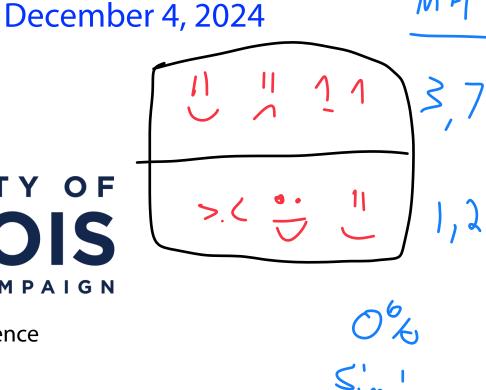
# Data Structures and Algorithms MinHash Sketch

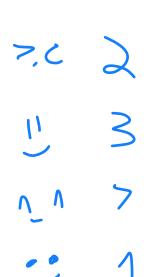
CS 225 Brad Solomon

UNIVERSITY OF

**Department of Computer Science** 

URBANA-CHAMPAIGN





# Thursday OH Time Change

Will be 10 - 10:50 AM instead of 11-12 PM

A hard time limit on OH

## Learning Objectives

Review the concept of cardinality and cardinality estimation

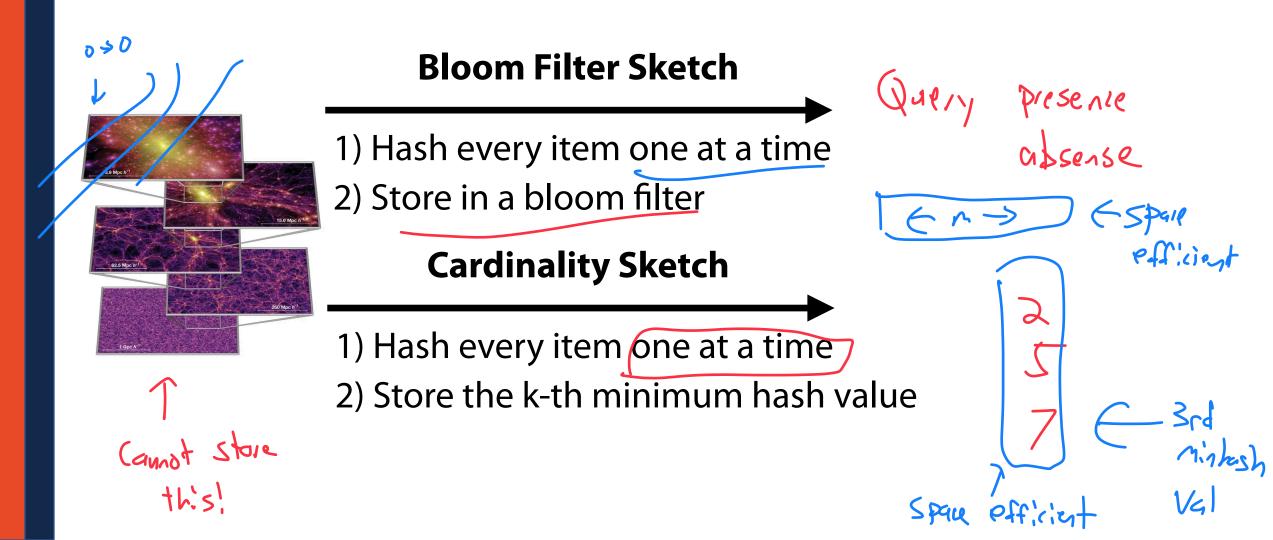
Improve our cardinality estimation approach

Demonstrate the relationship between cardinality and similarity

Introduce the MinHash Sketch for set similarity detection

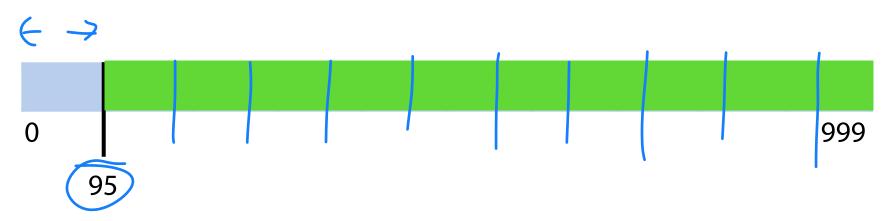
## Big Picture of Sketching

If you cant store or analyze a data collection using exact approaches...



# **Cardinality Estimation**

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



Conceptually: If we scatter N points randomly across the interval, we end up with N+1 partitions, each about 1000/(N+1) long

Assuming our first 'partition' is about average:  $95 \approx 1000/(N+1)$   $N+1 \approx 10.5$   $N \approx 9.5$ 

# Cardinality Sketch

$$\frac{1}{N+1} = \frac{\mathbf{E}[M_k]}{k}$$

$$= \left[\mathbf{E}[M_1] + (\mathbf{E}[M_2] - \mathbf{E}[M_1]) + \dots + (\mathbf{E}[M_k] - \mathbf{E}[M_{k-1}])\right] \cdot \frac{1}{k}$$

