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Finding Similar Items: Locality Sensitive Hashing

Mining of Massive Datasets

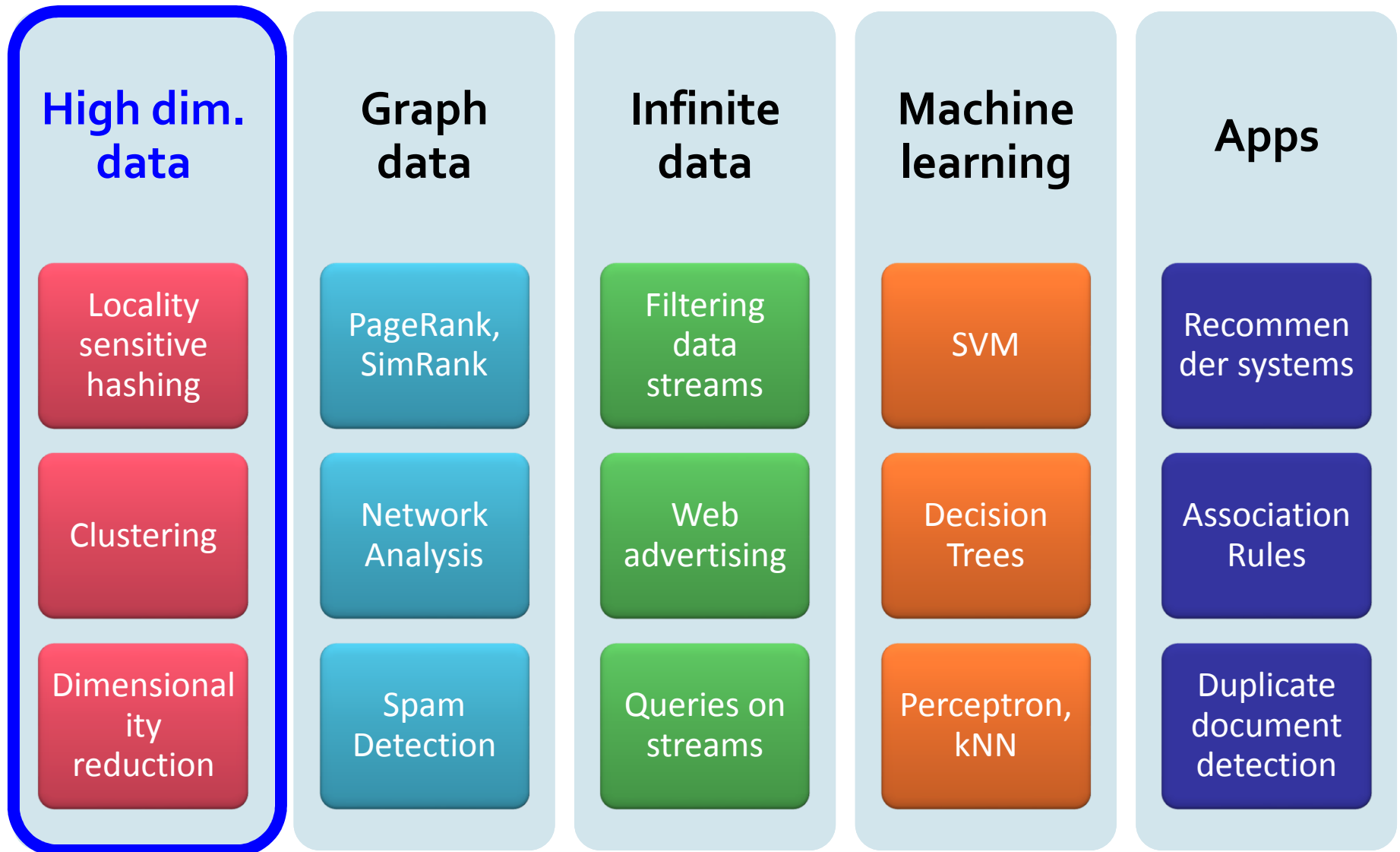
Jure Leskovec, Anand Rajaraman, Jeff Ullman

