## Data Structures and Algorithms <br> Cardinality Sketches

CS 225
Dec 2, 2022
Brad Solomon


Department of Computer Science

## Reminder: Final Exam Scheduling

You can sign up now for the final exam

There are no extensions or make-ups for the final exam

## Learning Objectives

Introduce the concept of cardinality and cardinality estimation

Demonstrate the relationship between cardinality and similarity

Introduce the MinHash Sketch for set similarity detection

## Bloom Filters

A probabilistic data structure storing a set of values
Has three key properties:
$k$, number of hash functions
$n$, expected number of insertions
$m$, filter size in bits
Expected false positive rate: $\left(1-\left(1-\frac{1}{m}\right)^{n k}\right)^{k} \approx\left(1-e^{\frac{-n k}{m}}\right)^{k}$
Optimal accuracy when: $\quad k^{*}=\ln 2 \cdot \frac{m}{n}$

## Count-Min Sketch

A probabilistic data structure storing a set of values
Has four key properties:
$k$, number of hash functions
$n$, expected number of insertions
$m$, filter size in registers
$b$, number of bits per register

|  |  | $h_{\{1,2,3, \ldots, k\}}$ |  |
| :--- | :--- | :--- | :--- |
| 0 | 3 | 1 | 0 |
| 0 | 0 | 2 | 3 |
| 2 | 0 | 1 | 0 |
| 3 | 1 | 0 | 1 |
| 0 | 0 | 2 | 2 |

Minimal increase reduces overcounting by identifying collisions.
(Count returned by sketch) $\geq$ (True count of the query)

The hidden problem with sketches...


## Cardinality

Cardinality is a measure of how many unique items are in a set

| 2 |
| :---: |
| 4 |
| 9 |
| 3 |
| 7 |
| 9 |
| 7 |
| 8 |
| 5 |
| 6 |

## Cardinality

Sometimes its not possible or realistic to count all objects!


Estimate: 60 billion - 130 trillion


Image: https://doi.org/10.1038/nature03597

| 5581 |
| :---: |
| 8945 |
| 6145 |
| 8126 |
| 3887 |
| 8925 |
| 1246 |
| 8324 |
| 4549 |
| 9100 |
| 5598 |
| 8499 |
| 8970 |
| 3921 |
| 8575 |
| 4859 |
| 4960 |
| 42 |
| 6901 |
| 4336 |
| 9228 |
| 3317 |
| 399 |
| 6925 |
| 2660 |
| 2314 |

## Cardinality Estimation

Imagine I fill a hat with numbered cards and draw one card out at random.
If I told you the value of the card was 95 , what have we learned?

## Cardinality Estimation

Imagine I fill a hat with a random subset of numbered cards from 0 to 999
If I told you that the minimum value was 95 , what have we learned?

## Cardinality Estimation

Imagine we have multiple sets (multiple minimums).

## Cardinality Estimation

Let $\min =95$. Can we estimate $N$, the cardinality of the set?


## Cardinality Estimation

Why do we care about "the hat problem"?

## Cardinality Estimation

Why do we care about "the hat problem"?

# m possible minima 



## Cardinality Estimation

Now imagine we have a SUHA hash $h$ over a range $m$.

Here a hash insert is equivalent to adding a card to our hat!

Now storing only the minimum hash value is a sketch!


## Cardinality Sketch

Let $M=\min \left(X_{1}, X_{2}, \ldots, X_{N}\right)$ where each $X_{i} \in[0,1]$ is an independent random variable

Claim: $\mathbf{E}[M]=\frac{1}{N+1}$

## Cardinality Sketch

Claim: $\mathbf{E}[M]=\frac{1}{N+1} \quad N \approx \frac{1}{M}-1$

Attempt 1

| 0.962 | 0.328 | 0.771 | 0.952 | 0.923 |
| :--- | :--- | :--- | :--- | :--- |

Attempt 2

| 0.253 | 0.839 | 0.327 | 0.655 | 0.491 |
| :--- | :--- | :--- | :--- | :--- |

Attempt 3

$$
\begin{array}{|l|l|l|l|l|}
\hline 0.134 & 0.580 & 0.364 & 0.743 & 0.931 \\
\hline
\end{array}
$$

## Cardinality Sketch

Consider an $N+1$ draw: $\quad$| $X_{1}$ | $X_{2}$ | $X_{3}$ |
| :--- | :--- | :--- | :--- | :--- |
| $\cdots$ | $\cdots X_{N}$ | $X_{N+1}$ |$\quad M=\min _{1 \leq i \leq N} X_{i}$

Claim: $\mathbf{E}[M]=\operatorname{Pr}\left(X_{N+1}<\min _{1 \leq i \leq N} X_{i}\right)$