$$0$$

$$M_1 M_2 M_3 \dots M_{k-1} M_k$$

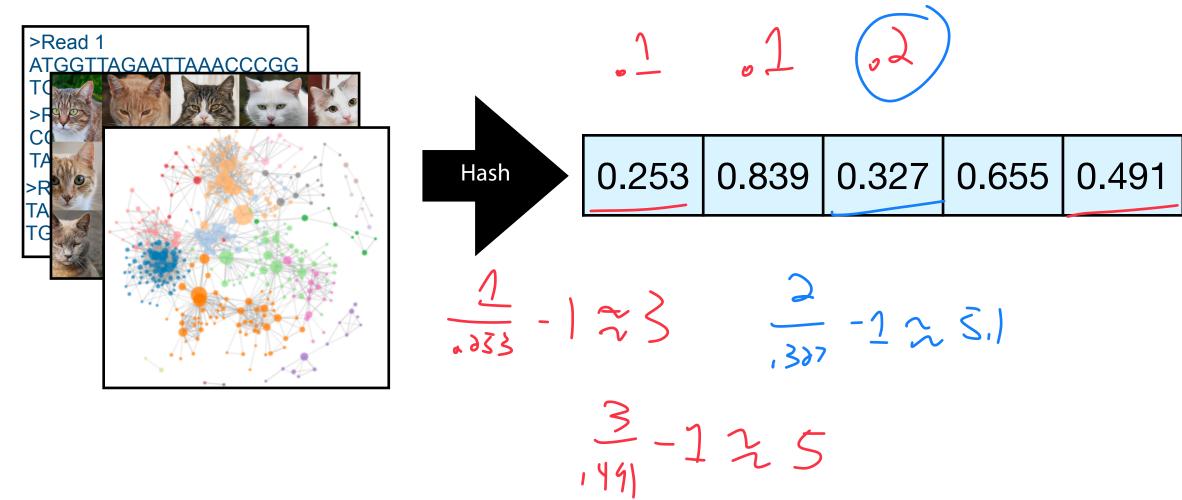
10 - 55

 $k^{th}$  minimum value (KMV)

Averages k estimates for  $\frac{1}{N+1}$ 

# **Cardinality Sketch**

Given any dataset and a SUHA hash function, we can **estimate the number of unique items** by tracking the **k-th minimum hash value**.



# **Applied Cardinalities**

#### Cardinalities

$$|A|$$

$$|B|$$

$$|A \cup B|$$

$$|A \cap B|$$

#### Set similarities

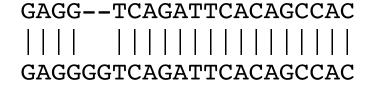
$$O = \frac{|A \cap B|}{min(|A|, |B|)}$$

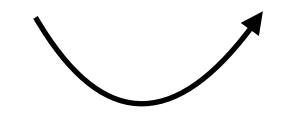
$$\mathcal{J} = \frac{|A \cap B|}{|A \cup B|}$$

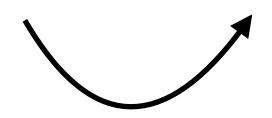
## Real-world Meaning



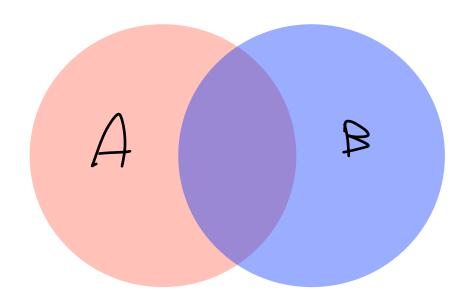


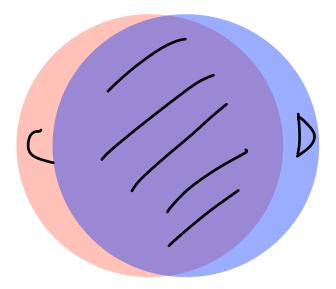




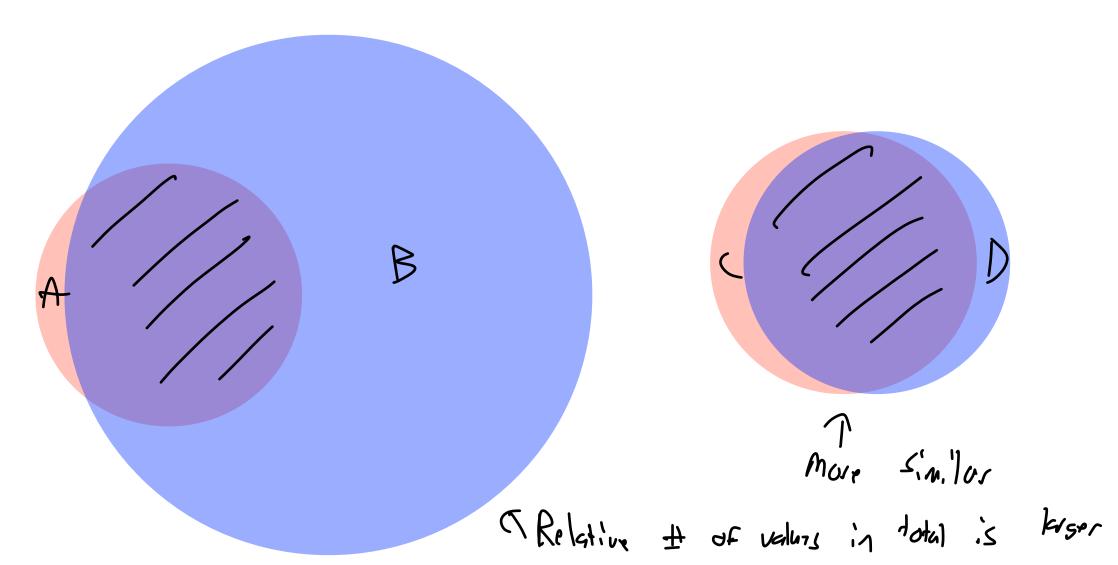


How can we describe how *similar* two sets are?

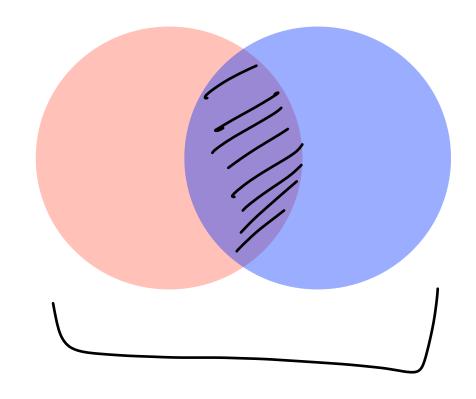




How can we describe how *similar* two sets are?



