Theory of Locality Sensitive Hashing

CS246: Mining Massive Datasets

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2 Announcements

Colab 0/1 Due Today

- Due at 11:59 PM

We will also be releasing Colab 2

- Due in 1 week (1/25 at 11:59 PM)

Homework 1

- Due in 1 week (1/25 at 11:59 PM)

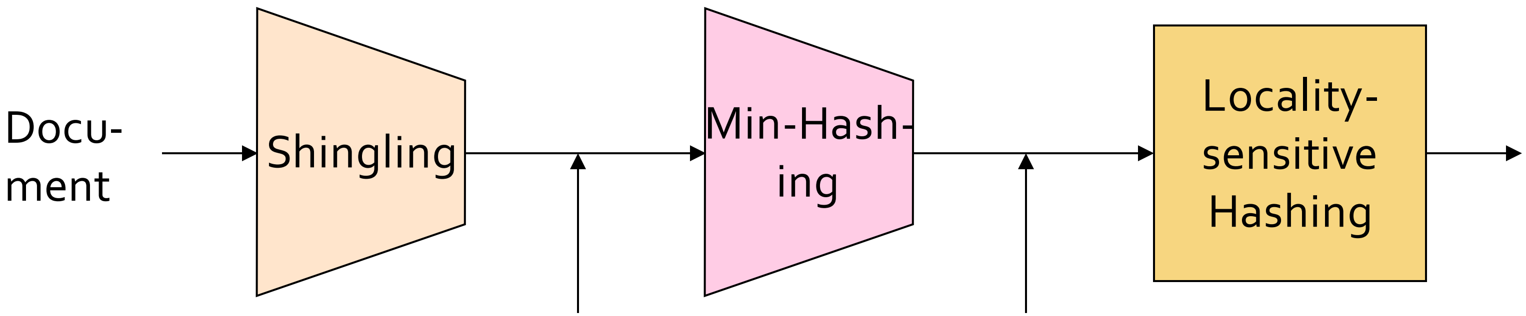
Recap: Finding similar documents

- **Task:** Given a large number (***N*** in the millions or billions) of documents, find "near duplicates"

- **Problem:**
  - Too many documents to compare all pairs

- **Solution:** Hash documents so that similar documents hash into the same bucket
  - Documents in the same bucket are then **candidate pairs** whose similarity is then evaluated

Recap: The Big Picture



The **set** of strings of length *k* that appear in the doc-ument

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

Candidate pairs: those pairs of signatures that we need to test for similarity

Recap 1: Shingles

- A *k*-shingle (or *k*-gram) is a sequence of *k* tokens that appears in the document
  - Example: **k=2**; $\mathbf{D_1}$ = abcab
    Set of 2-shingles: $\mathbf{C_1} = S(D_1) = \{ab, bc, ca\}$
- Represent a doc by a set of hash values of its *k*-shingles
- A natural **similarity measure** is then the **Jaccard similarity:**

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

  - Similarity of two documents is the Jaccard similarity of their shingles

Recap 2: Minhashing

- ***Min-Hashing***: Convert large sets into short signatures, while preserving similarity: **Pr[*h*(C_1) = *h*(C_2)] = *sim*(D_1, D_2)**

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*

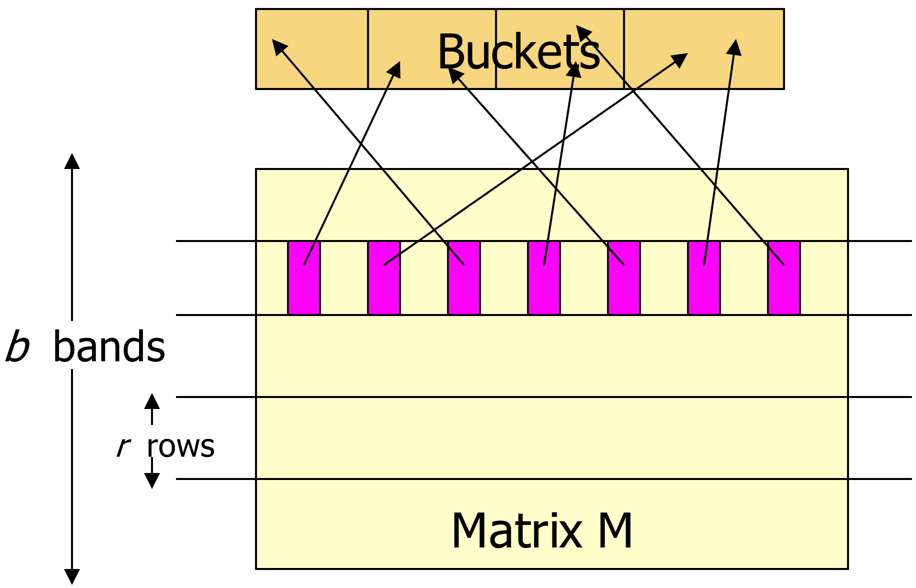
2	1	2	1
2	1	4	1
1	2	1	2

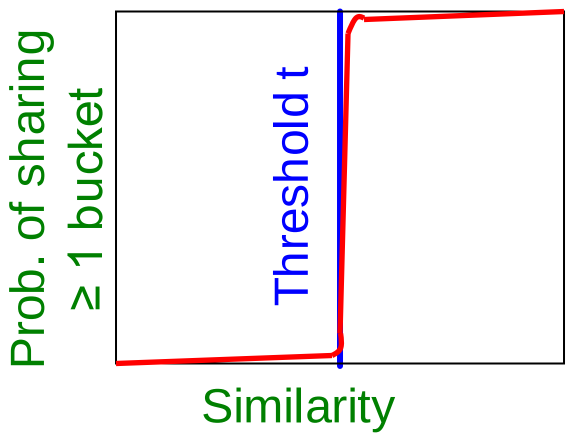
Similarities of columns and signatures (approx.) match!

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

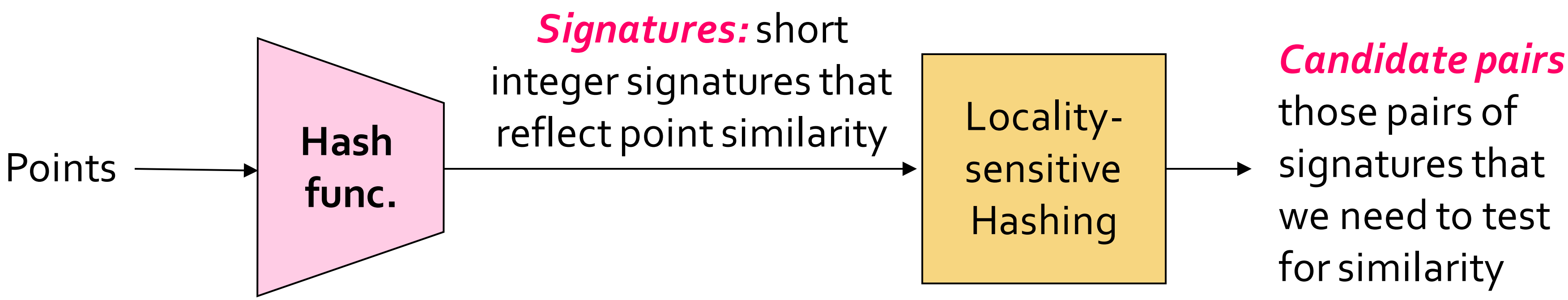
Recap 3: LSH

- **Hash columns of the signature matrix *M*:**
  Similar columns likely hash to same bucket
  - Divide matrix *M* into ***b*** bands of ***r*** rows (M=b·r)
  - ***Candidate*** column pairs are those that hash to the same bucket for ≥ **1** band