Stanford University

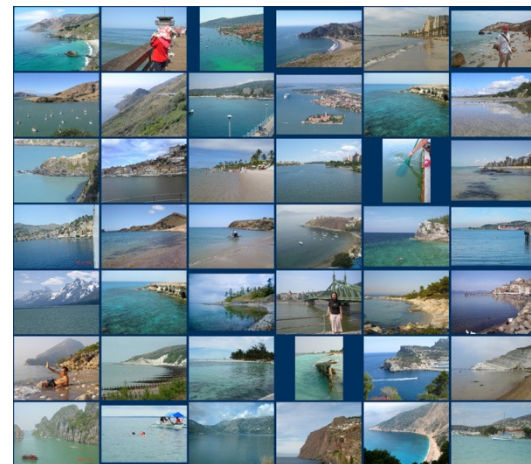
<http://www.mmds.org>



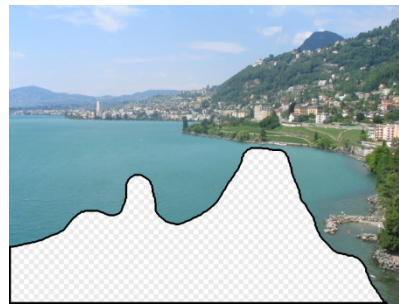
New thread: High dim. data



Scene Completion Problem



Scene Completion Problem

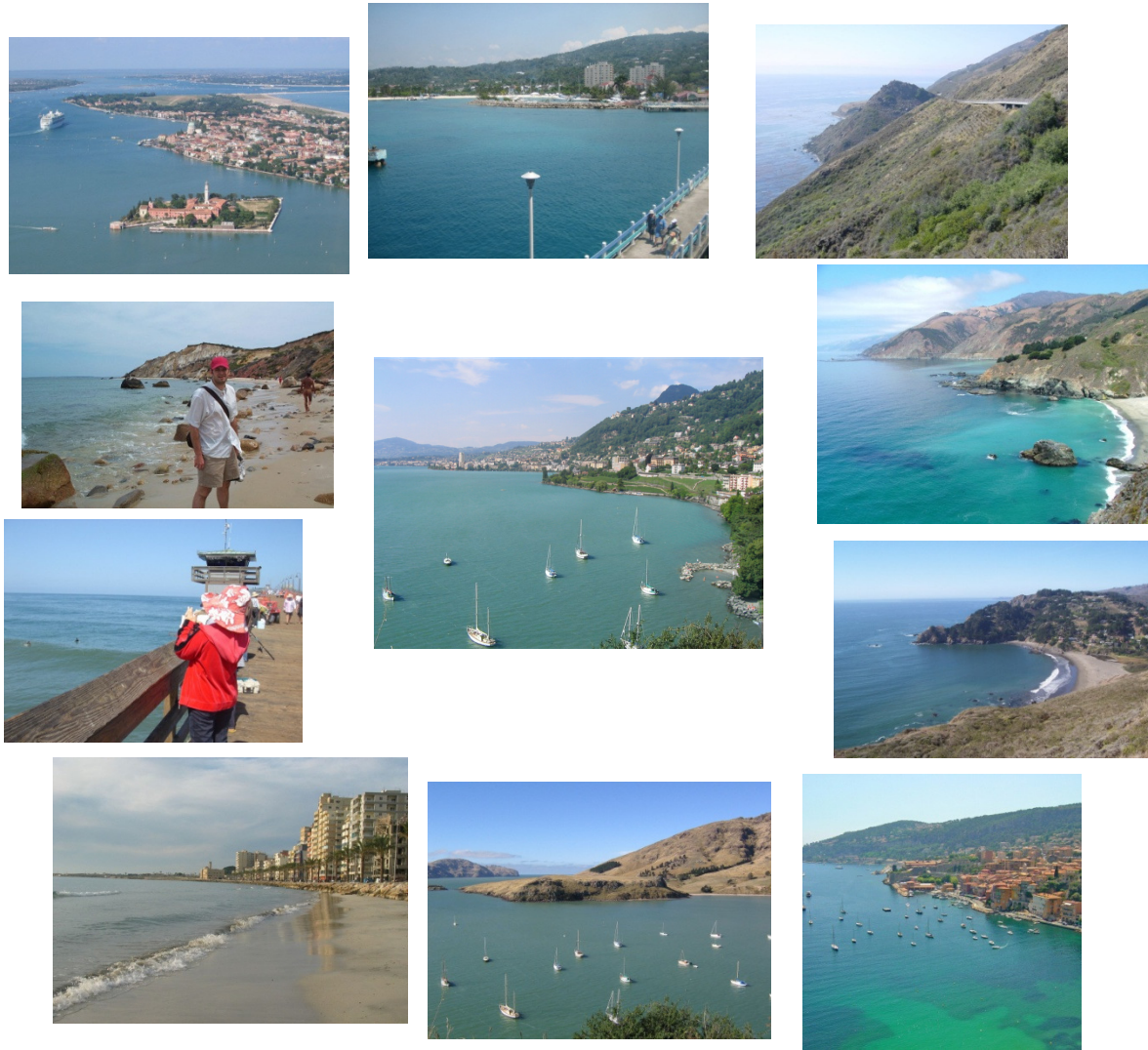


Scene Completion Problem



10 nearest neighbors from a collection of 20,000 images

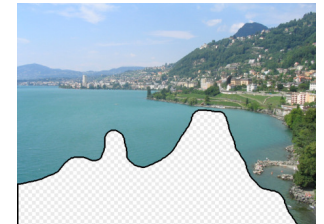
Scene Completion Problem



10 nearest neighbors from a collection of 2 million images

A Common Metaphor

- Many problems can be expressed as finding “similar” sets:
 - Find near-neighbors in high-dimensional space
- **Examples:**
 - Pages with similar words
 - For duplicate detection, classification by topic
 - Customers who purchased similar products
 - Products with similar customer sets
 - Images with similar features
 - Users who visited similar websites



Problem for Today's Lecture

- **Given: High dimensional data points x_1, x_2, \dots**

- **For example:** Image is a long vector of pixel colors

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 2 & 1 \\ 0 & 1 & 0 \end{bmatrix} \rightarrow [1 \ 2 \ 1 \ 0 \ 2 \ 1 \ 0 \ 1 \ 0]$$

- **And some distance function $d(x_1, x_2)$**

- Which quantifies the “distance” between x_1 and x_2

- **Goal:** Find **all pairs of data points (x_i, x_j)** that are within some distance threshold $d(x_i, x_j) \leq s$

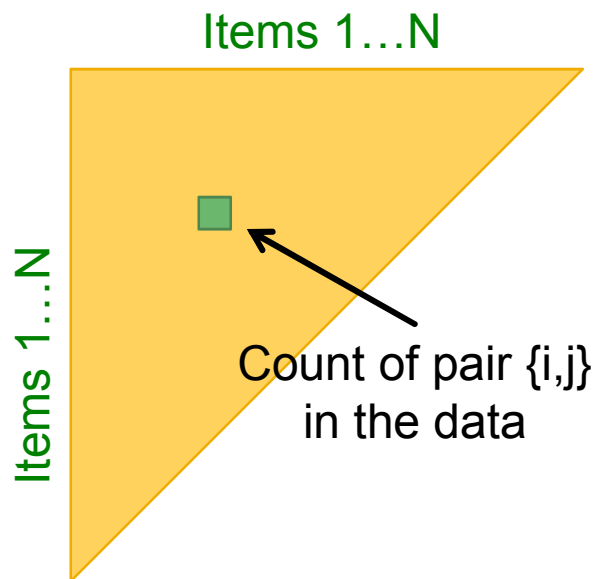
- **Note:** Naïve solution would take $O(N^2)$ ☹

where N is the number of data points

- **MAGIC: This can be done in $O(N)$!! How?**

Relation to Previous Lecture

- **Last time:** Finding frequent pairs

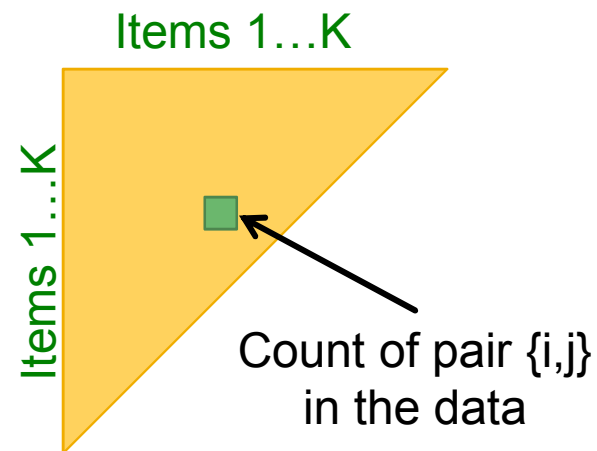


Naïve solution:

Single pass but requires space quadratic in the number of items

N ... number of distinct items

K ... number of items with support $\geq s$



A-Priori:

First pass: Find frequent singletons

For a pair to be a **frequent pair candidate**, its singletons have to be frequent!

Second pass:

Count only candidate pairs!

Relation to Previous Lecture

- Last time: Finding frequent pairs
- Further improvement: PCY
 - Pass 1:

- Count exact frequency of each item:



- Take pairs of items $\{i,j\}$, hash them into B buckets and count of the number of pairs that hashed to each bucket:




~~Basket 1: {1,2,3}~~

Pairs: {1,2} {1,3} {2,3}

Relation to Previous Lecture

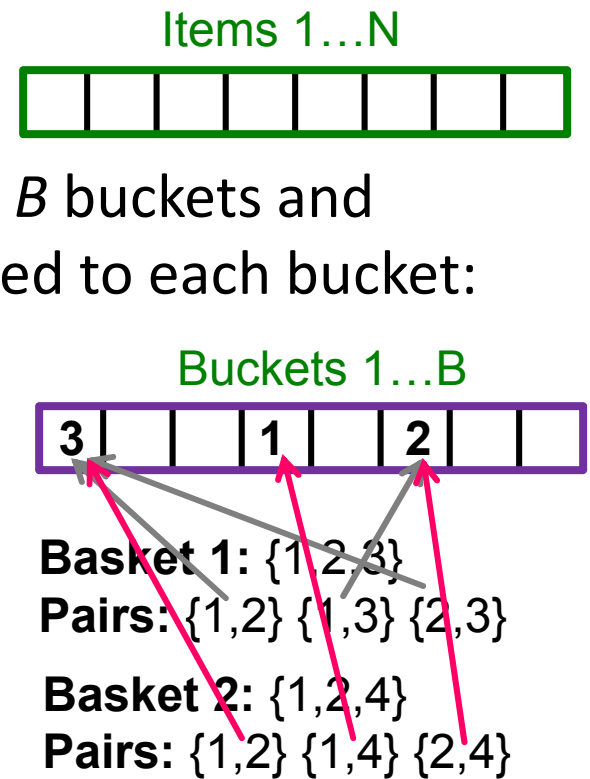
- Last time: Finding frequent pairs
- Further improvement: PCY

- Pass 1:

- Count exact frequency of each item: 
- Take pairs of items $\{i,j\}$, hash them into B buckets and count of the number of pairs that hashed to each bucket:

- Pass 2:

- For a pair $\{i,j\}$ to be a **candidate for a frequent pair**, its singletons $\{i\}$, $\{j\}$ have to be frequent and the pair has to hash to a frequent bucket!



Relation to Previous Lecture

- Last time: Finding Similar Documents

- Full **Previous lecture: A-Priori**

- **Main idea: Candidates**

- Instead of keeping a count of each pair, only keep a count of candidate pairs!

