Near duplicate detection

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Applications of NDD

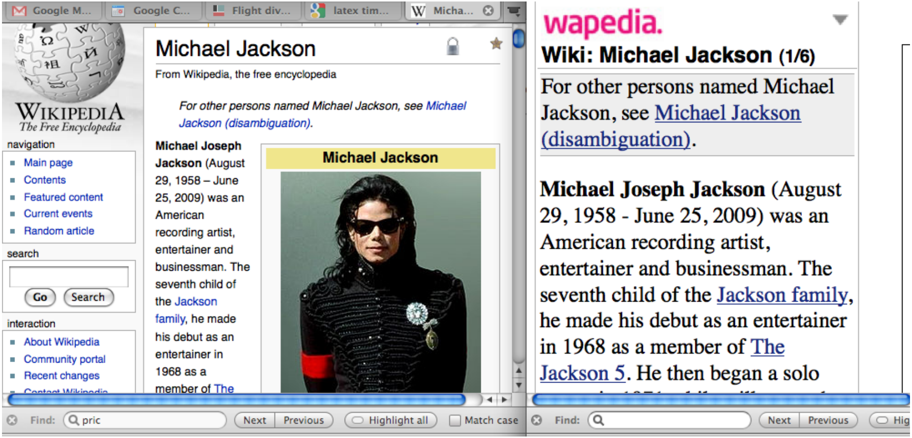
Many problems in data mining can be seen as searching in sets of similar items:

- Pages with similar words, for classification on topics.
- Topic suggestion to Twitter users with similar profiles (recommendation systems).
- Dual problem: identifying communities of users with similar interests
- Identifying same user in different contexts (e.g. social media platforms)

On the web

- The web is full of duplicated content.
- More so than many other collections
- Exact duplicates
  - Easy to eliminate
  - E.g., use hash/fingerprint
- Near-duplicates
  - Abundant on the web
  - Difficult to eliminate
- For the user, it's annoying to get a search result with near-identical documents.
- Marginal relevance is zero: even a highly relevant document becomes nonrelevant if it appears below a (near-)duplicate.
- We need to eliminate near-duplicates.

Near-duplicates: Example



Similar documents

Finding sets of documents (web pages) with much text in common:

- Mirror or quasi-mirror sites
  - Application: elimination of duplicates.
- Plagiarism, inclusion of extensive citations .
- Articles with similar content in different news sites .
  - Application: grouping articles as a “common history”.

Detecting near-duplicates

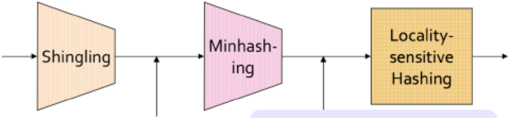
- Compute similarity with an edit-distance measure
- We want "syntactic" (as opposed to semantic) similarity.
    - True semantic similarity (similarity in content) is too difficult to compute.
- We do not consider documents near-duplicates if they have the same content, but express it with different words.
- Use similarity threshold θ to make the call "is/isn't a near-duplicate".
- E.g., two documents are near-duplicates if similarity $> \theta = 80\%$.

Three techniques useful for NDD

- Shingling: convert documents, e-mail, ecc, in sets of items.
- Minhashing: convert large sets in short sketches (or signatures), preserving similarity.
- Locality Sensitive Hashing (LSH): consider pairs of signature that could be similar with at least a given probability.

Architecture

Document



Sketch pairs to test for similarity

Shingles: Word sequences of length *k* occurring in the document

Sketches: short vectors of integers representing shingles, and preserving their similarity

Represent each document as set of shingles

Shingles are used as features to measure syntactic similarity of documents.