Today: Generalizing Min-hash



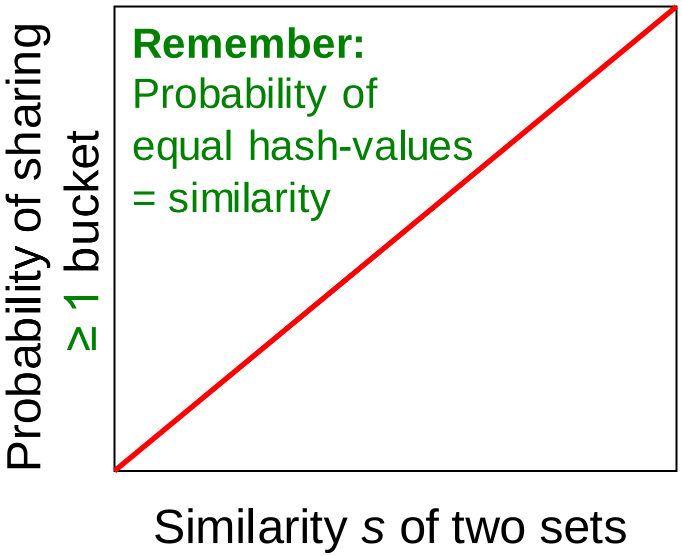
Design a **locality sensitive hash function (for a given distance/similarity metric)**

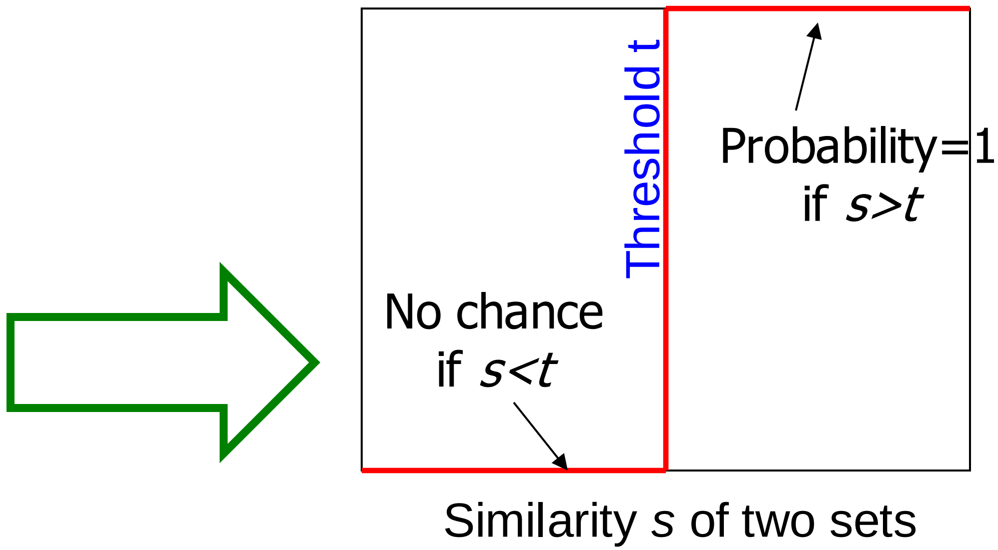
Apply the "Bands" technique

Think: Similarity = 1 – "distance"

The S-Curve

- **The S-curve is where the "magic" happens**





This is what 1 hash-code gives you

$\Pr[h_\pi(C_1) = h_\pi(C_2)] = sim(D_1, D_2)$

This is what we want!

How to get a step-function?

By choosing *r* and *b*!

How Do We Make the S-curve?

- **Remember:** ***b*** bands, ***r*** rows/band
- Let $sim(C_1, C_2) = s$

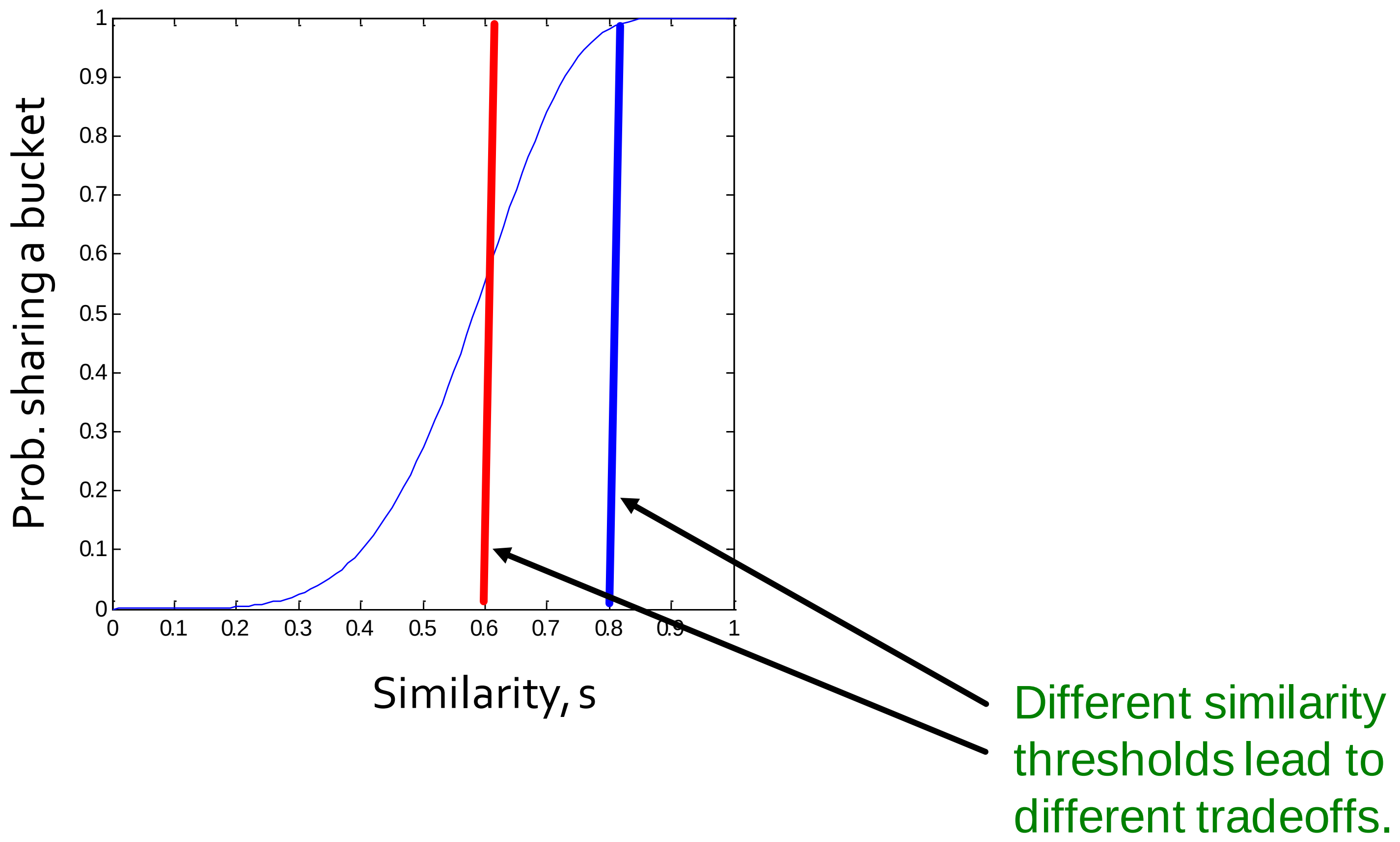
What's the prob. that at least 1 band is equal?