- Today's lecture: Find pairs of similar docs**

- Main idea: Candidates**

- -- **Pass 1:** Take documents and hash them to buckets such that documents that are similar hash to the same bucket

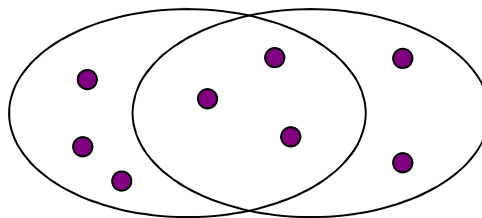
- -- **Pass 2:** Only compare documents that are **candidates** (i.e., they hashed to a same bucket)

- Benefits:** Instead of $O(N^2)$ comparisons, we need $O(N)$ comparisons to find similar documents

Finding Similar Items

Distance Measures

- **Goal: Find near-neighbors in high-dim. space**
 - We formally define “near neighbors” as points that are a “small distance” apart
- For each application, we first need to define what “**distance**” means
- **Today: Jaccard distance/similarity**
 - The **Jaccard similarity** of two **sets** is the size of their intersection divided by the size of their union:
$$\text{sim}(C_1, C_2) = |C_1 \cap C_2| / |C_1 \cup C_2|$$
 - **Jaccard distance:** $d(C_1, C_2) = 1 - |C_1 \cap C_2| / |C_1 \cup C_2|$



3 in intersection

8 in union

Jaccard similarity = 3/8

Jaccard distance = 5/8

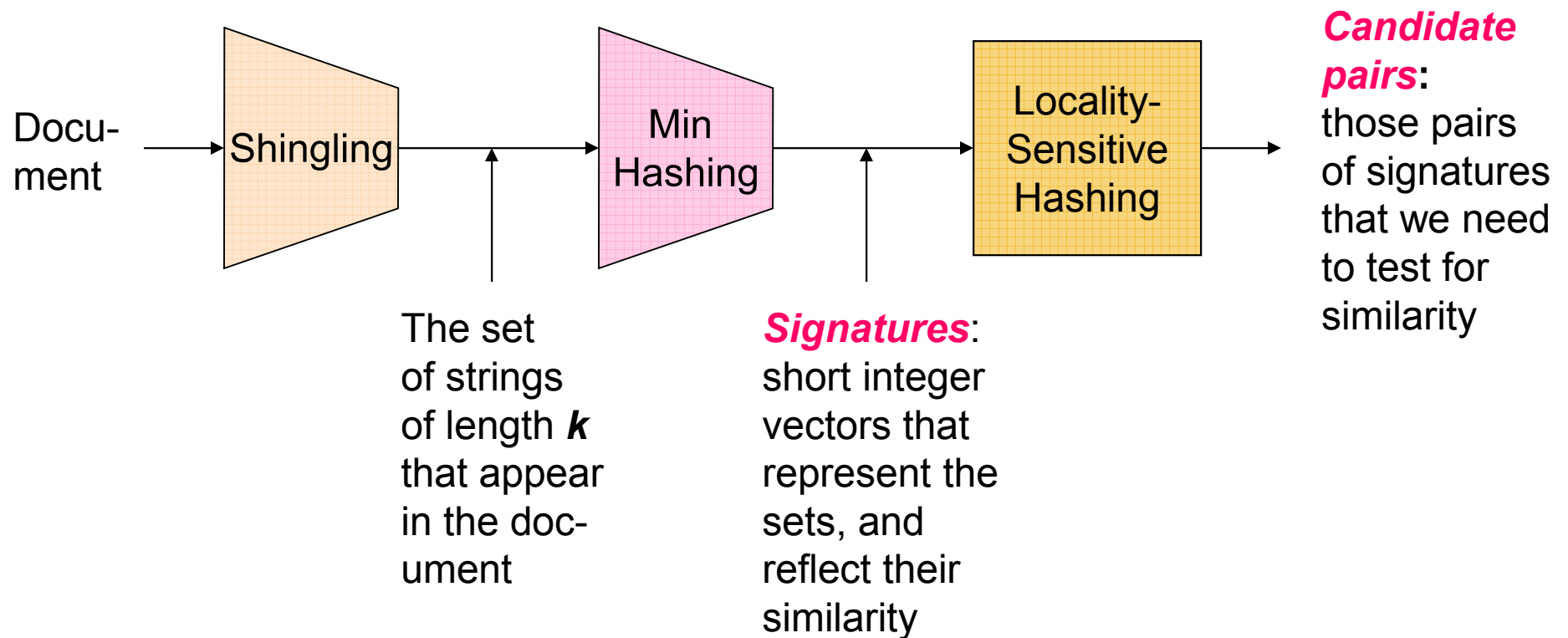
Task: Finding Similar Documents

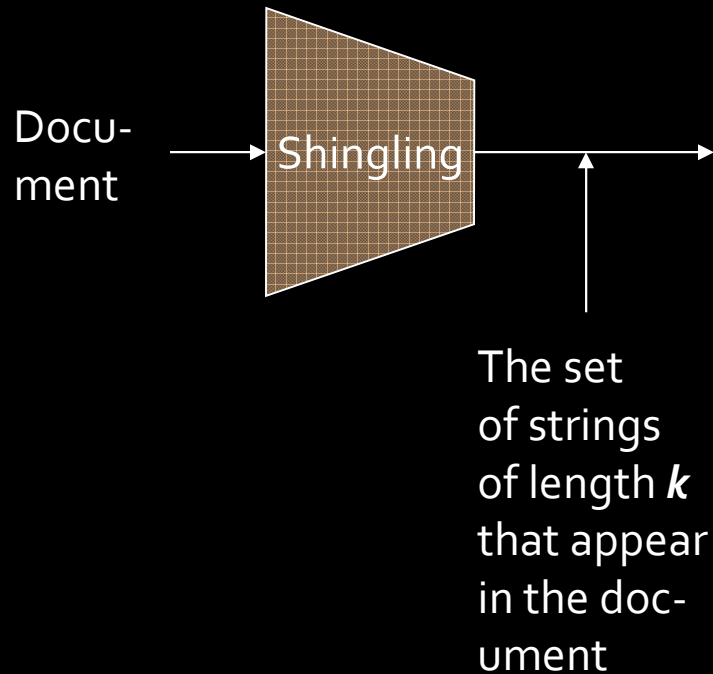
- **Goal:** Given a large number (N in the millions or billions) of documents, find “near duplicate” pairs
- **Applications:**
 - Mirror websites, or approximate mirrors
 - Don’t want to show both in search results
 - Similar news articles at many news sites
 - Cluster articles by “same story”
- **Problems:**
 - Many small pieces of one document can appear out of order in another
 - Too many documents to compare all pairs
 - Documents are so large or so many that they cannot fit in main memory

3 Essential Steps for Similar Docs

1. **Shingling:** Convert documents to sets
2. **Min-Hashing:** Convert large sets to short signatures, while preserving similarity
3. **Locality-Sensitive Hashing:** Focus on pairs of signatures likely to be from similar documents
 - **Candidate pairs!**

The Big Picture





Shingling

Step 1: *Shingling*: Convert documents to sets

Documents as High-Dim Data

- **Step 1: *Shingling*: Convert documents to sets**
- **Simple approaches:**
 - Document = set of words appearing in document
 - Document = set of “important” words
 - Don’t work well for this application. *Why?*
- **Need to account for ordering of words!**
- A different way: ***Shingles!***

Define: Shingles

- A ***k*-shingle** (or ***k*-gram**) for a document is a sequence of k tokens that appears in the doc
 - Tokens can be **characters**, **words** or something else, depending on the application
 - Assume tokens = characters for examples
- **Example:** $k=2$; document $D_1 = \text{abcab}$
Set of 2-shingles: $S(D_1) = \{\text{ab}, \text{bc}, \text{ca}\}$
 - **Option:** Shingles as a bag (multiset), count ab twice: $S'(D_1) = \{\text{ab}, \text{bc}, \text{ca}, \text{ab}\}$

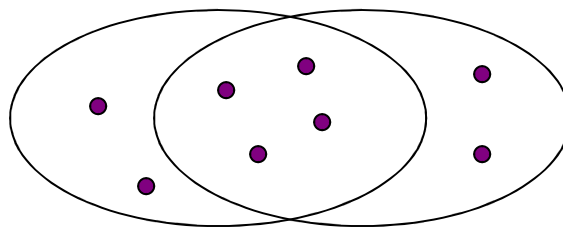
Compressing Shingles

- To **compress long shingles**, we can **hash** them to (say) 4 bytes
- **Represent a document by the set of hash values of its k -shingles**
 - **Idea:** Two documents could (rarely) appear to have shingles in common, when in fact only the hash-values were shared
- **Example: $k=2$** ; document $D_1 = \text{abcab}$
Set of 2-shingles: $S(D_1) = \{\text{ab}, \text{bc}, \text{ca}\}$
Hash the shingles: $h(D_1) = \{1, 5, 7\}$