- A shingle is just a word k-gram.
- A document is represented as a set of shingles
- For $n = 5$, "*In a hole in the ground there lived a hobbit*" would be represented as this set of shingles:
  - {In a hole in the, a hole in the ground, hole in the ground there, in the ground there lived, the ground there lived a, ground there lived a hobbit }
- Similar documents will have many shingles in common

Represent each document as set of shingles

- Modifying a word affects only k shingles (the ones at distance at most k from the word)
- Moving a paragraph affects $2k$ shingles (the ones at distance at most k from the paragraph borders)
- For $n = 3$, changing "*In a hole in the ground there lived a hobbit*" to "*In a hole in the ground there was a hobbit*" only changes shingles $\{$ ground there lived, there lived a, lived a hobbit$\}$

Documents as sets of shingles

- In general, different documents should have few shingles in common, especially for higher k
- We define the similarity of two documents as the Jaccard coefficient of their shingle sets.

Recall: Jaccard coefficient

- A commonly used measure of overlap of two sets
- Let A and B be two sets: their Jaccard coefficient is defined as:

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

  $(A \neq \emptyset$ or $B \neq \emptyset)$
- $J(A, A) = 1$
- $J(A, B) = 0$ if $A \cap B = 0$
- A and B don't have to be the same size.
- Always assigns a number between 0 and 1.

Jaccard coefficient: Example

- Three documents:
  d_1: "Jack London traveled to Oakland"
  d_2: "Jack London traveled to the city of Oakland"
  d_3: "Jack traveled from Oakland to London"
- Based on shingles of size 2 (2-grams or bigrams), what are the Jaccard coefficients $J(d_1, d_2)$ and $J(d_1, d_3)$?
- 1. $s(d_1)$={"Jack London", "London traveled", "traveled to", "to Oakland"}
  2. $s(d_2)$={"Jack London", "London traveled", "traveled to", "to the", "the city", "city of", "of Oakland"}
  3. $s(d_3)$={"Jack traveled", "traveled from", "from Oakland", "Oakland to", "to London'}
- there are
- $J(d_1, d_2) = 3/8 = 0.375$
- $J(d_1, d_3) = J(d_2, d_3) = 0$

Represent each document as a sketch

- The number of shingles per document is large: computing Jaccard directly from M is expensive
- To increase efficiency, we will represent documents by means of sketches, cleverly chosen subsets of their shingles.
- Let k be a predefined sketch size and let S be the overall set of shingles: document sketches are derived by means of a set of k different random permutations $\pi_1 \ldots \pi_k$ of S
- Each π_i maps a shingle to a different integer in $\{1, \ldots, |S|\}$
- The sketch of a document d is defined as:

$$\left(\min_{s \in d} \pi_1(s), \min_{s \in d} \pi_2(s), \ldots, \min_{s \in d} \pi_k(s)\right)$$

(a vector of s integers).

From sets of documents+shingles to boolean matrices

A set of documents can be represented as a boolean matrix M, where

- columns are associated to documents
- rows correspond to all shingles appearing in any document
- $M(i, j) = 1$ iff the i-th shingle appear in the j-th document
- The matrix is usually sparse

The Jaccard similarity of two documents can be derived from the corresponding columns

Four types of rows

- For any pair of columns S_1, S_2, rows can be classified in four types according to the values of the corresponding values in the matrix: each type has a different effect on numerator N and denominator D of $J(S_1, S_2)$

	S_1	S_2	effect on N	effect on D
a	1	1	increase	increase
b	1	0	same	increase
c	0	1	same	increase
d	0	0	same	same

- In fact, $J(S_1, S_2) = \dfrac{\#a}{\#a + \#b + \#c}$
- Many rows are of type d

Minhashing

Permutations of shingles correspond here to permutations of rows of M. The above considerations can be accordingly translated as follows.

- Given a row permutation π, for any document d corresponding to a column c_i in M, let us define as the Minhash of d under permutation π, denoted as $\mathrm{MH}_\pi(d)$ the index j of the first row (according to π) such that $M(j,i)=1$.
- As an extension, given a set Π_k of k permutations, for any document d corresponding to a column c_i in M, $\mathrm{MH}_{\Pi_k}(d)$ is defined as the vector of integers $(j_1,\ldots,j_k)$ such that j_r is the index of the first row (according to permutation π_r) such that $M(j_r,i)=1$.