- Pick some band (***r*** rows)
  - Prob. that elements in a single row of columns C_1 and C_2 are equal $= s$
  - Prob. that all rows in a band are equal $= s^r$
  - Prob. that some row in a band is not equal $= 1 - s^r$
- Prob. that all bands are not equal $= (1 - s^r)^b$
- Prob. that at least 1 band is equal $= 1 - (1 - s^r)^b$

$$P(C_1, C_2 \text{ is a candidate pair}) = 1 - (1 - s^r)^b$$

Picking *r* and *b*: The S-curve

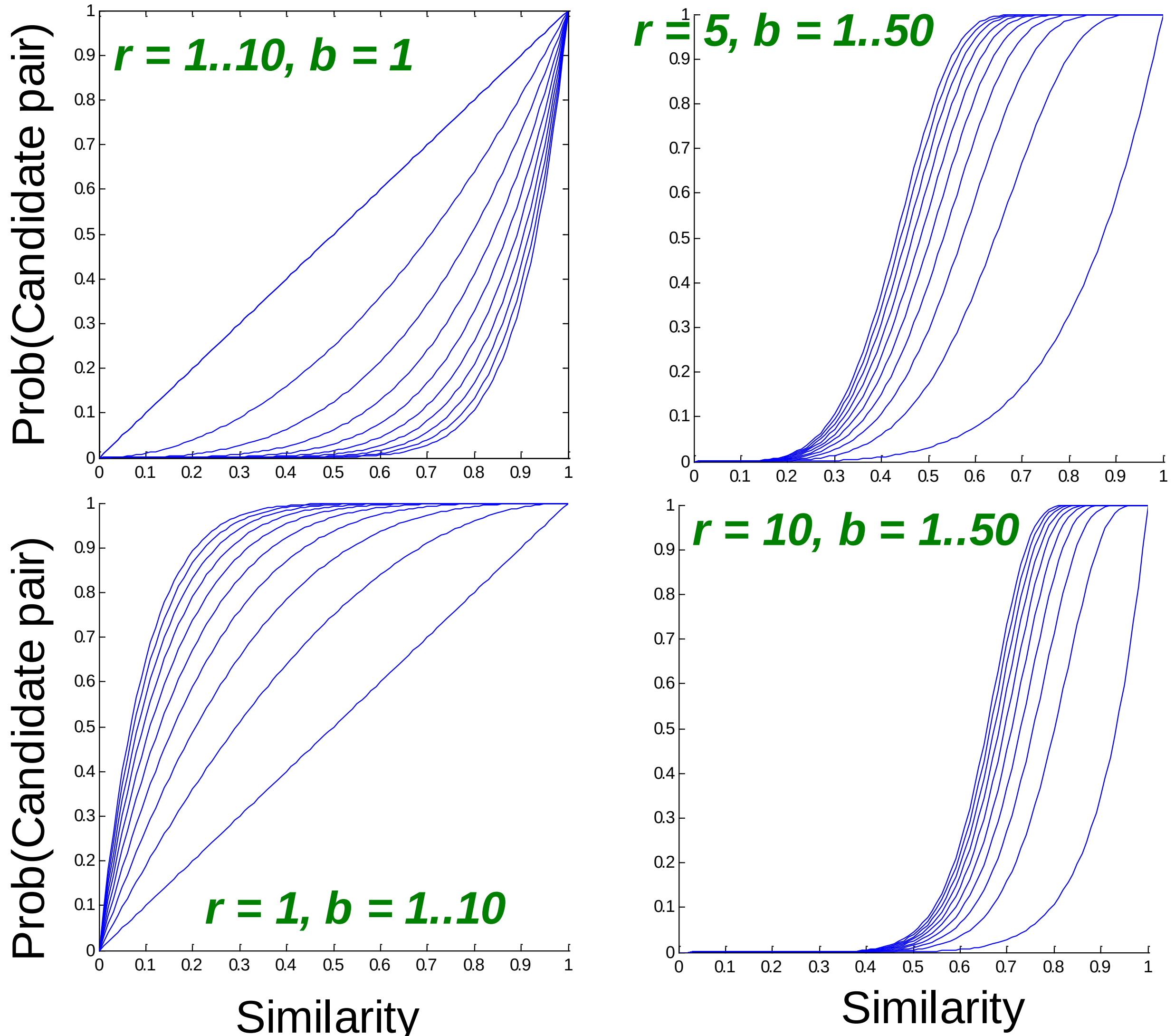
- **Picking *r* and *b* to get the best S-curve**
  - 50 hash-functions (r=5, b=10)



S-curves as a func. of *b* and *r*

Given a fixed threshold ***t***.

We want choose ***r*** and ***b*** such that the ***P(Candidate pair)*** has a "step" right around ***t***.