Similarity Metric for Shingles

- Document D_1 is a set of its k -shingles $C_1 = S(D_1)$
- Equivalently, each document is a 0/1 vector in the space of k -shingles
 - Each unique shingle is a dimension
 - Vectors are very sparse
- A natural similarity measure is the **Jaccard similarity**:

$$\text{sim}(D_1, D_2) = |C_1 \cap C_2| / |C_1 \cup C_2|$$

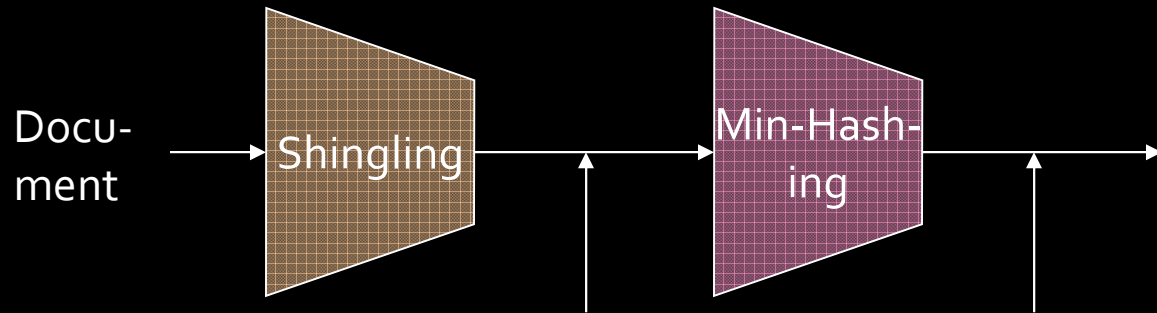


Working Assumption

- Documents that have lots of shingles in common have similar text, even if the text appears in different order
- **Caveat:** You must pick k large enough, or most documents will have most shingles
 - $k = 5$ is OK for short documents
 - $k = 10$ is better for long documents

Motivation for Minhash/LSH

- Suppose we need to find near-duplicate documents among $N = 1$ million documents
- Naïvely, we would have to compute **pairwise Jaccard similarities** for **every pair of docs**
 - $N(N - 1)/2 \approx 5 * 10^{11}$ comparisons
 - At 10^5 secs/day and 10^6 comparisons/sec, it would take **5 days**
- For $N = 10$ million, it takes more than a year...



The set of strings of length k that appear in the document

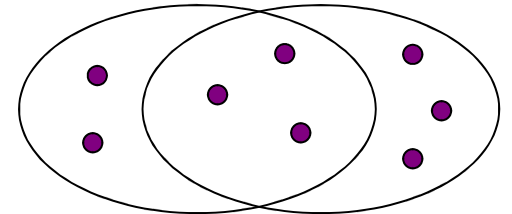
Signatures: short integer vectors that represent the sets, and reflect their similarity

MinHashing

Step 2: **Minhashing:** Convert large sets to short signatures, while preserving similarity

Encoding Sets as Bit Vectors

- Many similarity problems can be formalized as **finding subsets that have significant intersection**
- **Encode sets using 0/1 (bit, boolean) vectors**
 - One dimension per element in the universal set
- Interpret **set intersection as bitwise AND**, and **set union as bitwise OR**
- **Example:** $C_1 = 10111$; $C_2 = 10011$
 - Size of intersection = **3**; size of union = **4**,
 - **Jaccard similarity** (not distance) = **3/4**
 - **Distance:** $d(C_1, C_2) = 1 - (\text{Jaccard similarity}) = 1/4$



From Sets to Boolean Matrices

- **Rows** = elements (shingles)
- **Columns** = sets (documents)
 - 1 in row e and column s if and only if e is a member of s
 - Column similarity is the Jaccard similarity of the corresponding sets (rows with value 1)
 - **Typical matrix is sparse!**
- **Each document is a column:**
 - **Example:** $\text{sim}(C_1, C_2) = ?$
 - Size of intersection = 3; size of union = 6, Jaccard similarity (not distance) = $3/6$
 - $d(C_1, C_2) = 1 - (\text{Jaccard similarity}) = 3/6$

	Documents			
Shingles	1	1	1	0
	1	1	0	1
	0	1	0	1
	0	0	0	1
	1	0	0	1
	1	1	1	0
	1	0	1	0

Outline: Finding Similar Columns

- **So far:**
 - Documents → Sets of shingles
 - Represent sets as boolean vectors in a matrix
- **Next goal: Find similar columns while computing small signatures**
 - **Similarity of columns == similarity of signatures**

Outline: Finding Similar Columns

- **Next Goal: Find similar columns, Small signatures**
- **Naïve approach:**
 - **1) Signatures of columns:** small summaries of columns
 - **2) Examine pairs of signatures** to find similar columns
 - **Essential:** Similarities of signatures and columns are related
 - **3) Optional:** Check that columns with similar signatures are really similar
- **Warnings:**
 - Comparing all pairs may take too much time: **Job for LSH**
 - These methods can produce false negatives, and even false positives (if the optional check is not made)

Hashing Columns (Signatures)

- **Key idea:** “hash” each column C to a small *signature* $h(C)$, such that:
 - (1) $h(C)$ is small enough that the signature fits in RAM
 - (2) $sim(C_1, C_2)$ is the same as the “similarity” of signatures $h(C_1)$ and $h(C_2)$

- **Goal: Find a hash function $h(\cdot)$ such that:**
 - If $sim(C_1, C_2)$ is high, then with high prob. $h(C_1) = h(C_2)$
 - If $sim(C_1, C_2)$ is low, then with high prob. $h(C_1) \neq h(C_2)$

- **Hash docs into buckets. Expect that “most” pairs of near duplicate docs hash into the same bucket!**

Min-Hashing

- **Goal: Find a hash function $h(\cdot)$ such that:**
 - if $sim(C_1, C_2)$ is high, then with high prob. $h(C_1) = h(C_2)$
 - if $sim(C_1, C_2)$ is low, then with high prob. $h(C_1) \neq h(C_2)$
- **Clearly, the hash function depends on the similarity metric:**
 - Not all similarity metrics have a suitable hash function
- **There is a suitable hash function for the Jaccard similarity: It is called **Min-Hashing****

Min-Hashing

- Imagine the rows of the boolean matrix permuted under **random permutation** π
- Define a “**hash**” function $h_{\pi}(\mathbf{C})$ = the index of the **first** (in the permuted order π) row in which column \mathbf{C} has value **1**:

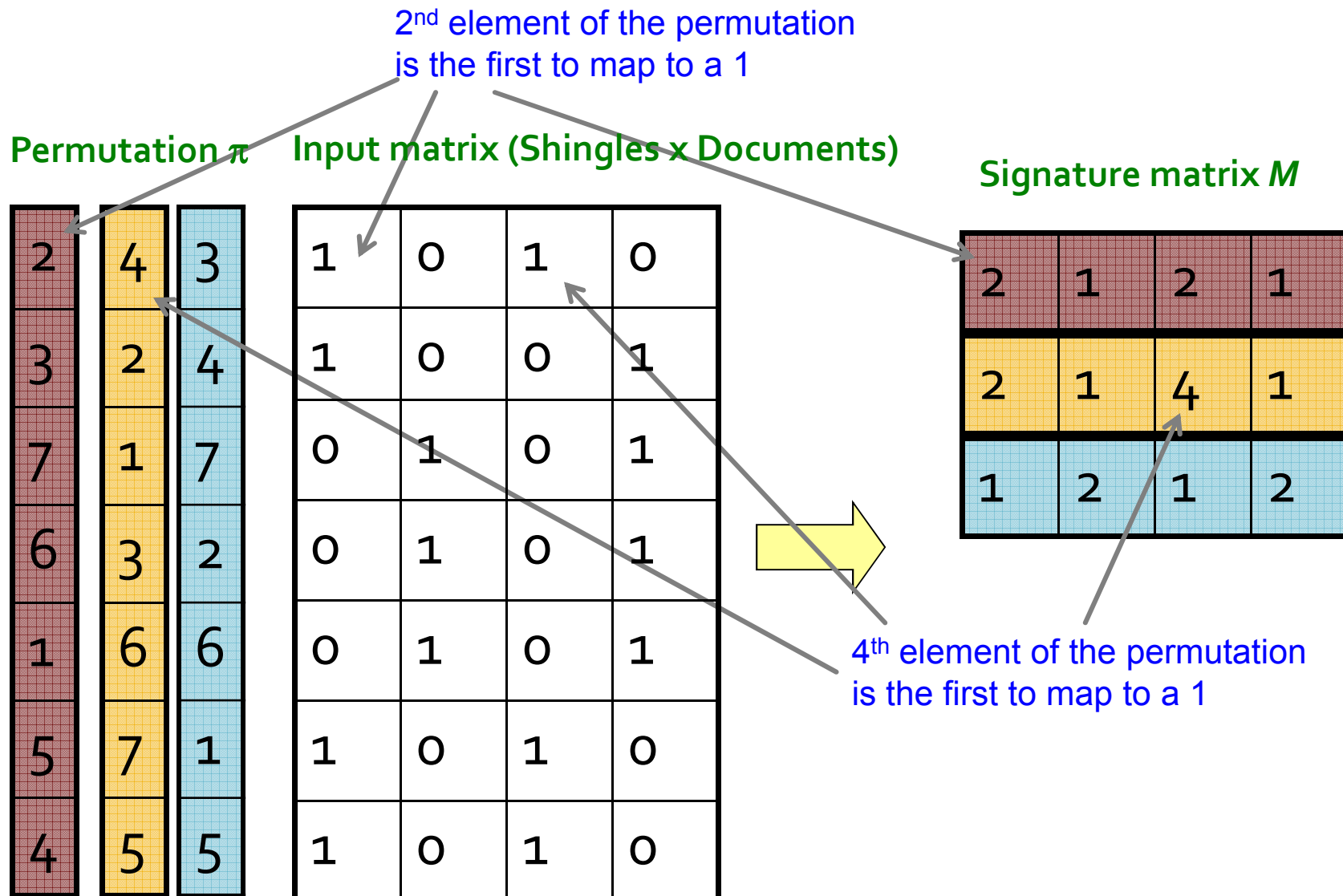
$$h_{\pi}(\mathbf{C}) = \min_{\pi} \pi(\mathbf{C})$$