Minhashing

- The sketch vector $\mathrm{MH}_{\Pi_k}(d)$ can be interpreted as a signature of d
- Signatures can be visualized as columns in a new matrix M', where columns correspond to documents while rows correspond to hash functions. The values in column c_i are then defined as $\mathrm{MH}_{\Pi_k}(d_i)$, where d_i is the document corresponding to c_i

Minhashing example

Shingle/document matrix M

d_1	d_2	d_3	d_4
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

Minhashing example

Permutations

1
3
7
6
2
5
4

M

d_1	d_2	d_3	d_4
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'

S_1	S_2	S_3	S_4
1	2	1	2

Minhashing example

Permutations

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

M

d_1	d_2	d_3	d_4
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'

S_1	S_2	S_3	S_4
2	1	4	1
1	2	1	2

Minhashing example

Permutations

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

M

d_1	d_2	d_3	d_4
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'

S_1	S_2	S_3	S_4
2	1	2	1
2	1	4	1
1	2	1	2

Detecting near-duplicates from sketches

Assume a single permutation π. Check is performed as follows:

- If $\text{MH}_{\pi(d_1)} = \text{MH}_{\pi(d_2)}$ then d_1 and d_2 probably are near-duplicates.
- If $\text{MH}_{\pi(d_1)} \neq \text{MH}_{\pi(d_2)}$ then d_1 and d_2 are probably not near-duplicates.

Detecting near-duplicates from sketches

Why does it work? Let us estimate the probability that, by randomly choosing π, we get $\mathrm{MH}_\pi(d_1) = \mathrm{MH}_\pi(d_2)$.

- $\mathrm{MH}_\pi(d_1)$ can be, with equal probability, any shingle occurring in d_1 (that is, each item in c_1 with value 1, they are $\#a + \#b$); the same for $\mathrm{MH}_\pi(d_2)$ (that is, any item in c_2 with value 1, they are $\#a + \#c$)
- the number of possible pairs $(\mathrm{MH}_\pi(d_1), \mathrm{MH}_\pi(d_2))$ (that is of pairs of rows with values 1 in c_1 and c_2) is $(\#a + \#b)(\#a + \#c) - \#b\#c$
- the number of possible pairs with $\mathrm{MH}_\pi(d_1) = \mathrm{MH}_\pi(d_2)$ (that is of rows with values 1 both in c_1 and in c_2) is $\#a^2$
- the probability that $\mathrm{MH}_\pi(d_1) = \mathrm{MH}_\pi(d_2)$ is then given by

$$p_h(d_1, d_2) = \frac{\#a^2}{(\#a + \#b)(\#a + \#c) - \#b\#c} = \frac{\#a}{\#a + \#b + \#c}$$

Detecting near-duplicates from sketches

- But

$$\frac{\#a^2}{(\#a+\#b)(\#a+\#c)-\#b\#c}=\frac{\#a}{\#a+\#b+\#c}$$

  is the Jaccard coefficient $J(d_1,d_2)$, that is our similarity measure between d_1 and d_2. So, estimating $p_\pi(d_1,d_2)$ corresponds to estimating the similarity between d_1 and d_2
- How can we get a good estimate of $p_\pi(d_1,d_2)$ more efficiently than computing $J(d_1,d_2)$ (which implies taking into account all their shingles?)

Detecting near-duplicates from sketches

- Observe that $p_\pi(d_1, d_2)$ is independent from the particular hash function h applied (our only requirement is that h induces a permutation of the matrix rows, which we assume true with high probability): by randomly selecting h and applying it to (d_1, d_2) we know that the probability that the event $\text{MH}_\pi(d_1) = \text{MH}_\pi(d_2)$ occurs is $p_\pi(d_1, d_2) = p(d_1, d_2)$.
- Selecting π and observing whether $\text{MH}_\pi(d_1) = \text{MH}_\pi(d_2)$ can be seen as sampling a stone from an urn containing $\#a$ red stones and $\#b + \#c$ black stones and checking whether the sampled stone is red