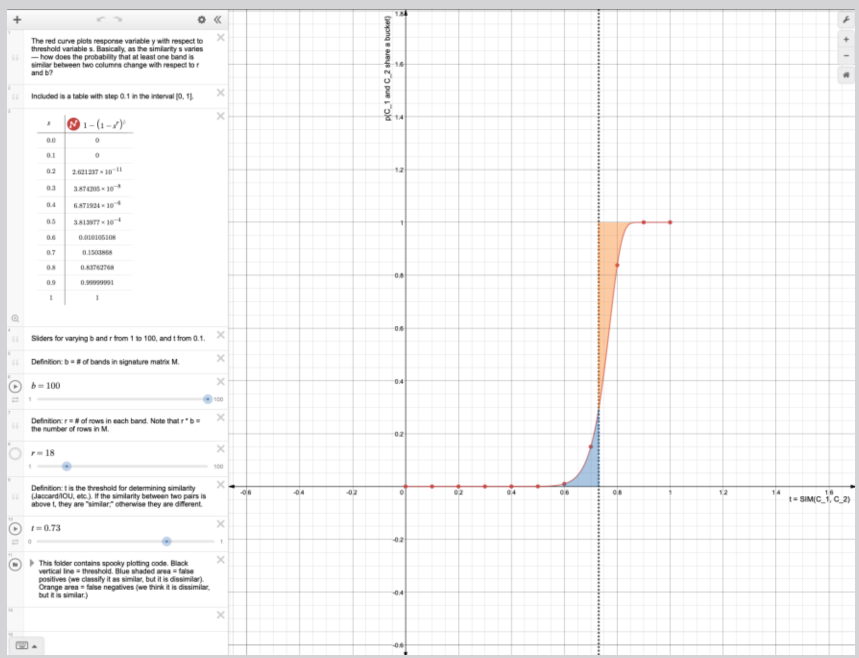
prob = 1 - (1 - s ^{r}***)*** ^{b}

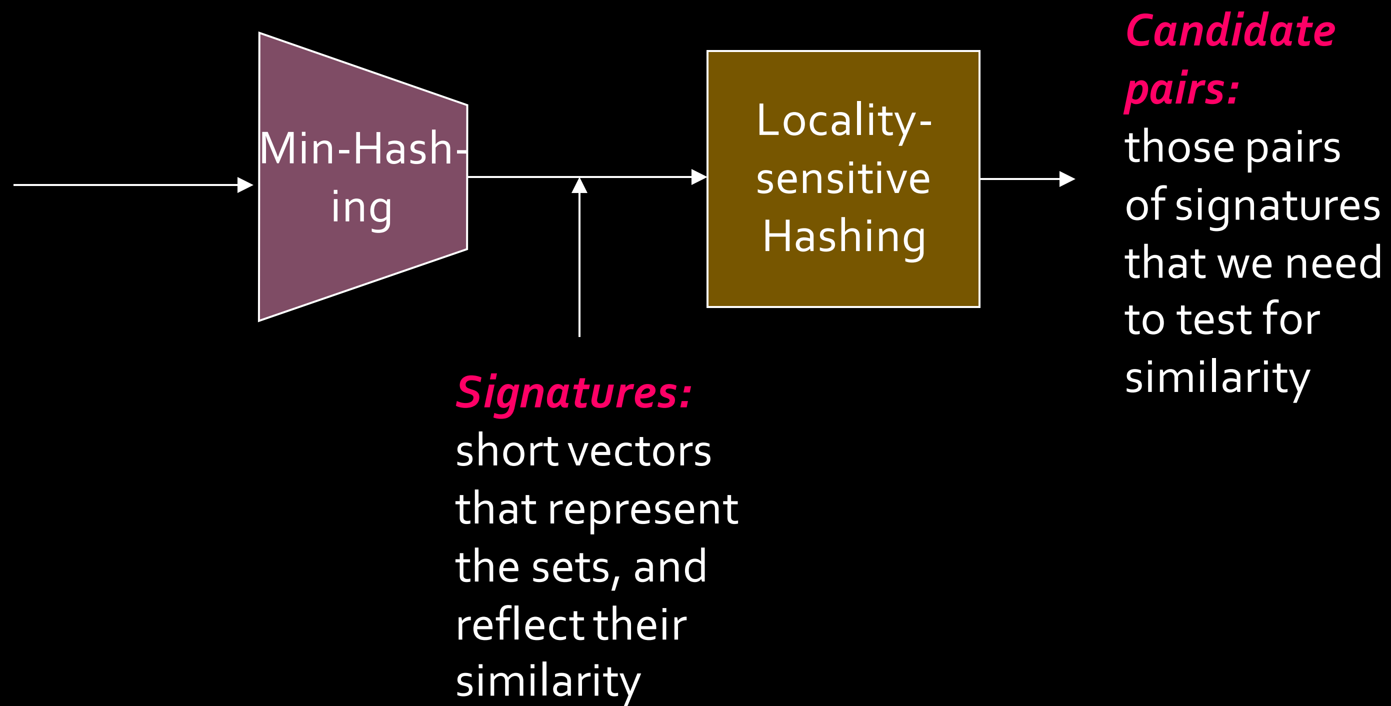
Visualizing S-Curves

Visualization of the effect of threshold, band size, and # of rows in LSH

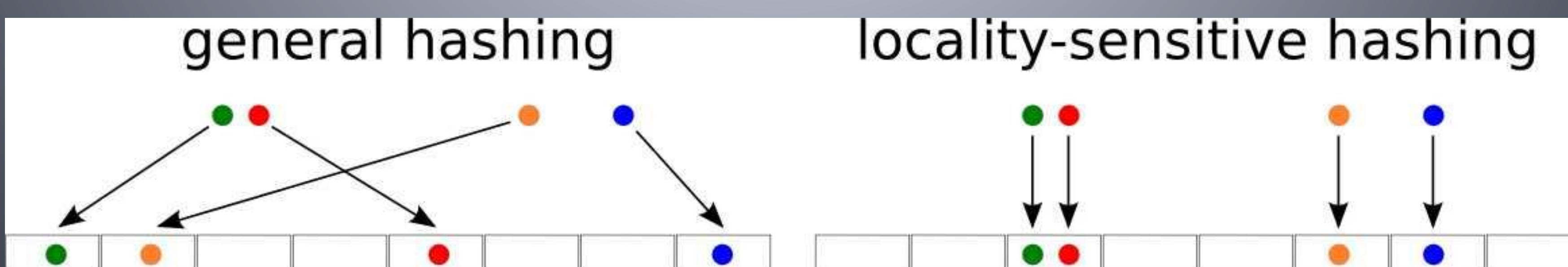
by Trenton Chang (Thank you!!)

https://www.desmos.com/calculator/lzzvfjiujn





Theory of LSH



Theory of LSH

- **We have used LSH to find similar documents**
  - More generally, we found similar columns in large sparse matrices with high Jaccard similarity
- **Can we use LSH for other distance measures?**
  - e.g., Euclidean distances, Cosine distance
  - **Let's generalize what we've learned!**

Distance Measures

- $\boldsymbol{d}(\cdot)$ is a **distance measure** if it is a function from pairs of points **x,y** to real numbers such that:
  - $d(x,y) \geq 0$
  - $d(x,y) = 0 \;\; iff \; x = y$
  - $d(x,y) = d(y,x)$
  - $d(x,y) \leq d(x,z) + d(z,y)$ (triangle inequality)
- Jaccard distance for sets = 1 - Jaccard similarity
- Cosine distance for vectors = angle between the vectors
- Euclidean distances:
  - L_2 *norm*: d(x,y) = square root of the sum of the squares of the differences between *x* and *y* in each dimension
    - The most common notion of "distance"
  - L_1 *norm*: sum of absolute value of the differences in each dimension
    - *Manhattan distance* = distance if you travel along axes only