- Use several (e.g., 100) independent hash functions (that is, permutations) to create a signature of a column

Min-Hashing Example

Note: Another (equivalent) way is to store row indexes:

1	5	1	5
2	3	1	3
6	4	6	4



The Min-Hash Property

0	0
0	0
1	1
0	0
0	1
1	0

- Choose a random permutation π
- Claim: $\Pr[h_\pi(C_1) = h_\pi(C_2)] = \text{sim}(C_1, C_2)$
- Why?
 - Let X be a doc (set of shingles), $y \in X$ is a shingle
 - Then: $\Pr[\pi(y) = \min(\pi(X))] = 1/|X|$
 - It is equally likely that any $y \in X$ is mapped to the *min* element
 - Let y be s.t. $\pi(y) = \min(\pi(C_1 \cup C_2))$
 - Then either: $\pi(y) = \min(\pi(C_1))$ if $y \in C_1$, or $\pi(y) = \min(\pi(C_2))$ if $y \in C_2$
 - One of the two cols had to have 1 at position y
 - So the prob. that **both** are true is the prob. $y \in C_1 \cap C_2$
 - $\Pr[\min(\pi(C_1)) = \min(\pi(C_2))] = |C_1 \cap C_2| / |C_1 \cup C_2| = \text{sim}(C_1, C_2)$

Four Types of Rows

- Given cols C_1 and C_2 , rows may be classified as:

	<u>C_1</u>	<u>C_2</u>
A	1	1
B	1	0
C	0	1
D	0	0

- a = # rows of type A, etc.
- **Note:** $\text{sim}(C_1, C_2) = a/(a + b + c)$
- **Then:** $\Pr[h(C_1) = h(C_2)] = \text{Sim}(C_1, C_2)$
 - Look down the cols C_1 and C_2 until we see a 1
 - If it's a type-A row, then $h(C_1) = h(C_2)$
If a type-B or type-C row, then not

Similarity for Signatures

- We know: $\Pr[h_{\pi}(C_1) = h_{\pi}(C_2)] = \text{sim}(C_1, C_2)$
- Now generalize to multiple hash functions
- The *similarity of two signatures* is the fraction of the hash functions in which they agree
- **Note:** Because of the Min-Hash property, the similarity of columns is the same as the expected similarity of their signatures

Min-Hashing Example

Permutation π

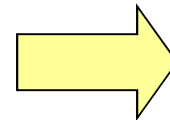
2	4	3
3	2	4
7	1	7
6	3	2
1	6	6
5	7	1
4	5	5

Input matrix (Shingles x Documents)

1	0	1	0
1	0	0	1
0	1	0	1
0	1	0	1
0	1	0	1
1	0	1	0
1	0	1	0

Signature matrix M

2	1	2	1
2	1	4	1
1	2	1	2



Similarities:

	1-3	2-4	1-2	3-4
Col/Col	0.75	0.75	0	0
Sig/Sig	0.67	1.00	0	0

Min-Hash Signatures

- **Pick $K=100$ random permutations of the rows**
- Think of $\mathit{sig}(\mathbf{C})$ as a column vector
- $\mathit{sig}(\mathbf{C})[i]$ = according to the i -th permutation, the index of the first row that has a 1 in column C
$$\mathit{sig}(\mathbf{C})[i] = \min (\pi_i(\mathbf{C}))$$
- **Note:** The sketch (signature) of document C is small **~ 100 bytes!**
- **We achieved our goal! We “compressed” long bit vectors into short signatures**

Implementation Trick

- **Permuting rows even once is prohibitive**
- **Row hashing!**
 - Pick $K = 100$ hash functions k_i
 - Ordering under k_i gives a random row permutation!
- **One-pass implementation**
 - For each column C and hash-func. k_i keep a “slot” for the min-hash value
 - Initialize all $sig(C)[i] = \infty$
 - **Scan rows looking for 1s**
 - Suppose row j has 1 in column C
 - Then for each k_i :
 - If $k_i(j) < sig(C)[i]$, then $sig(C)[i] \leftarrow k_i(j)$

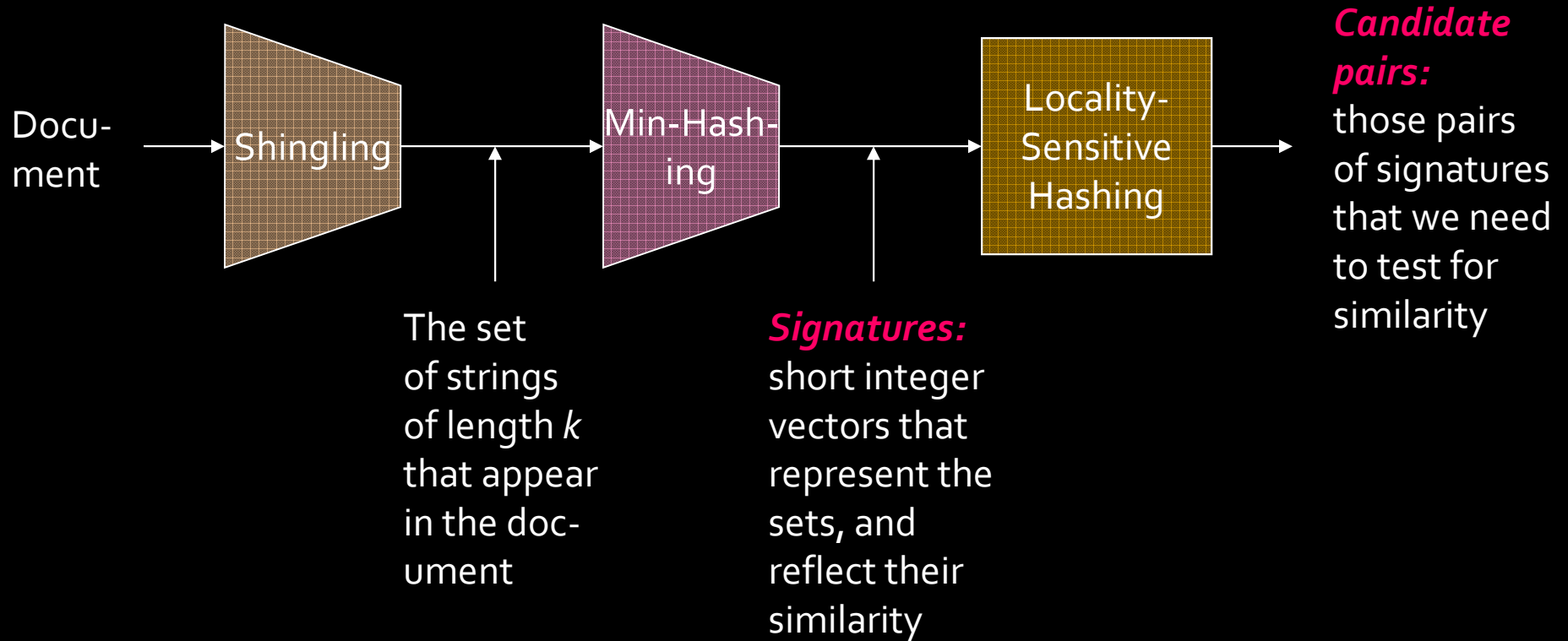
How to pick a random hash function $h(x)$?