Detecting near-duplicates from sketches

- Performing a random sample of k independent permutations $\pi_1, \ldots, \pi_k$ and observing whether $\mathrm{MH}_{\pi_i}(d_1) = \mathrm{MH}_{\pi_i}(d_2)$ for each π_i corresponds to sampling k stones from the urn (with replacement) and checking how many sampled stoned are red
- This is a sequence of Bernoulli trials with probability $p(d_1, d_2)$. In this case, the number of red stones (functions such that $\mathrm{MH}_{\pi_i}(d_1) = \mathrm{MH}_{\pi_i}(d_2)$) is distributed according to a binomial distribution

$$p(\mathrm{MH}_{\pi_i}(d_1) = \mathrm{MH}_{\pi_i}(d_2) \text{ for exactly } r \text{ functions}) = \binom{r}{k} p(d_1, d_2)^r (1 - p(d_1, d_2))^{k-r}$$

which has mean $kp(d_1, d_2)$

Detecting near-duplicates from sketches

- $J(d_1, d_2)$ can be estimated by estimating $p(d_1, d_2)$ from the sample of size k provided by the set functions Π_k.
- by standard statistics, an unbiased estimator of p is $\hat{p} = \frac{r}{k}$, where r is the number of functions $h \in \Pi_k$ such that $\mathrm{MH}_\pi(d_1) = \mathrm{MH}_\pi(d_2)$
- the corresponding standard error is given by the sample standard deviation $\hat{s} = \sqrt{\frac{\hat{p}(1-\hat{p})}{k}}$: this makes it possible to a define confidence interval on $J(d_1, d_2)$ at any given confidence level θ as $[\hat{p} - Z_\theta \hat{s}, \hat{p} + Z_\theta \hat{s}]$, where Z_θ is the Z-score at probability θ (number of standard deviation from the man of a gaussian such that the tail probability is $1 - \theta$)
- the precision of the estimation improves as k increases

Random hash functions as permutations

Sketches can be efficiently computed by means of random hash functions.

- We can map shingles in S to integers by fingerprinting, that is by applying a given hash function h which maps any sequence of unigrams to a sequence of (say) m bytes, that is to an integer interval $0..2^m - 1$
- For suitably large m, with high probability there is no collision between pairs of shingles in S, that is $h(s_1) \neq h(s_2)$ for all $s_1, s_2 \in S$.
- Then, for suitably large m, h defines a permutation of shingles with high probability

Implementing Minhashing

- Let k be the number of hash functions.
- To each column d_j (document) and function h_i, a slot $s_{i,j}$ is associated.
- Iteratively compute, for each $r = 0, \dots$ up to the number of rows minus 1, all values $h_i(r)$
- At the end of the k-th iteration, $s_{i,j}$ stores the minimum value $\min r$, for all $0 \leq r \leq k-1$ and $M(j, h_i(r)) = 1$
- That is, $s_{i,j}$ stores the minimum index, in the permutation of rows induced by h_i, of a row with value 1 in correspondence to document d_j (the index of the first shingle of d_j)
- This is the current MinHash (for all considered shingles) of document d_j when function h_i is applied

At the end, $s_{i,j}$ will store MinHash for d_j and h_i.

Example

i	d_1	d_2
0	1	1
1	0	0
2	1	1
3	1	0
4	0	1

$$h_1(x) = x \bmod 5$$
$$h_2(x) = (2x+1) \bmod 5$$

h_1	d_1	d_2
0	1	1
1	0	0
2	1	1
3	1	0
4	0	1

h_2	d_1	d_2
0	0	0
1	1	0
2	1	1
3	1	1
4	0	1

$\min(h_1(d_1))=0=0=\min(h_1(d_2))$

$\min(h_2(d_1))=1\neq 2=\min(h_2(d_2))$

$$\hat{J}(d_1, d_2) = \frac{1}{2} = .5$$

$$J(d_1, d_2) = \frac{2}{5} = .4$$

Example

i	d_1	d_2
0	1	1
1	0	0
2	1	1
3	1	0
4	0	1

	$M(h_i(r),1)$	$M(h_i(r),2)$	$s_{1,i}$	$s_{2,i}$
h_1			∞	∞
h_2			∞	∞
$h_1(0) = 0$	1	1	0	0
$h_2(0) = 1$	0	0	∞	∞
$h_1(1) = 1$	0	0	0	0
$h_2(1) = 3$	1	0	1	∞
$h_1(2) = 2$	1	1	0	0
$h_2(2) = 0$	1	1	1	2
$h_1(3) = 3$	1	0	0	0
$h_2(3) = 2$	1	1	1	2
$h_1(4) = 4$	0	1	0	0
$h_2(4) = 4$	0	1	1	2

