalable.wordpress.com/2012/05/01/probabilistic-structures-web-analytics-data-mining/>

HyperLogLog

- >> Able to estimate cardinalities beyond **10^9** , with error rate of **2%**, using only **1.5kb** memory
- >> See this one a lot in ad serving and analytics contexts
- >> Many OSS implementations exist; well-known implementation in Redis⁸

⁸ <http://redis.io/commands/pfcount>

Matching Exercise

- >> Can we track the most-retweeted tweets with the *#walkingdead* hashtag?
- >> How many people have visited this article today?
- >> Do we have to include this server in our search list?

Matching Exercise

- >> Can we track the most-retweeted tweets with the *#walkingdead* hashtag?
 - >> **Count-min sketch**
- >> How many people have visited this article today?
 - >> **HyperLogLog**
- >> Do we have to include this server in our search list?
 - >> **Bloom filter**

Conclusions

- >> Optimizing search space to specific dataset problems should always result in space/performance gains; trade-off is time
- >> We can split the difference by tuning general-purpose space-optimized structures if we are willing to give up a small amount of accuracy
- >> "*Big Data*" doesn't have to mean **MOAR**; can also mean making informed compromises on accuracy VS time, money, & complexity

Additional Reading

- >> <https://www.mapr.com/blog/some-important-streaming-algorithms-you-should-know-about>
- >> <http://www.infoq.com/presentations/abstract-algebra-analytics>
- >> <http://pages.cs.wisc.edu/~cao/papers/summary-cache/node8.html>
- >> <http://www.umiacs.umd.edu/~amit/Papers/goyalSketchEMNLP11.pdf>

Additional Reading

- >> <https://sites.google.com/site/countminsketch/home/faq>
- >> <http://tech.adroll.com/blog/data/2013/07/10/hll-minhash.html>
- >> <http://highscalability.com/blog/2012/4/5/big-data-counting-how-to-count-a-billion-distinct-objects-us.html>

A man wearing a black top hat and a green suit with question marks on it. He has a confused expression on his face. The background is a solid blue color.

Questions?