Cardinality Sketch

$$
\begin{array}{lllll}
I_{1} & I_{2} & I_{3} & I_{N}, & I_{N+1}
\end{array}
$$

Consider an $N+1$ draw: $\quad$\begin{tabular}{|l|l|l|l|l|}
\hline$X_{1}$ \& $X_{2}$ \& $X_{3}$ <br>
\hline

$\quad$

$X_{N}$ \& $X_{N+1}$ <br>
\hline
\end{tabular}$\quad M=\min _{1 \leq i \leq N} X_{i}$

Claim: $\mathbf{E}[M]=\operatorname{Pr}\left(X_{N+1}<\min _{1 \leq i \leq N} X_{i}\right) \quad I_{i}= \begin{cases}1 & \text { if } X_{i}<\min _{j \neq i} X_{j} \\ 0 & \text { otherwise }\end{cases}$

$$
\begin{gathered}
\operatorname{Pr}\left(X_{N+1}<\min _{1 \leq i \leq N} X_{i}\right)=\mathbf{E}\left[I_{N+1}\right]=\frac{1}{N+1}=\mathbf{E}[M] \\
0
\end{gathered}
$$

## Cardinality Sketch

The minimum hash is a valid sketch of a dataset but can we do better?

## Cardinality Sketch

Claim: Taking the $k^{\text {th }}$-smallest hash value is a better sketch!
Claim: $\mathbf{E}\left[M_{k}\right]=\frac{k}{N+1}$

$$
\begin{array}{llllll}
0 & M_{1} & M_{2} & M_{3} & \ldots & M_{k}
\end{array}
$$

## Cardinality Sketch

Claim: Taking the $k^{\text {th }}$-smallest hash value is a better sketch!
Claim: $\mathbf{E}\left[M_{k}\right]=\frac{k}{N+1}$

$$
=\left[\mathbf{E}\left[M_{1}\right]+\left(\mathbf{E}\left[M_{2}\right]-\mathbf{E}\left[M_{1}\right]\right)+\ldots+\left(\mathbf{E}\left[M_{k}\right]-\mathbf{E}\left[M_{k-1}\right]\right)\right] \cdot \frac{1}{k}
$$

## Cardinality



True cardinality $=1,000$
Trial

## Cardinality

Given any dataset and a SUHA hash function, we can estimate the number of unique items by tracking the minimum hash values.


## Applied Cardinalities

Cardinalities
|A|
$|B|$
$|A \cup B|$
$|A \cap B|$

## Set similarities

$$
O=\frac{|A \cap B|}{\min (|A|,|B|)}
$$

$$
J=\frac{|A \cap B|}{|A \cup B|}
$$

Real-world Meaning
AGGCCACAGTGTATTATGACTG ||||l|||l| ||||||l| AGGCCACAGTGAGTTATGACTG

AAAAAAAAAAAGATGT-AAGTA ||||||||||||||| |||| AAAAAAAAAAAGATGTAAAGTA

GAGG--TCAGATTCACAGCCAC |l|| |||||||||||||| GAGGGGTCAGATTCACAGCCAC

## Set Similarity

How can we describe how similar two sets are?

## Set Similarity

How can we describe how similar two sets are?

## Set Similarity

To measure similarity of $A \& B$, we need both a measure of how similar the sets are but also the total size of both sets.

$$
J=\frac{|A \cap B|}{|A \cup B|}
$$

$J$ is the Jaccard coefficient

## Set Similarity



## Similarity Sketches

But what do we do when we only have a sketch?

## Similarity Sketches

Imagine we have two datasets represented by their $k$ th minimum values


Image inspired by: Ondov B, Starrett G, Sappington A, Kostic A, Koren S, Buck CB, Phillippy AM. Mash Screen: high-throughput sequence containment estimation for genome discovery. Genome Biol 20, 232 (2019)

## Similarity Sketches

Claim: Under SUHA, set similarity can be estimated by sketch similarity!


Image inspired by: Ondov B, Starrett G, Sappington A, Kostic A, Koren S, Buck CB, Phillippy AM. Mash Screen: high-throughput sequence containment estimation for genome discovery. Genome Biol 20, 232 (2019)

## The MinHash Sketch

Let sets $A$ and $B$ be two arbitrary sets of at least 8 elements
The eight minimum hash values for sets $A$ and $B$ is a MinHash Sketch
Sketch A

| 3 | 15 |
| :---: | :---: |
| 7 | 17 |
| 8 | 22 |
| 11 | 23 |

Sketch B

| 2 | 9 |
| :---: | :---: |
| 3 | 11 |
| 6 | 17 |
| 7 | 23 |


| 0 |  | 8 |  |  | 16 |  | 24 |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | ---: | :--- | :--- |
| A | 3 | 7 | 8 | 11 | 15 | 17 | 2223 | $\ldots$ |  |
| B | 2 | 3 | 6 | 7 | 9 | 11 |  | 17 | 23 |