final sketches

Exercise

	d_1	d_2	d_3
s_1	0	1	1
s_2	1	0	1
s_3	0	1	0
s_4	1	0	0

$$h(x) = 5x + 5 \mod 4$$
$$g(x) = (3x + 1) \mod 4$$

Estimate $\hat{J}(d_1, d_2)$, $\hat{J}(d_1, d_3)$, $\hat{J}(d_2, d_3)$

Efficient near-duplicate detection

- We have an extremely efficient method for estimating similarity for a single pair of documents
- But we still have to estimate $O(N^2)$ values where N is the number of documents: still intractable
- However, often we need to derive all pairs whose similarity is above a given threshold
- One solution: locality sensitive hashing (LSH)

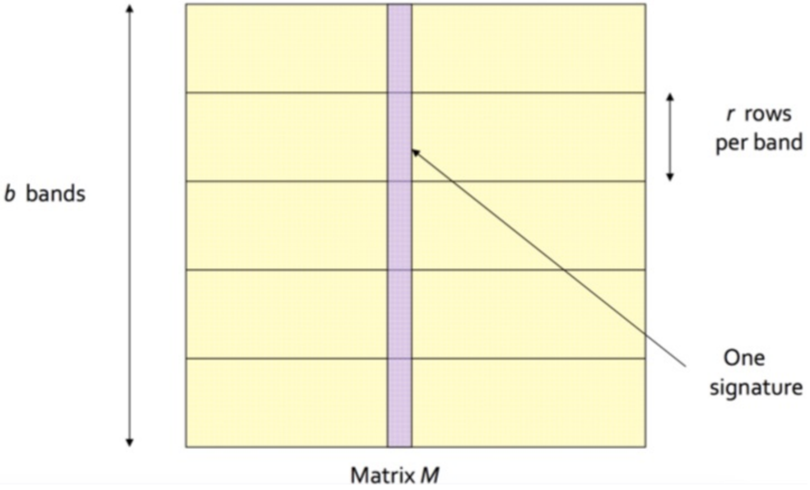
Candidate pairs

- pick a similarity threshold s, $0 \leq s \leq 1$
- goal: find pairs of documents with Jaccard similarity at least s
- columns i and j are a candidate pair if their signatures agree in at least a fraction s of their rows
- we expect pairs of documents to have the same similarity as their signatures

Locality-Sensitive Hashing (LSH) for signatures

- Idea: Hash columns of signatures matrix M' to a predefined set of buckets in such a way that similar columns are likely to be hashed to the same bucket, with high probability
- A pair of columns hashed to the same bucket is a candidate pair for similarity, to be verified more accurately
- False positives (dissimilar pairs hashed to same bucket); false negatives (similar pairs hashed to different buckets)

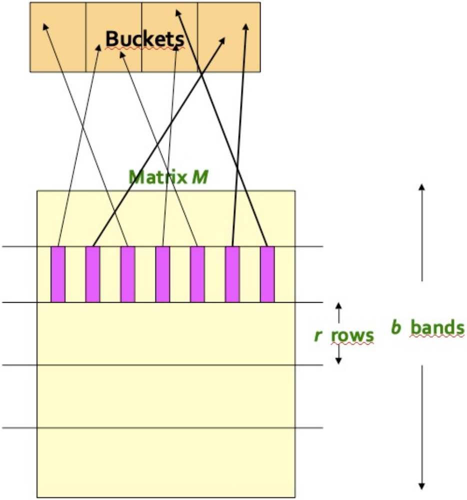
Partition in bands



Partition in bands

- Divide the signature matrix M into b bands, each of r rows.
- For each band B_i, a hash function h_i is defined which maps vectors of r integers to k buckets, with k large enough
- We could use the same hash functions for all bands, but different bucket arrays
- A pair of columns is a candidate pair if they are hashed to the same bucket for at least 1 band
- Tune b (and correspondingly r) to catch most similar pairs, but few not similar ones.