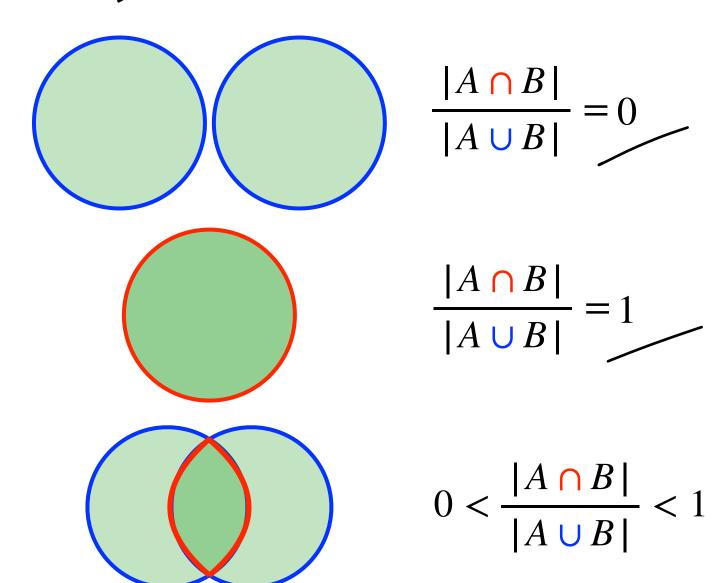
To measure **similarity** of A & B, we need both a measure of how similar the sets are but also the total size of both sets.



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

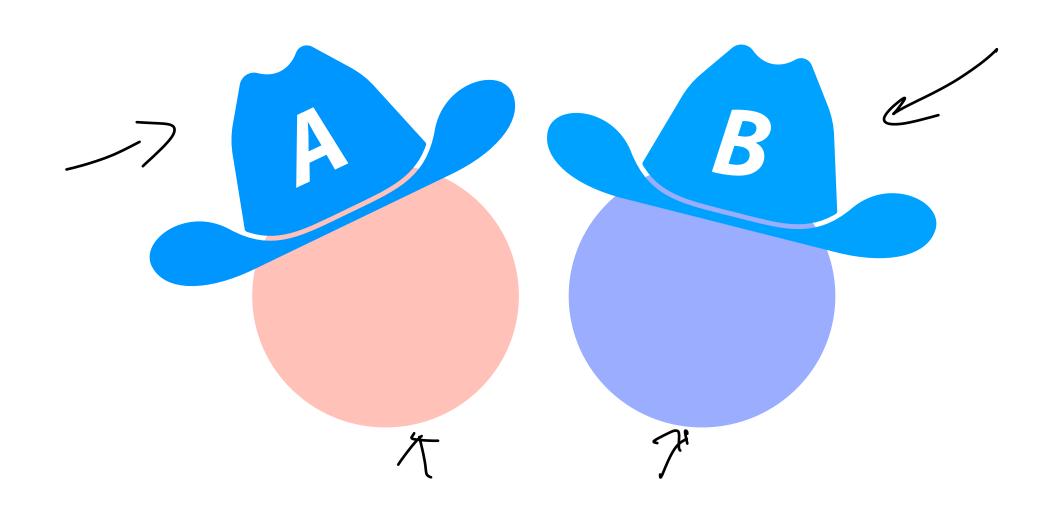
J is the **Jaccard coefficient** 





# Similarity Sketches

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



## Similarity Sketches

Imagine we have two datasets represented by their kth minimum values

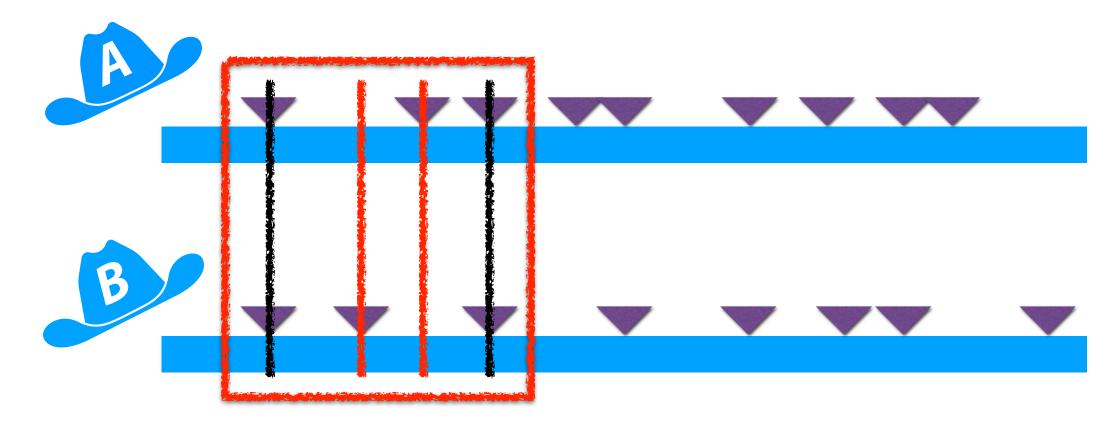


Image inspired by: Ondov B, Starrett G, Sappington A, Kostic A, Koren S, Buck CB, Phillippy AM. **Mash Screen:** high-throughput sequence containment estimation for genome discovery. *Genome Biol* 20, 232 (2019)