Families of Hash Functions

- A "hash function" is any function that allows us to say whether two elements are **"equal"**
  - **Shorthand:** ***h(x) = h(y)*** means "***h says x and y are equal***"
- A ***family*** of hash functions is any set of hash functions from which we can ***efficiently pick one at random***
  - **Example:** The set of Min-Hash functions generated from permutations of rows

Locality-Sensitive (LS) Families

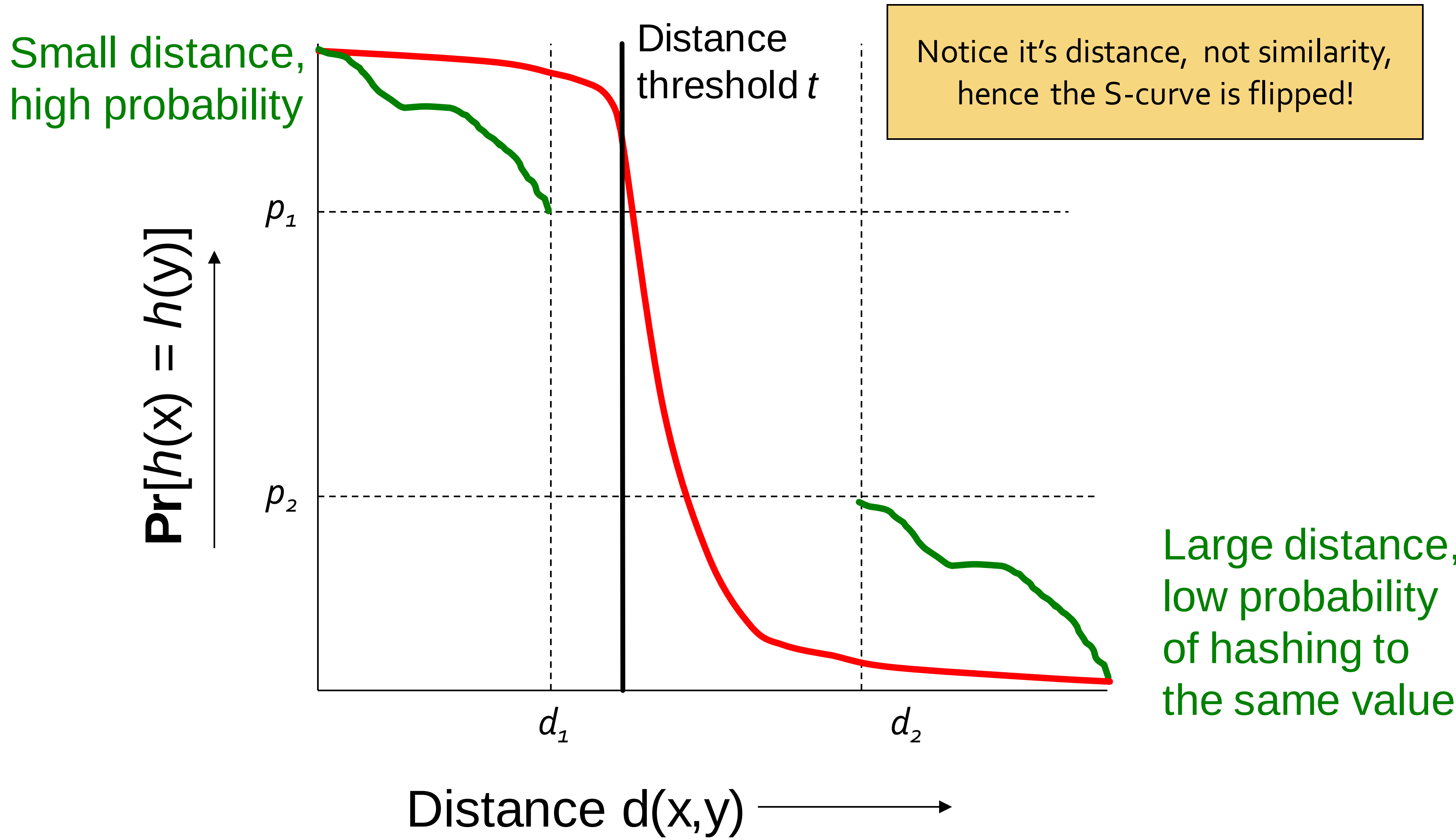
- **Suppose we have a space *S* of points with a distance measure *d(x,y)***

Critical assumption

- A family ***H*** of hash functions is said to be ***(d_1, d_2, p_1, p_2)-sensitive*** if for any ***x*** and ***y*** in ***S***:
  1. If $d(x, y) \leq d_1$, then the probability over all $h \in H$, that $h(x) = h(y)$ is at least p_1
  2. If $d(x, y) \geq d_2$, then the probability over all $h \in H$, that $h(x) = h(y)$ is at most p_2

With a LS Family we can do LSH!

A (d_1,d_2,p_1,p_2)-sensitive function



Example of LS Family: Min-Hash

- **Let:**
  - ***S*** = space of all sets,
  - ***d*** = Jaccard distance,
  - ***H*** is family of Min-Hash functions for all permutations of rows
- Then for any hash function $h \in H$:

$$Pr[h(x) = h(y)] = 1 - d(x, y)$$

  - Simply restates theorem about Min-Hashing in terms of distances rather than similarities

Example: LS Family – (2)

- **Claim:** **Min-hash *H*** is a (1/3, 2/3, 2/3, 1/3)-sensitive family for ***S*** and ***d***.

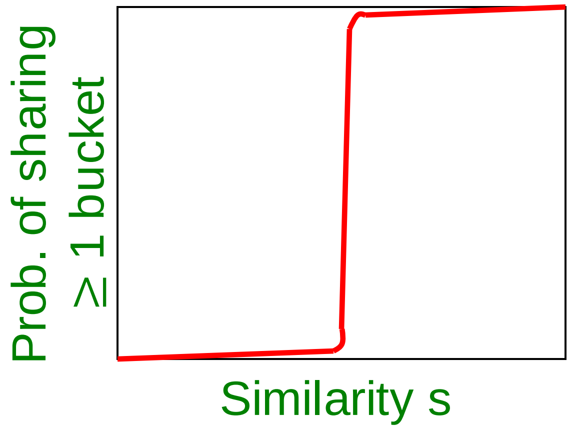
If distance ≤ 1/3
(so similarity ≥ 2/3)

Then probability that Min-Hash values agree is ≥ 2/3

- **For Jaccard similarity, Min-Hashing gives a $(d_1,d_2,(1-d_1),(1-d_2))$-sensitive family for any $d_1<d_2$**

Amplifying a LS-Family

- **Can we reproduce the "S-curve" effect we saw before for any LS family?**



- The "**bands**" technique we learned for signature matrices carries over to this more general setting
- **Can do LSH with any *(d_1, d_2, p_1, p_2)-sensitive* family!**

- **Two constructions:**
  - **AND** construction like "rows in a band"
  - **OR** construction like "many bands"