Band hashing



- Columns 2 and 6 are probably identical (candidate pair)
- Columns 6 and 7 are different (wrt to this band, they could be declared candidate pairs by hashing the other bands)

Example

- Assume we have 10^5 columns (documents).
- Each signature is a vector of length 100.
- Each signature element is an integer 4 bytes long.
- Then all signatures are 40MB long.
- The naive approach requires $10^5 \times (10^5 - 1) \times .5 \simeq 5 \times 10^9$ pairs of signatures to be compared: could take months
- Let us apply LSH: choose, for example, $b = 20$, $r = 5$

False negatives

Assume we wish all document pairs with similarity at least .8

- Let columns C_1, C_2 be signatures of similar documents: that is, they have equal values in at least a .8 fraction of their rows
- The probability that columns C_1, C_2 collide in a given band is then $(0.8)^5 = 0.328$.
- The probability that C_1, C_2 do not collide in any of the 20 bands is then $(1 - 0.328)^{20} \simeq 0.00035$.
    - that is, there is a chance of 1 over about 3000 that two 0.8 similar columns do not collide anywhere, and are declared not similar (false negative)
    - we would find 99.965% pairs of truly similar documents: very few false negatives

False positives

- Assume columns C_1, C_2 are signatures of not similar documents: they have equal values in a .3 fraction of their rows
- The probability that columns C_1, C_2 collide in a given band is then $(0.3)^5 = 0.00243$.
- The probability that C_1, C_2 collide in at least one of the 20 bands is then $1 - (1 - 0.00243)^{20} \simeq 0.0474$.
  - that is, approximately 4.74% pairs of docs with similarity 0.3% end up becoming candidate pairs (false positive)
  - they will be checked more precisely and it will turn out they are not similar (at .8 threshold)

Collision probability in a band

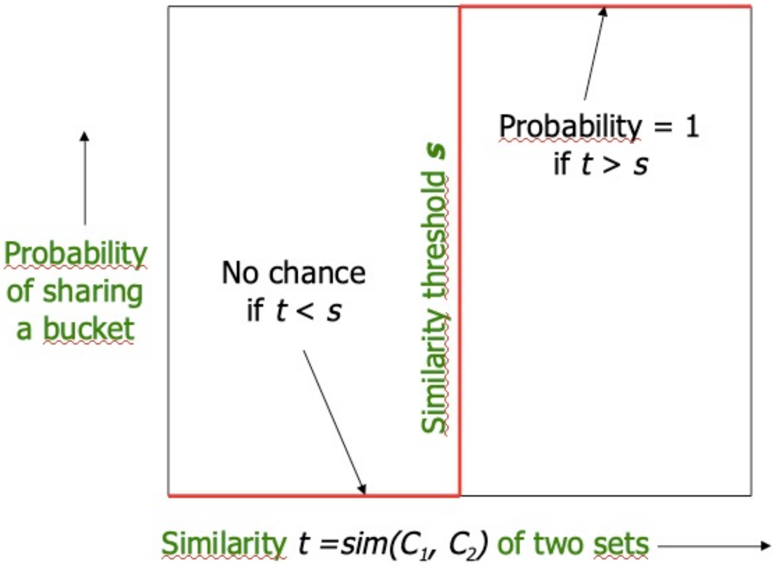
- The probability that two given columns C_1, C_2 have equal rows in a certain band is s^r
- The probability that two given columns C_1, C_2 differ in at least one row in a certain band is $1 - s^r$
- The probability that two given columns C_1, C_2 differ in at least one row in all bands is $(1 - s^r)^b$
- The probability that two given columns C_1, C_2 have equal rows in at least one band (they are a candidate pair) is $1 - (1 - s^r)^b$