Universal hashing:

$h_{a,b}(x) = ((a \cdot x + b) \bmod p) \bmod N$
where:

a, b ... random integers

p ... prime number ($p > N$)



Locality Sensitive Hashing

Step 3: *Locality-Sensitive Hashing:*

Focus on pairs of signatures likely to be from similar documents

LSH: First Cut

2	1	4	1
1	2	1	2
2	1	2	1

- **Goal:** Find documents with Jaccard similarity at least s (for some similarity threshold, e.g., $s=0.8$)
- **LSH – General idea:** Use a function $f(x,y)$ that tells whether x and y is a *candidate pair*: a pair of elements whose similarity must be evaluated
- **For Min-Hash matrices:**
 - Hash columns of *signature matrix* M to many buckets
 - Each pair of documents that hashes into the same bucket is a *candidate pair*

Candidates from Min-Hash

2	1	4	1
1	2	1	2
2	1	2	1

- Pick a similarity threshold s ($0 < s < 1$)
- Columns \mathbf{x} and \mathbf{y} of \mathbf{M} are a **candidate pair** if their signatures agree on at least fraction s of their rows:
 $M(i, \mathbf{x}) = M(i, \mathbf{y})$ for at least frac. s values of i
 - We expect documents \mathbf{x} and \mathbf{y} to have the same (Jaccard) similarity as their signatures

LSH for Min-Hash

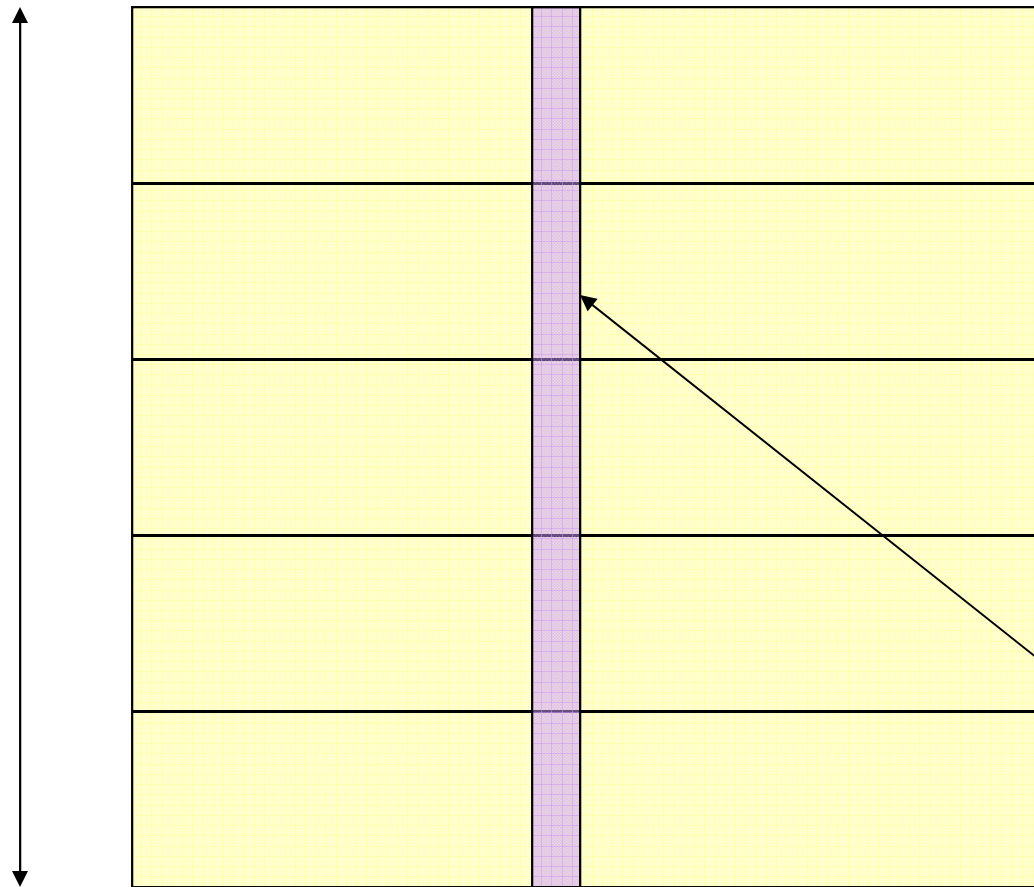
2	1	4	1
1	2	1	2
2	1	2	1

- **Big idea: Hash columns of signature matrix M several times**
- Arrange that (only) **similar columns** are likely to **hash to the same bucket**, with high probability
- **Candidate pairs are those that hash to the same bucket**

Partition M into b Bands

2	1	4	1
1	2	1	2
2	1	2	1

b bands



r rows
per band

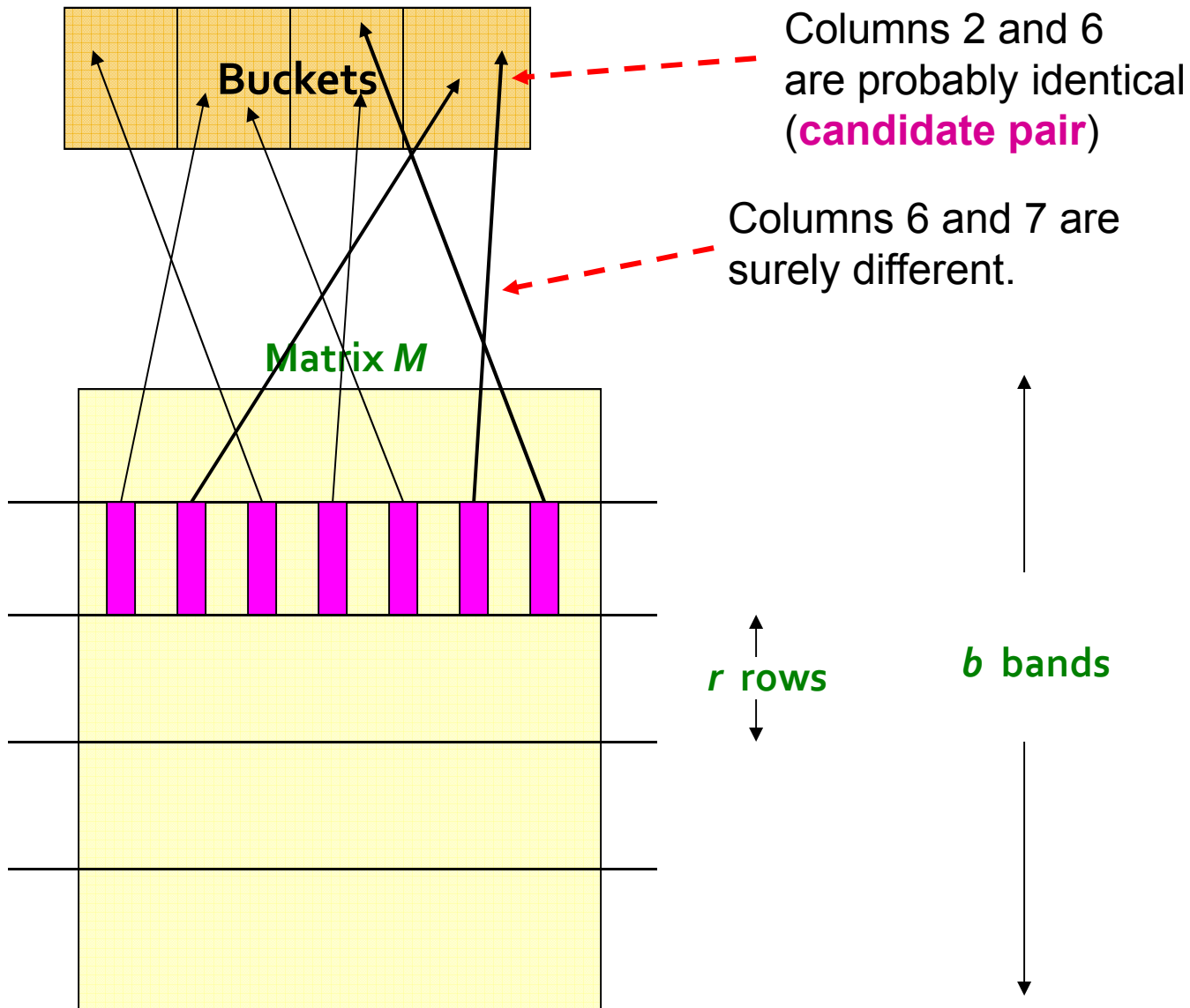
One
signature

Signature matrix M

Partition M into Bands

- Divide matrix M into b bands of r rows
- For each band, hash its portion of each column to a hash table with k buckets
 - Make k as large as possible
- **Candidate** column pairs are those that hash to the same bucket for ≥ 1 band
- Tune b and r to catch most similar pairs, but few non-similar pairs