## Similarity Sketches

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

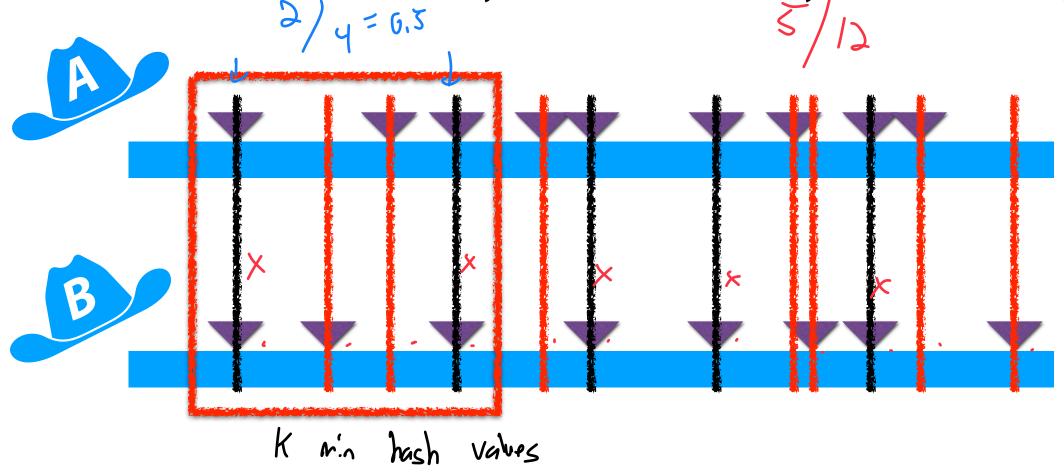
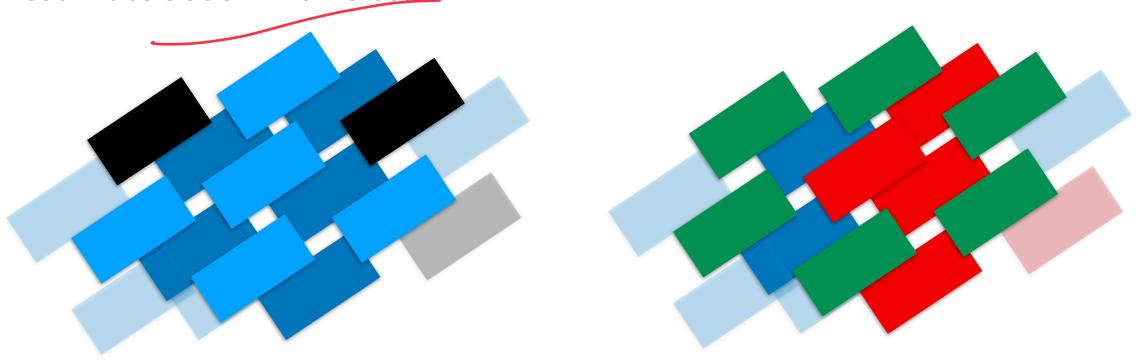


Image inspired by: Ondov B, Starrett G, Sappington A, Kostic A, Koren S, Buck CB, Phillippy AM. **Mash Screen:** high-throughput sequence containment estimation for genome discovery. *Genome Biol* 20, 232 (2019)

#### MinHash Sketch

The **k-th minimum value sketch** is built by tracking k minima but only uses one value (the k-th minima) to get **cardinality!** 

We can extend this approach into a full **MinHash sketch** that can also estimate **set similarities**.

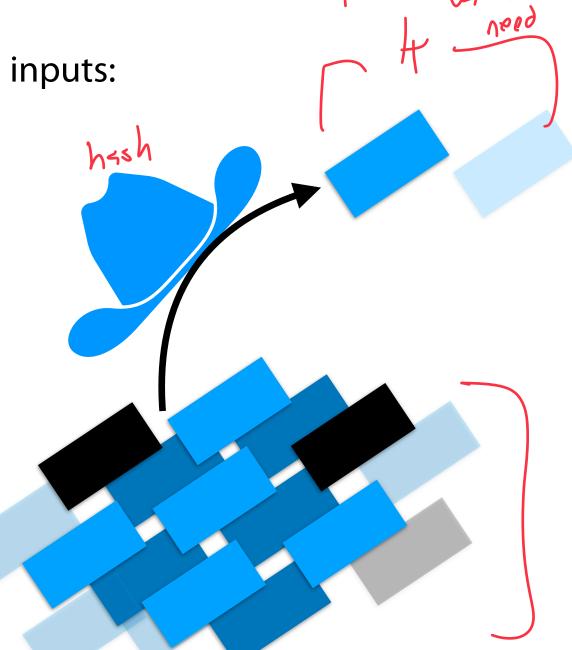


## **MinHash Construction**

A MinHash sketch has three required inputs:

1. A hashable dataset

- 2. A hash function with sis hard!
- 3. The Size of K



## MinHash Construction



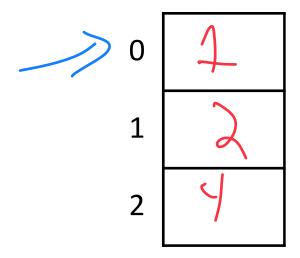
$$S = \{ 16, 8, 4, 13, 15 \}$$

$$h(x) = x \% 7$$

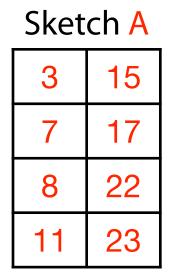
$$k = 3$$

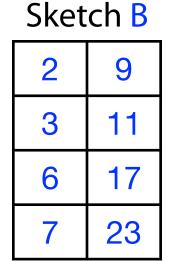
#### Algorithm is trivial:

- 1. Hash each item
- 2. Keep the k-minimum values in memory (Ignore collisions / duplicates)



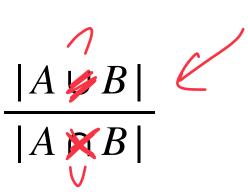
Given sets A and B sampled uniformly from [0, 100], store the bottom-8 **MinHash:** 







We want to estimate the Jaccard Coefficient:  $\frac{|A \triangleright B|}{|A| \cdot |A|}$ 