Amplifying Hash Functions: AND and OR

AND of Hash Functions

- Given family H, construct family H' consisting of r functions from H
- For $h = [h_1,\ldots,h_r]$ in H', we say **h(x) = h(y)** if and only if $h_i(x) = h_i(y)$ for **all** i $\quad 1 \leq i \leq r$
  - Note this corresponds to creating a band of size **r**

- **Theorem:** If H is (d_1, d_2, p_1, p_2)-sensitive, then **H'** is $(d_1, d_2, (p_1)^r, (p_2)^r)$-sensitive
- **Proof:** Use the fact that h_i's are **independent**

Also lowers probability for small distances (Bad)

Lowers probability for large distances (Good)

Subtlety Regarding Independence

- **Independence of hash functions (HFs) really means that the prob. of two HFs saying "yes" is the product of each saying "yes"**
  - **But** two particular hash functions could be highly correlated
    - For example, in Min-Hash if their permutations agree in the first one million entries
  - **However**, the probabilities in definition of a LSH-family are over all possible members of ***H, H'*** (i.e., average case and not the worst case)

OR of Hash Functions

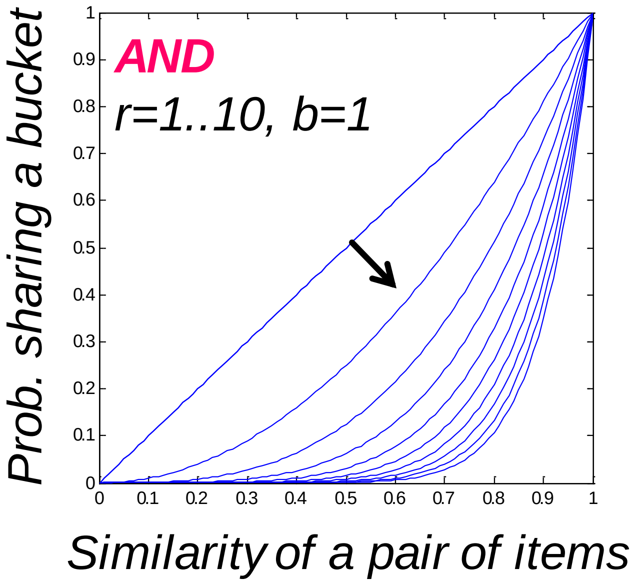
- Given family ***H***, construct family ***H'*** consisting of ***b*** functions from ***H***
- For $h = [h_1, \ldots, h_b]$ in ***H'***, $\mathbf{h(x) = h(y)}$ if and only if $\mathbf{h_i(x) = h_i(y)}$ for **at least 1** i
- **Theorem:** If ***H*** is (d_1, d_2, p_1, p_2)-sensitive, then ***H'*** is $(d_1, d_2, 1-(1-p_1)^b, 1-(1-p_2)^b)$-sensitive
- **Proof:** Use the fact that h_i's are **independent**

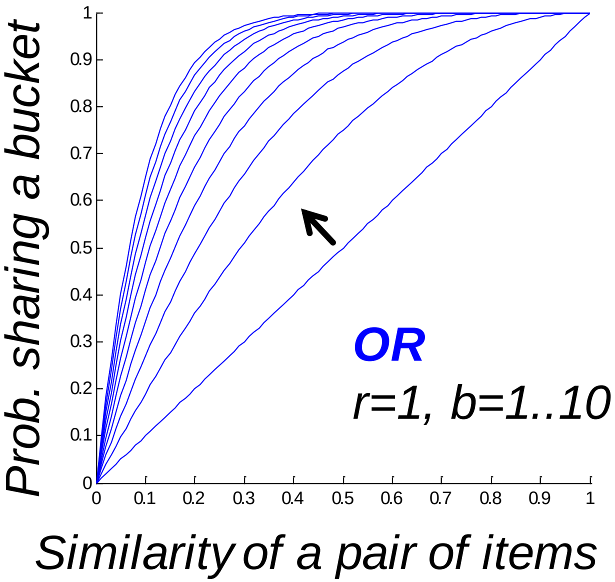
Raises probability for small distances (Good)

Raises probability for large distances (Bad)

Effect of AND and OR Constructions

- **AND** makes all probs. **shrink**, but by choosing ***r*** correctly, we can make the lower prob. approach 0 while the higher does not
- **OR** makes all probs. **grow**, but by choosing ***b*** correctly, we can make the higher prob. approach 1 while the lower does not





Combine AND and OR Constructions

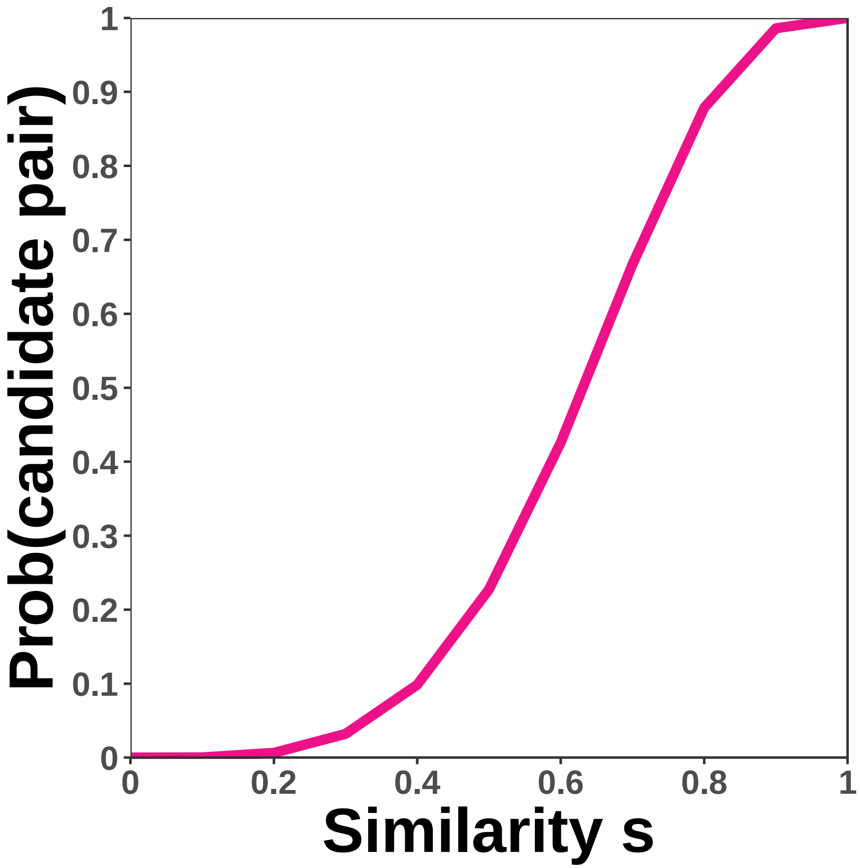
- By choosing ***b*** and ***r*** correctly, we can make the lower probability approach 0 while the higher approaches 1
- As for the signature matrix, we can use the AND construction followed by the OR construction
  - Or vice-versa
  - Or any sequence of AND's and OR's alternating