The MinHash Sketch
To get similarity, we want to estimate $|A \cup B|$ and $|A \cap B| \ldots$
Sketch A

| 3 | 15 |
| :---: | :---: |
| 7 | 17 |
| 8 | 22 |
| 11 | 23 |


| 0 |  | 8 |  |  | 16 |  | 24 |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| A | 3 | 7 | 8 | 11 | 15 | 17 | 2223 | $\ldots$ |  |
| B | 2 | 3 | 6 | 7 | 9 | 11 |  | 17 | 23 |

## The MinHash Sketch

To get similarity, we want to estimate $|A \cup B|$ and $|A \cap B| \ldots$ Sketch of
Sketch A

| 3 | 15 |
| :---: | :---: |
| 7 | 17 |
| 8 | 22 |
| 11 | 23 |

Sketch B

| 2 | 9 |
| :---: | :---: |
| 3 | 11 |
| 6 | 17 |
| 7 | 23 |


| $\|A \cup B\|$ |  |
| :---: | :---: |
| 2 | 8 |
| 3 | 9 |
| 6 | 11 |
| 7 | 15 |


|  | 0 |  | 8 |  |  | 16 |  | 24 |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| A | 3 | 7 | 8 | 11 | 15 | 17 | 2223 | $\ldots$ |  |
| B | 2 | 3 | 6 | 7 | 9 | 11 |  | 17 | 23 |

The MinHash Sketch
To get similarity, we want to estimate $|A \cup B|$ and $|A \cap B| \ldots$
Sketch A

| 3 | 15 |
| :---: | :---: |
| 7 | 17 |
| 8 | 22 |
| 11 | 23 |


| 0 |  | 8 |  |  | 16 |  | 24 |  |  |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| A | 3 | 7 | 8 | 11 | 15 | 17 | 2223 | $\ldots$ |  |
| B | 2 | 3 | 6 | 7 | 9 | 11 |  | 17 | 23 |

Inclusion-Exclusion Principle
$|A \cap B|=$

## The MinHash Sketch

Using inclusion-exclusion principle and KMV, we can estimate similarity!

| Sketch A |  | Sketch B |  | $\begin{aligned} & \text { Sketch of } \\ & \|A \cup B\| \end{aligned}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 3 | 15 | 2 | 9 | 2 | 8 |
| 7 | 17 | 3 | 11 | 3 | 9 |
| 8 | 22 | 6 | 17 | 6 | 11 |
| 11 | 23 | 7 | 23 | 7 | 15 |

$k$ th minimum value (KMV) with $k=8$, assuming hash range is integers in $[0,100)$ :

$$
\begin{aligned}
& =\frac{800 / 23-1+800 / 23-1-800 / 15-1}{800 / 15-1} \\
& =\frac{34.782+34.782-53.333-1}{53.333-1} \\
& \approx 0.29
\end{aligned}
$$

$$
\frac{|A|+|B|-|A \cup B|}{|A \cup B|}
$$

## The MinHash Sketch

Claim: Cardinality of the intersection can also be estimated directly!

| Sketch A |  | Sketch B |  | Sketch of$\|A \cup B\|$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 3 | 15 | 2 | 9 | 2 | 8 |
| 7 | 17 | 3 | 11 | 3 | 9 |
| 8 | 22 | 6 | 17 | 6 | 11 |
| 11 | 23 | 7 | 23 | 7 | 15 |

1) Sequence decomposed into kmers
$S_{1}$ : CATGGACCGACCAG
CAT GAC GAC ATG ACC ACC TGG CCG CCA GGA CGA CAG

GCAGTACCGATCGT : $S_{2}$ GTA CGA CGT
AGT CCG TCG
CAG ACC ATC
GCA TAC GAT

## MinHash in practice



Mash: fast genome and metagenome distance estimation using MinHash
Ondov et al (2016) Genome Biology

# Reviewing probabilistic data sketches 

What sketch would I use for the following:

Does a specific object exist in my data?

How often is a specific object repeated in my data?

How many unique objects do I have in my set?

How similar are two datasets?

## Bonus Slides (Taking it one step further...)

Bottom-k minhash has low accuracy if the cardinality of sets are skewed


Ondov, Brian D., Gabriel J. Starrett, Anna Sappington, Aleksandra Kostic, Sergey Koren, Christopher B. Buck, and Adam M. Phillippy. Mash Screen: High-throughput sequence containment estimation for genome discovery. Genome biology 20.1 (2019): 1-13.

K-Hash Minhash
What if instead we used $k$ different hashes and took the min each time?


## K-Partition Minhash

What if we instead took the minimum of $k$-partitions?



01
01100000

10
10110101
11010110

11
01101011

## HyperLogLog



Baker, Daniel et al. "Dashing: fast and accurate genomic distances with HyperLogLog." Genome biology 20.1 (2019): 1-12.