	^
ketch	Δ
NCLLII	$\overline{}$

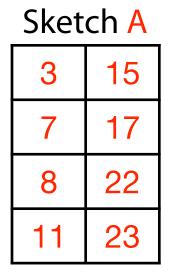
3	15
7	17
8	22
11	23

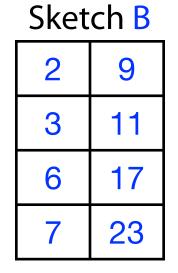
Sketch B

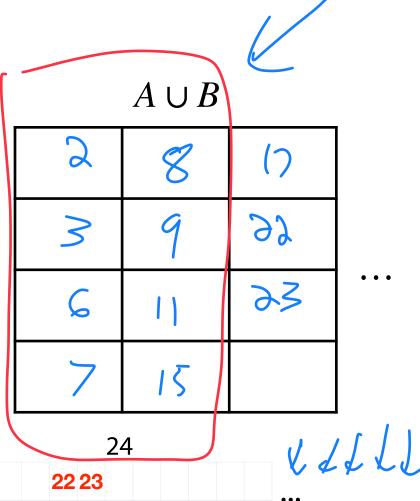
2	9
3	11
6	17
7	23

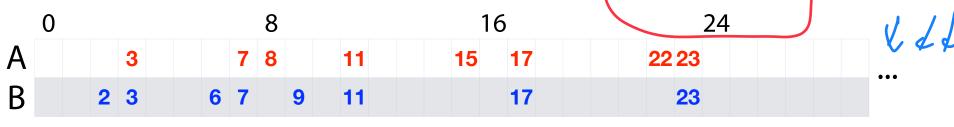


What do we know about  $A \cup B$ ?

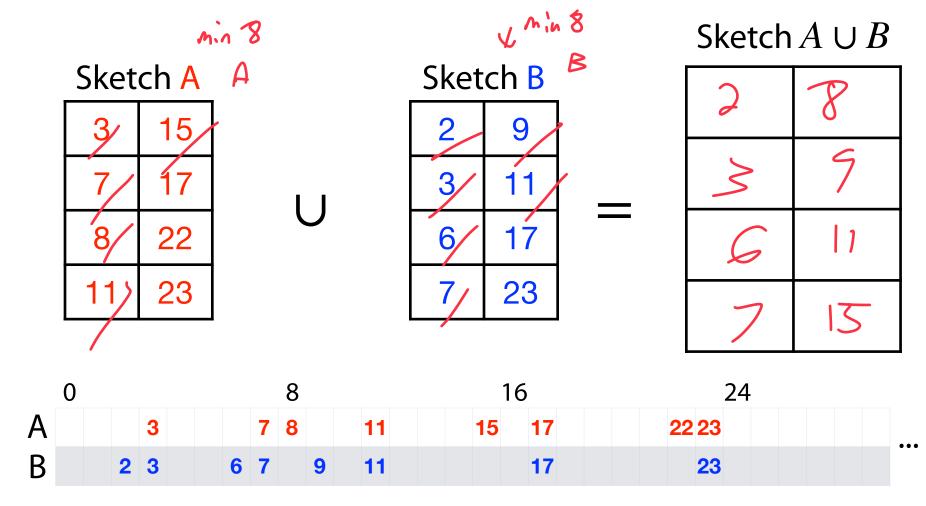








#### We dont $know A \cup B$ , but we can make a sketch!





#### Estimate $|A \cup B|$ (the cardinality of the union) from sketch:

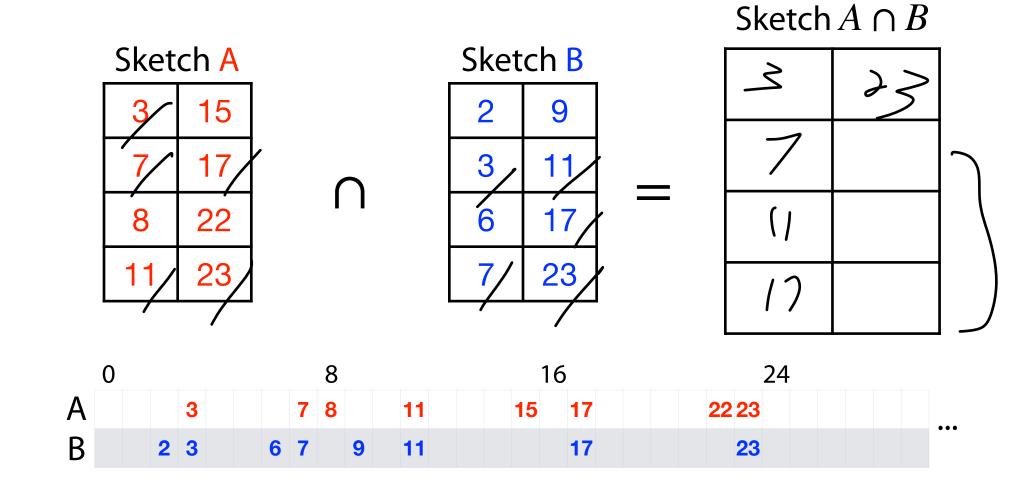
Sketch  $A \cup B$ 

2839611715

Our sets sampled from [0, 100].

$$\frac{15}{100} = \frac{8}{141} \rightarrow N = \frac{800}{15} - 1 = 50.3$$

Can we build a 8-Minhash of  $A \cap B$ ?



Not guaranteed to be able to get a full sketch of the intersection!