La **probabilità** che **una data banda** due colonne con indice di similarità s abbiano **tutte** le r righe **uguali** $\Rightarrow$ s^r

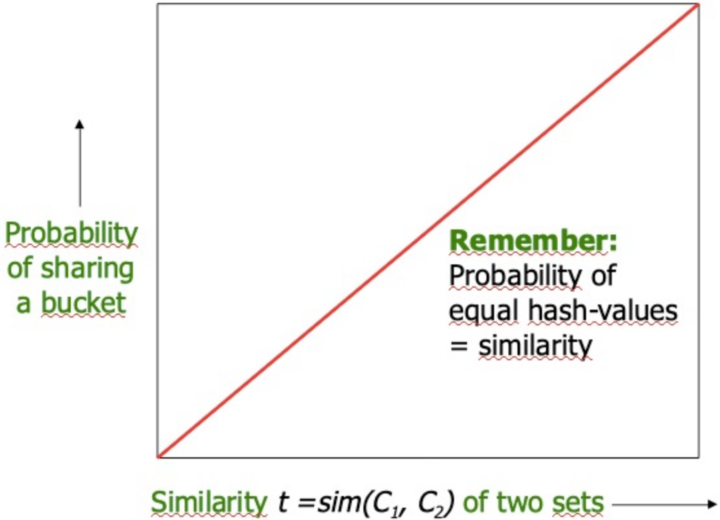
LSH Involves a Tradeof

- Pick
  - The number of MinHashes (rows of M')
  - The number of bands b
  - 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

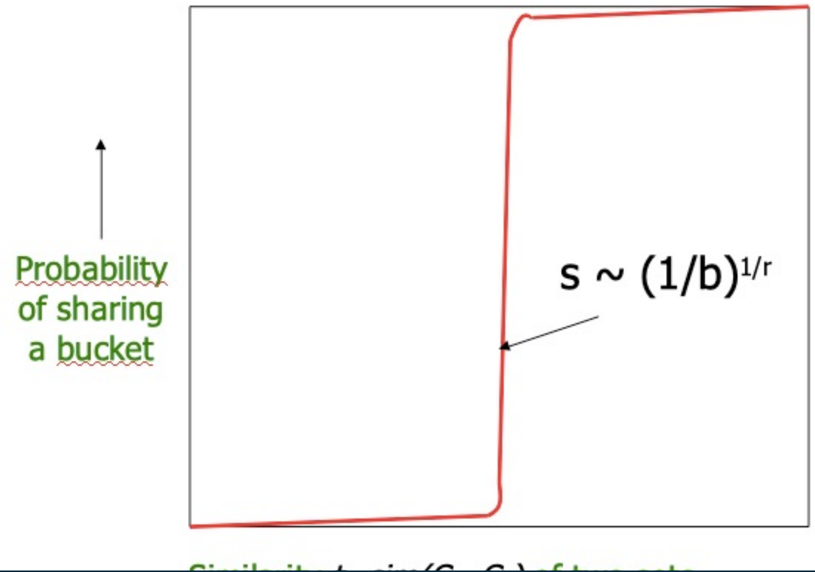
What we want


Probability of sharing a bucket
No chance if $t < s$
Similarity threshold s
Probability = 1 if $t > s$
Similarity $t = sim(C_1, C_2)$ of two sets

What we get with 1 row



What we get with b bands, r rows



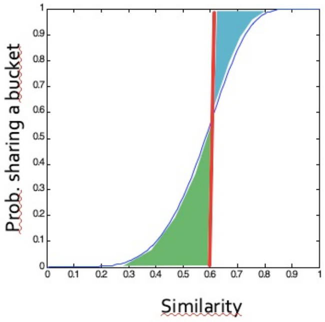
Example: $b = 20$, $r = 5$

- Similarity threshold s
- Probability that at least 1 band is identical (collision)

s	$1-(1-s^r)^b$
.2	.006
.3	.047
.4	.186
.5	.47
.6	.802
.7	.975
.8	.9996

Picking 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