Composing Constructions

- *r*-way **AND** followed by *b*-way **OR** construction
  - **Exactly what we did with Min-Hashing**
    - **AND:** If bands match in **all** *r* values hash to same bucket
    - **OR:** Cols that have ≥ 1 common bucket → **Candidate**
- Take points ***x*** and ***y*** s.t. $Pr[h(x) = h(y)] = s$
  - ***H*** will make **(x,y)** a candidate pair with prob. **s**
- Construction makes **(x,y)** a candidate pair with probability $1-(1-s^r)^b$ **The S-Curve!**
  - **Example:** Take **H** and construct **H'** by the **AND** construction with $r = 4$. Then, from **H'**, construct **H''** by the **OR** construction with $b = 4$

Table for Function $1-(1-s^4)^4$

s	$p=1-(1-s^4)^4$
.2	**.0064**
.3	.0320
.4	.0985
.5	.2275
.6	.4260
.7	.6666
.8	**.8785**
.9	.9860

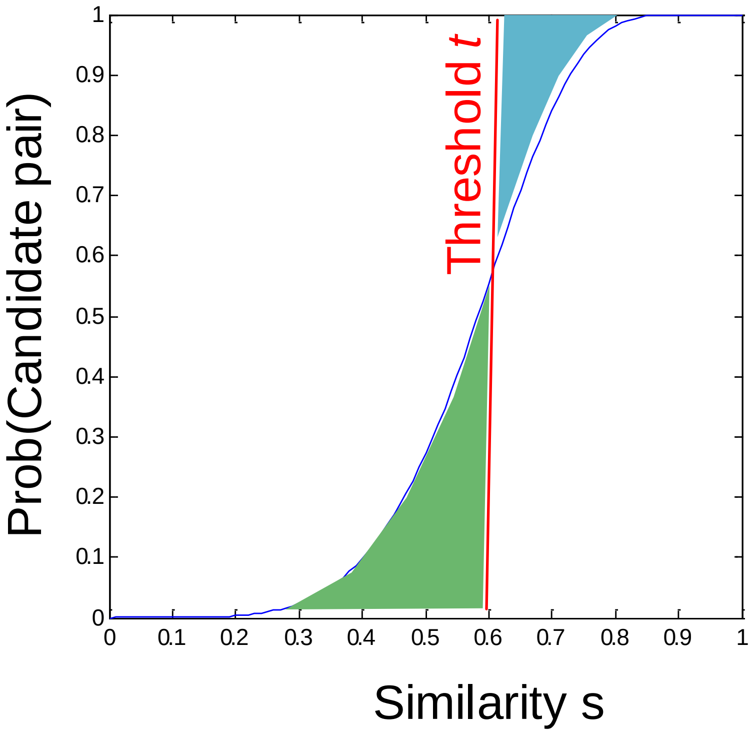


***r* = 4, *b* = 4** transforms a (.2,.8,.8,.2)-sensitive family into a (.2,.8,.8785,.0064)-sensitive family.

How to choose *r* and *b*

Picking *r* and *b*: The S-curve

- **Picking *r* and *b* to get desired performance**
  - **50 hash-functions** (***r*** *= 5,* ***b*** *= 10*)

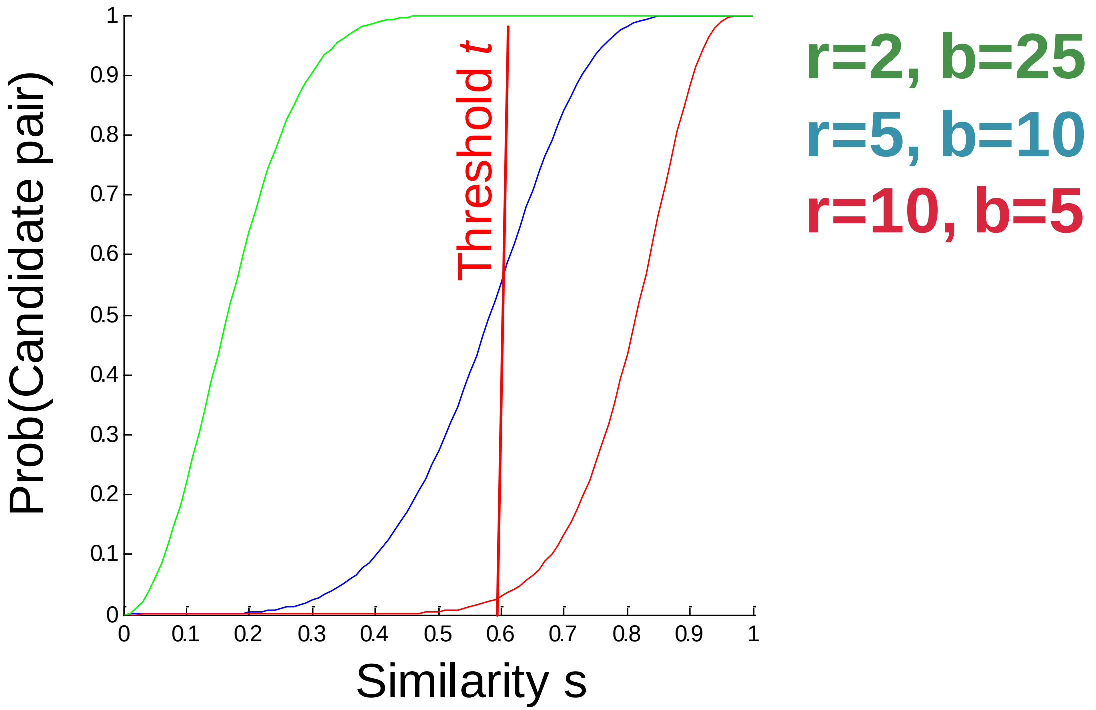


Blue area *X*: False Negative rate
These are pairs with ***sim > t*** but the ***X*** fraction won't share a band and then will **never become candidates.** This means we will never consider these pairs for (slow/exact) similarity calculation!

Green area Y: False Positive rate
These are pairs with ***sim < t*** but we will consider them as candidates. This is not too bad, we will consider them for (slow/exact) similarity computation and discard them.