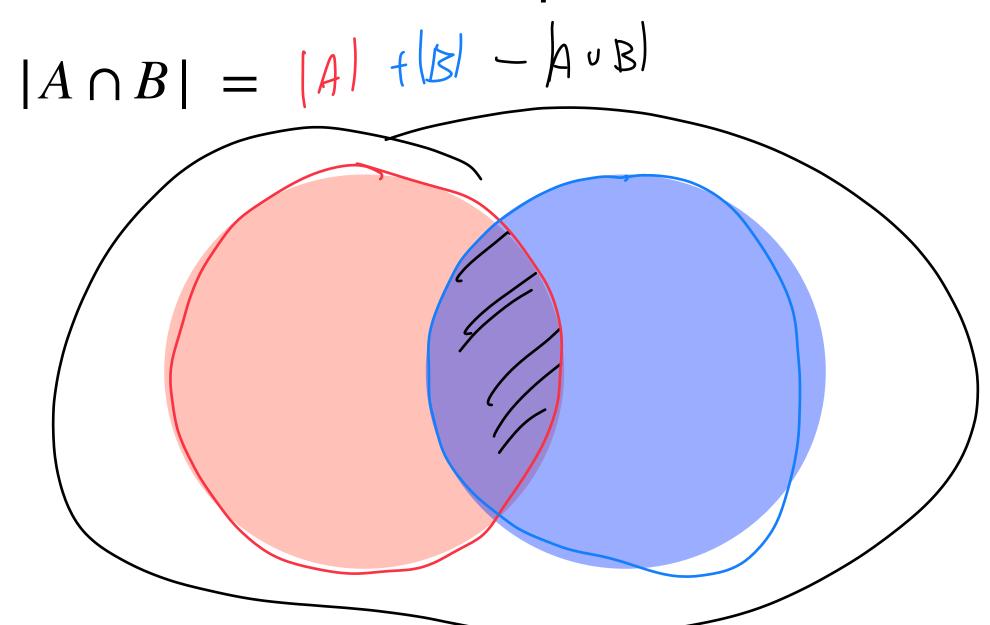
·	Sket	ch A		Sket	ch B	S	ketch	$A \cap$
	က	15		2	9		3	23
	7	17		3	11	<u> </u>	7	
	8	22	1 1	6	17	_	11	
	11	23		7	23		17	



Using MinHash sketches, we can estimate |A|, |B|, and  $|A \cup B|$ 

Is this enough to estimate the Jaccard?

## Inclusion-Exclusion Principle



## MinHash Indirect Jaccard Estimation

Sketch of

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

k = 8 MinHash sketches Our sets sampled from [0, 100]

					SKEU	
Sketch A		_	Sketch B		$ 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	4		1	7	1
$\sim$ :	35				~ -	53

$$= \frac{(800/23-1) + (800/23-1) - (800/15-1)}{800/15-1}$$

$$= \frac{34.782 + 34.782 - 53.333 - 1}{53.333 - 1} \approx 0.29$$

#### MinHash Direct Jaccard Estimate

We can also estimate cardinality directly using our sketches!

Sketch A

Site territ		
3 15		
7	17	
8	22	
11	23	

Sketch B

2	9
3	11
6	17
7	23

Intersection

M	23
7	
1/	
17	

Union

2	WO	17
M	5	9)
Ç	17	73
7	15	

Good (andom sub-samples

</11

## MinHash Sketch



We can convert any hashable dataset into a MinHash sketch



We lose our original dataset, but we can still estimate two things:

## Alternative MinHash Sketch Approaches

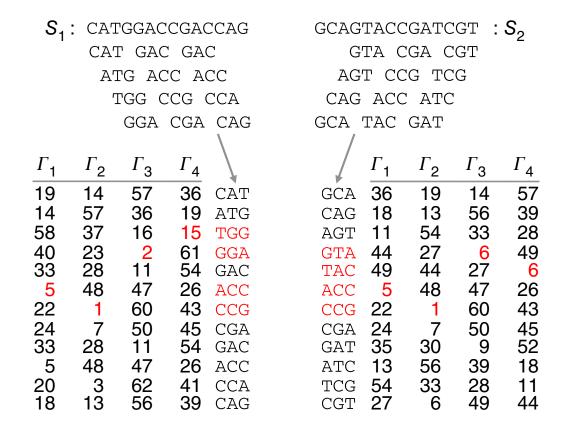
Rather than use one single hashes and take bottom-k, we can also use k hashes — if you have access to that many independent hashes!

1) Sequence decomposed into **kmers** 

S<sub>1</sub>: 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

- 1) Sequence decomposed into **kmers**
- 2) Multiple hash functions (Γ) map kmers to values.



1) Sequence decomposed into **kmers** 

2) Multiple hash functions (
$$\Gamma$$
) map kmers to values.

3) The smallest values for each hash function is chosen

$$\left[ \frac{5}{5}, \frac{1}{1}, 6, 6 \right]$$
  
Sketch  $\left( S_2 \right)$ 

57

39

28

49 6

26

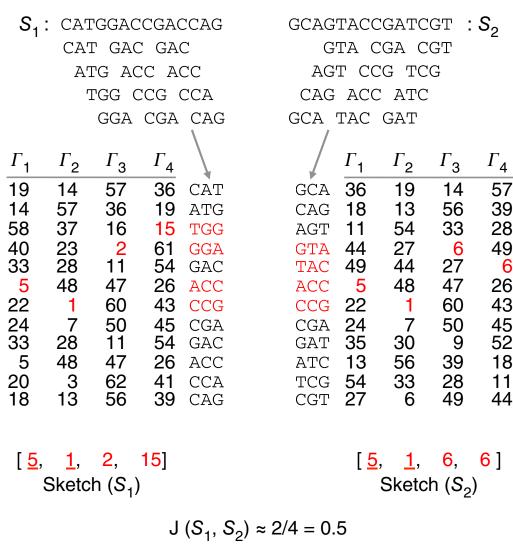
45 52

18

11

- 1) Sequence decomposed into **kmers**
- 2) Multiple hash functions (Γ) map kmers to values.