Hashing Bands



Simplifying Assumption

- There are **enough buckets** that columns are unlikely to hash to the same bucket unless they are **identical** in a particular band
- Hereafter, we assume that “**same bucket**” means “**identical in that band**”
- Assumption needed only to simplify analysis, not for correctness of algorithm

Example of Bands

2	1	4	1
1	2	1	2
2	1	2	1

Assume the following case:

- Suppose 100,000 columns of M (100k docs)
- Signatures of 100 integers (rows)
- Therefore, signatures take 40Mb
- Choose $b = 20$ bands of $r = 5$ integers/band
- **Goal:** Find pairs of documents that are at least $s = 0.8$ similar

C_1, C_2 are 80% Similar

2	1	4	1
1	2	1	2
2	1	2	1

- Find pairs of $\geq s=0.8$ similarity, set $b=20$, $r=5$
- **Assume:** $\text{sim}(C_1, C_2) = 0.8$
 - Since $\text{sim}(C_1, C_2) \geq s$, we want C_1, C_2 to be a **candidate pair**: We want them to hash to at **least 1 common bucket** (at least one band is identical)
- **Probability C_1, C_2 identical in one particular band:** $(0.8)^5 = 0.328$
- Probability C_1, C_2 are **not** similar in all of the 20 bands: $(1-0.328)^{20} = 0.00035$
 - i.e., about 1/3000th of the 80%-similar column pairs are **false negatives** (we miss them)
 - **We would find 99.965% pairs of truly similar documents**

C_1, C_2 are 30% Similar

2	1	4	1
1	2	1	2
2	1	2	1

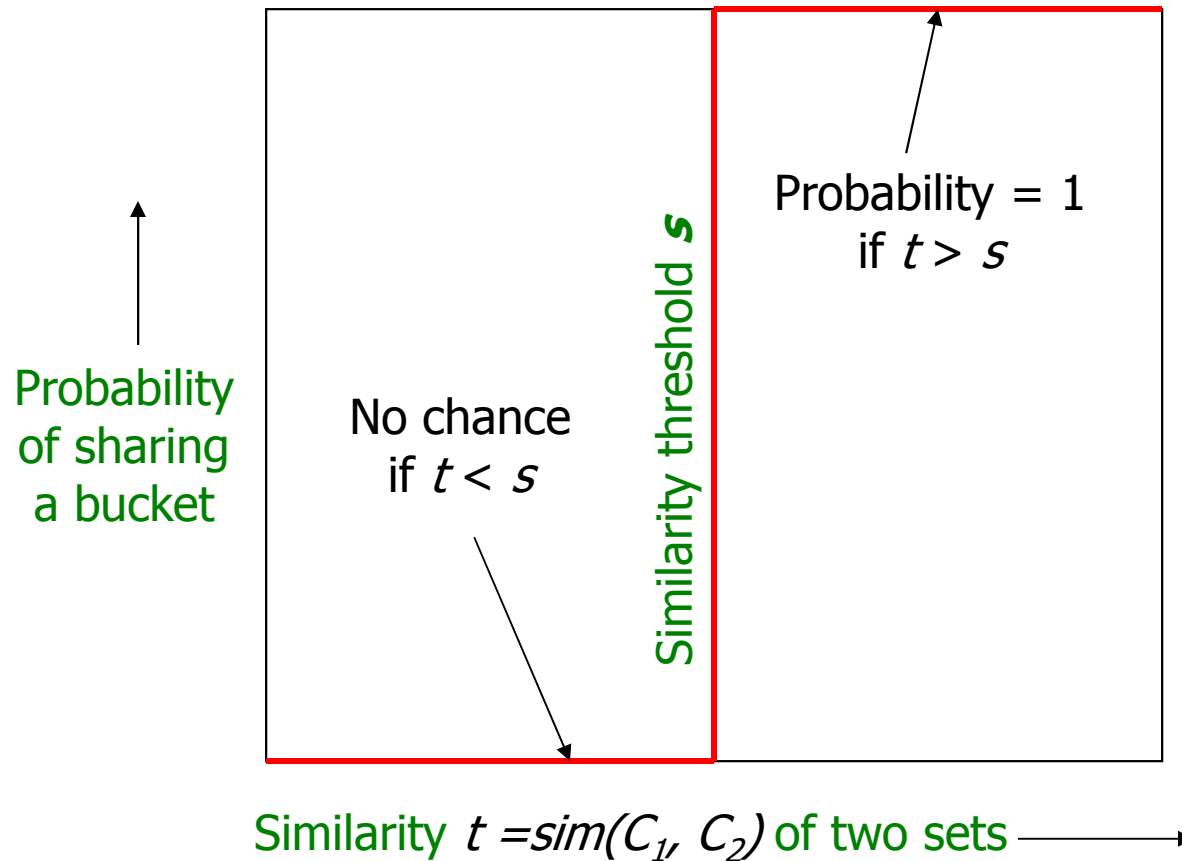
- Find pairs of $\geq s=0.8$ similarity, set $b=20, r=5$
- Assume: $\text{sim}(C_1, C_2) = 0.3$
 - Since $\text{sim}(C_1, C_2) < s$ we want C_1, C_2 to hash to **NO common buckets** (all bands should be different)
- Probability C_1, C_2 identical in one particular band: $(0.3)^5 = 0.00243$
- Probability C_1, C_2 identical in at least 1 of 20 bands: $1 - (1 - 0.00243)^{20} = 0.0474$
 - In other words, approximately 4.74% pairs of docs with similarity 0.3% end up becoming **candidate pairs**
 - They are **false positives** since we will have to examine them (they are candidate pairs) but then it will turn out their similarity is below threshold s

LSH Involves a Tradeoff

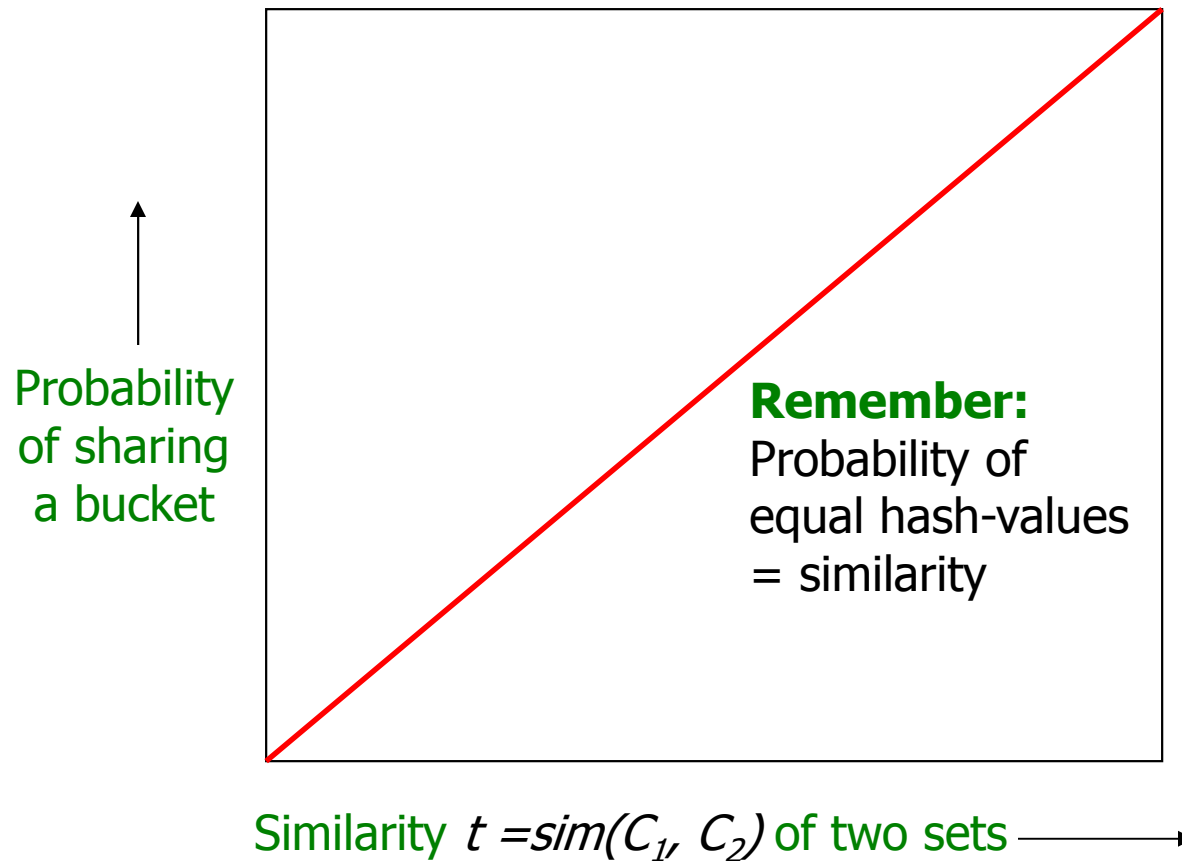
2	1	4	1
1	2	1	2
2	1	2	1

- **Pick:**
 - The number of Min-Hashes (rows of M)
 - The number of bands b , and
 - The number of rows r per band to balance false positives/negatives
- **Example:** If we had only 15 bands of 5 rows, the number of false positives would go down, but the number of false negatives would go up