- 3) The smallest values for each hash function is chosen
- 4) The Jaccard similarity can be estimated by the overlap in the **Min**imum **Hash**es (**MinHash**)



$$J(S_1, S_2) \approx 2/4 = 0.5$$

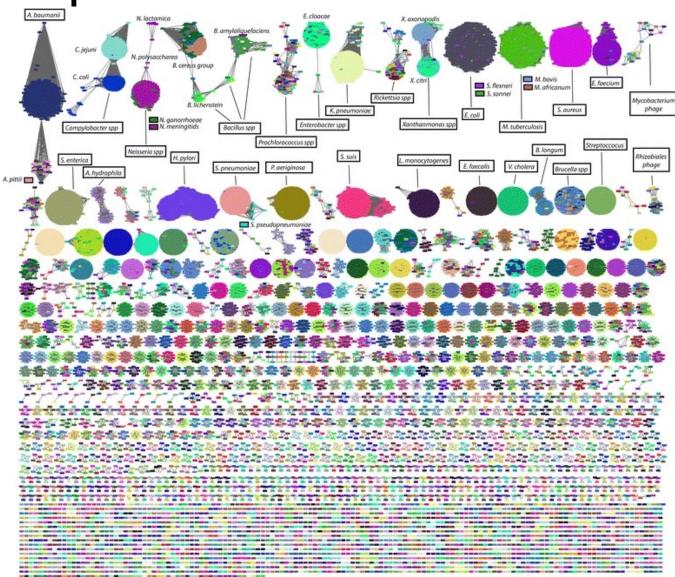
$$S_1: CATGGACCGACCAG$$

$$| | | | | | |$$

$$S_2: GCAGTACCGATCGT$$

Assembling large genomes with single-molecule sequencing and locality-sensitive hashing Berlin et al (2015) *Nature Biotechnology* 

MinHash in practice



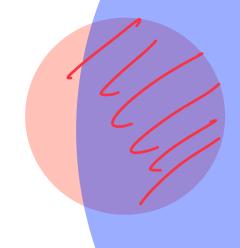
Microbiel Genes

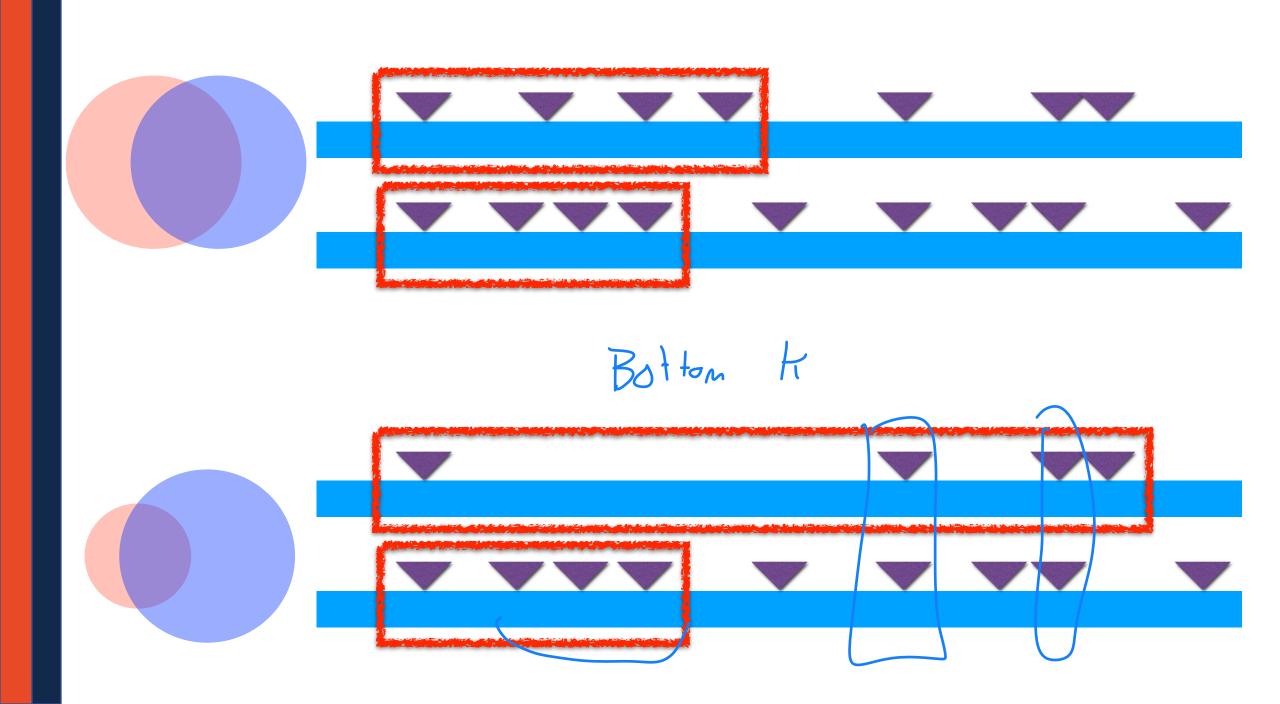
Mash: fast genome and metagenome distance estimation using MinHash Ondov et al (2016) *Genome Biology* 

## Alternative MinHash Sketch Approaches

What if I have a dataset which is **much** larger than another?