Analysis of LSH – What We Want



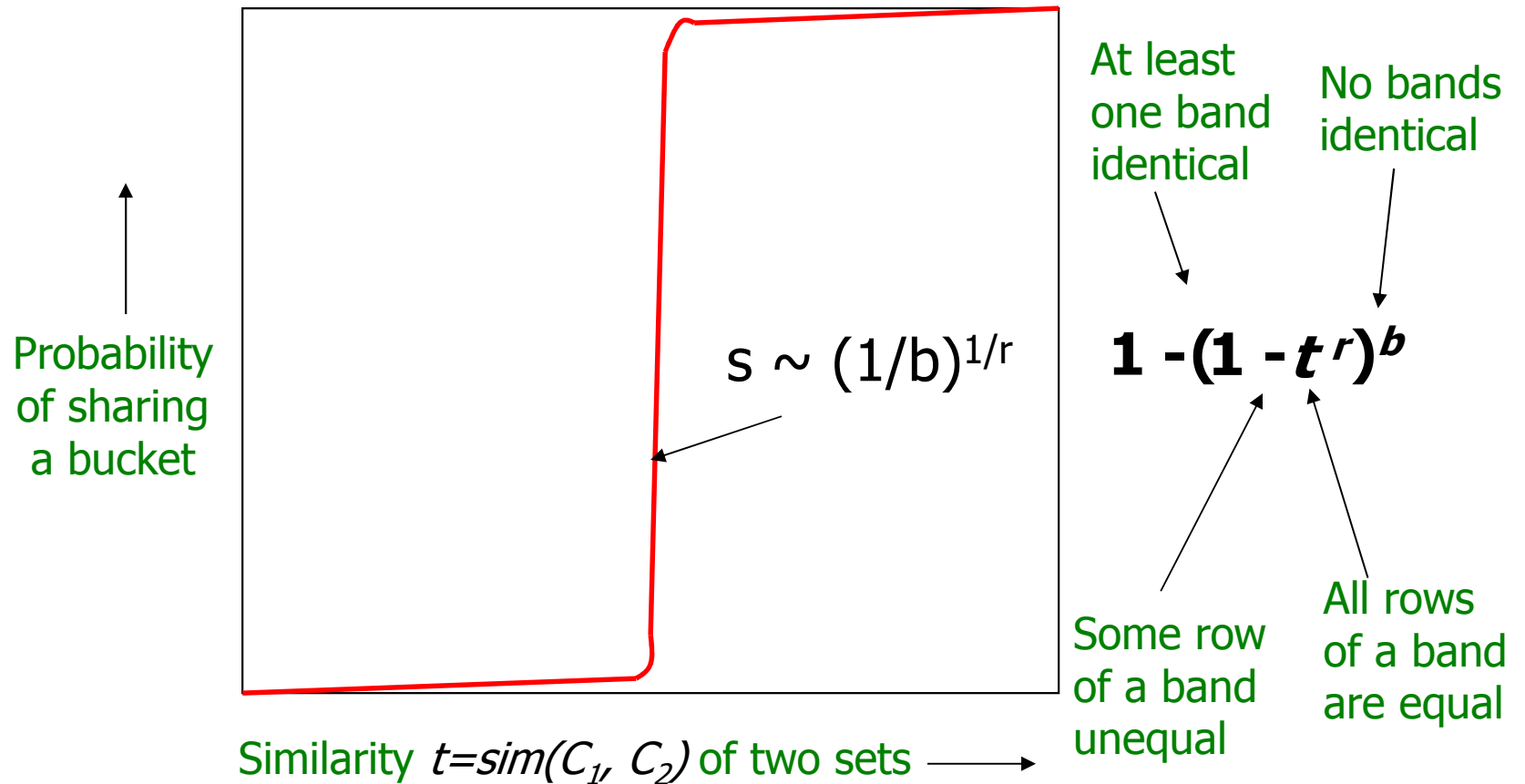
What 1 Band of 1 Row Gives You



b bands, r rows/band

- Columns C_1 and C_2 have similarity t
- Pick any band (r rows)
 - Prob. that all rows in band equal = t^r
 - Prob. that some row in band unequal = $1 - t^r$
- Prob. that no band identical = $(1 - t^r)^b$
- Prob. that at least 1 band identical =
 $1 - (1 - t^r)^b$

What b Bands of r Rows Gives You



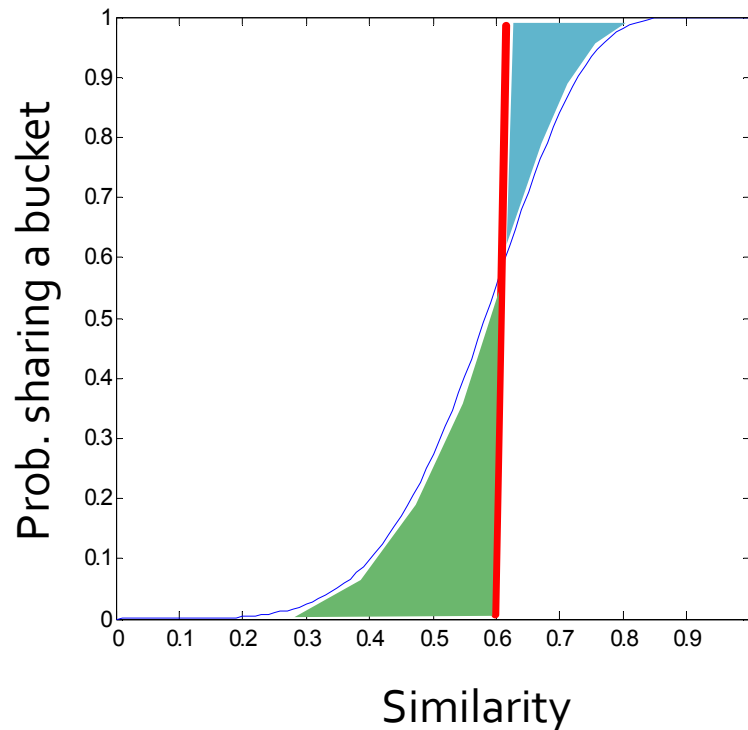
Example: $b = 20; r = 5$

- Similarity threshold s
- Prob. that at least 1 band is identical:

s	$1-(1-s^r)^b$
.2	.006
.3	.047
.4	.186
.5	.470
.6	.802
.7	.975
.8	.9996

Picking r and b : The S-curve

- Picking r and b to get the best S-curve
 - 50 hash-functions ($r=5$, $b=10$)



Blue area: False Negative rate
Green area: False Positive rate

LSH Summary

- Tune M , b , r to get almost all pairs with similar signatures, but eliminate most pairs that do not have similar signatures
- Check in main memory that **candidate pairs** really do have **similar signatures**
- **Optional:** In another pass through data, check that the remaining candidate pairs really represent similar documents

Summary: 3 Steps

- **Shingling:** Convert documents to sets
 - We used hashing to assign each shingle an ID
- **Min-Hashing:** Convert large sets to short signatures, while preserving similarity
 - We used **similarity preserving hashing** to generate signatures with property $\Pr[h_{\pi}(C_1) = h_{\pi}(C_2)] = \text{sim}(C_1, C_2)$
 - We used hashing to get around generating random permutations
- **Locality-Sensitive Hashing:** Focus on pairs of signatures likely to be from similar documents
 - We used hashing to find **candidate pairs** of similarity $\geq s$