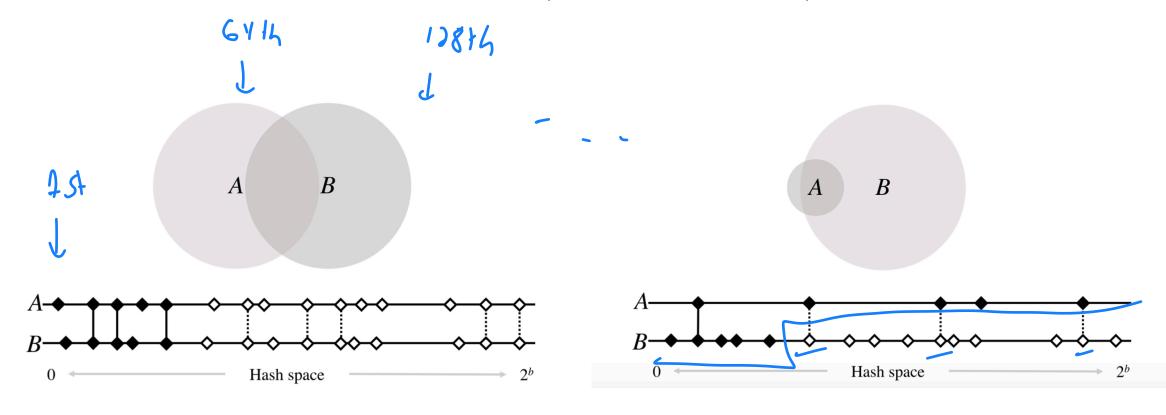
$$S_1 = \{1, 3, 40, 59, 82, 101\}$$
 $S_2 = \{1, 2, 3, 4, 5, 6, 7, ..., 59, 82, 101\} ...\}$ 
 $K = \{5\}$ 
 $S_1 = \{1, 3, 40, 59, 82, 101\}$ 
 $S_2 = \{1, 2, 3, 4, 5, 6, 7, ..., 59, 82, 101\}$ 
 $S_3 = \{1, 2, 3, 4, 5, 6, 7, ..., 59, 82, 101\}$ 
 $S_4 = \{1, 3, 40, 59, 82, 101\}$ 
 $S_4 = \{1, 3, 40, 59, 82, 101\}$ 
 $S_4 = \{1, 3, 40, 59, 82, 101\}$ 
 $S_4 = \{1, 2, 3, 4, 5, 6, 7, ..., 59, 82, 101\}$ 





#### Alternative MinHash sketches

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

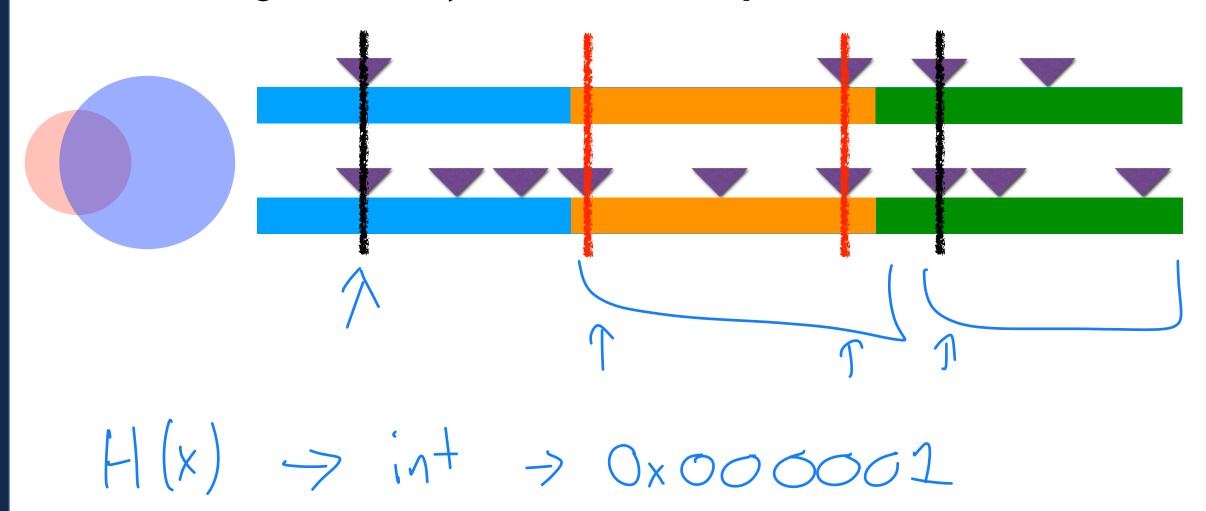


Ondov, Brian D., Gabriel J. Starrett, Anna Sappington, Aleksandra Kostic, Sergey Koren, Christopher B. Buck, and Adam M. Phillippy. **Mash Screen: High-throughput sequence containment estimation for genome discovery**. *Genome biology* 20.1 (2019): 1-13.



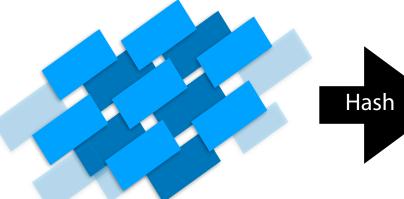
## Alternative MinHash Sketch Approaches

If there is a large cardinality difference, use k-partitions!

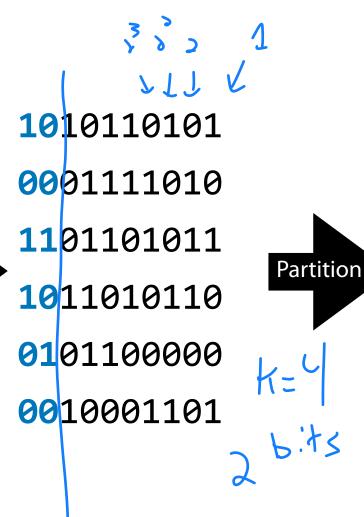


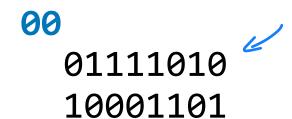
### K-Partition Minhash

by This only works it actually uniform dist









01100000

### Probabilistic Data Structures



Probabilistic data structures trade accuracy for efficiency

Most can maintain surprisingly good accuracy

"Cheat" Big O limitations on conventional data analysis

SEX pectation under SUNA