Picking *r* and *b*: The S-curve

- **Picking *r* and *b* to get desired performance**
  - **50 hash-functions (*r* * *b* = *50*)**



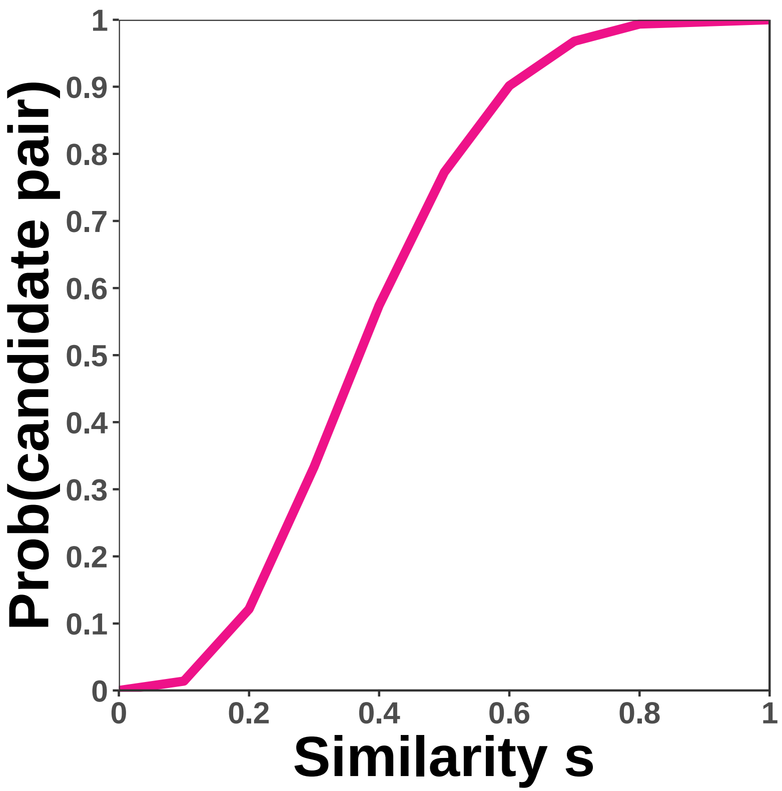
OR-AND Composition

- Apply a ***b***-way **OR** construction followed by an ***r***-way **AND** construction
- Transforms similarity ***s*** (probability p) into $(1-(1-s)^b)^r$
  - **The same S-curve, mirrored horizontally and vertically**

- **Example:** Take **H** and construct **H'** by the **OR** construction with ***b*** = 4. Then, from **H'**, construct **H''** by the **AND** construction with ***r*** = 4

Table for Function $(1-(1-s)^4)^4$

s	$p=(1-(1-s)^4)^4$
.1	.0140
.2	**.1215**
.3	.3334
.4	.5740
.5	.7725
.6	.9015
.7	.9680
.8	**.9936**



The example transforms a (.2,.8,.8,.2)-sensitive family into a (.2,.8,.9936,.1215)-sensitive family

Cascading Constructions

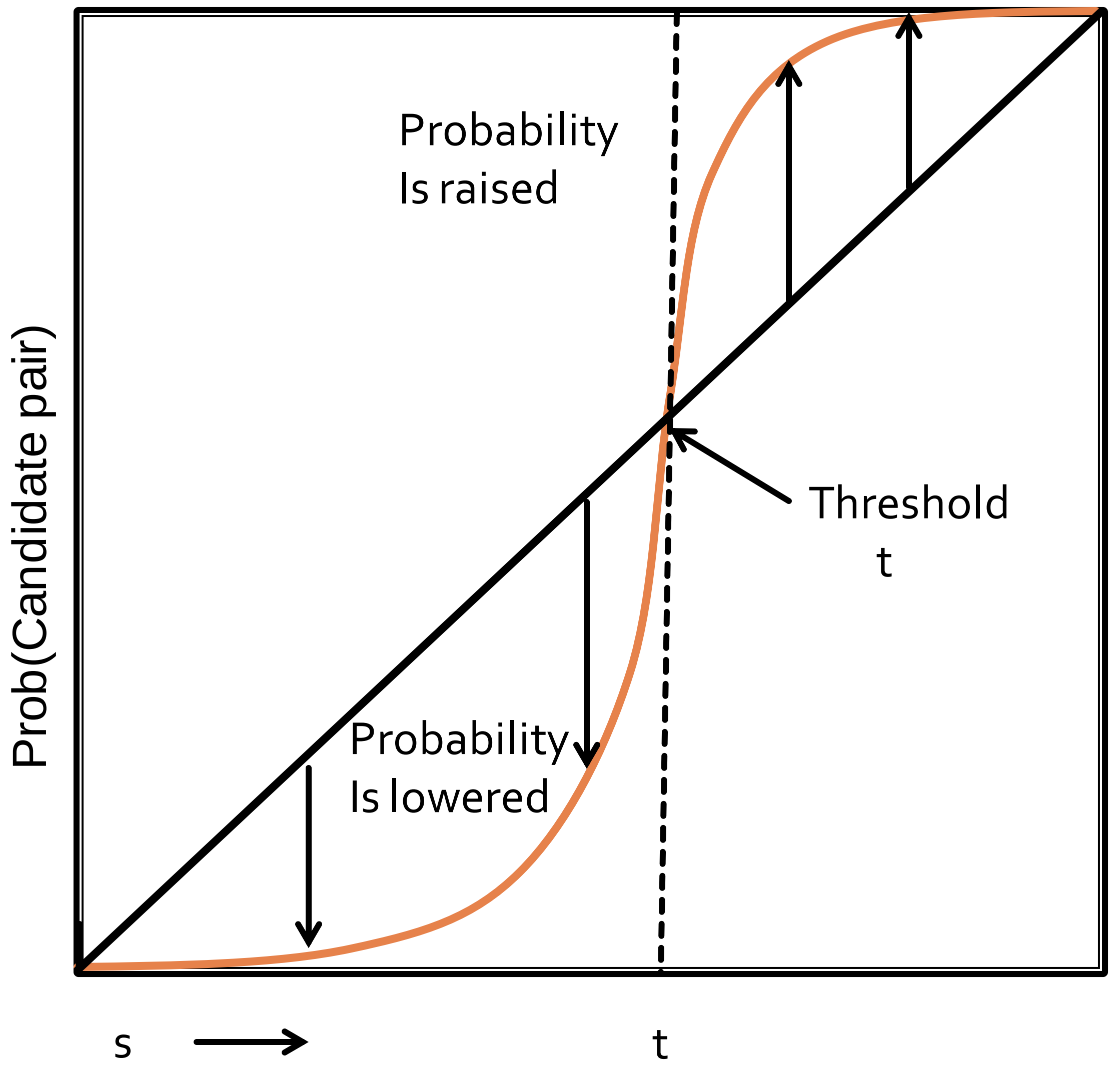
- **Example:** Apply the **(4,4) OR-AND** construction followed by the **(4,4) AND-OR** construction

- **Transforms a (.2, .8, .8, .2)-sensitive family into a (.2, .8, .9999996, .0008715)-sensitive family**
  - **Note this family uses 256 (=4*4*4*4) of the original hash functions**

General Use of S-Curves

- For each AND-OR S-curve $1-(1-s^r)^b$, there is a *threshold* *t*, for which $1-(1-t^r)^b = t$
- Above *t*, high probabilities are increased; below *t*, low probabilities are decreased
- You improve the sensitivity as long as the low probability is less than *t*, and the high probability is greater than *t*
  - Iterate as you like (computation is not an issue)
- Similar observation for the OR-AND type of S-curve: $(1-(1-s)^b)^r$

Visualization of Threshold



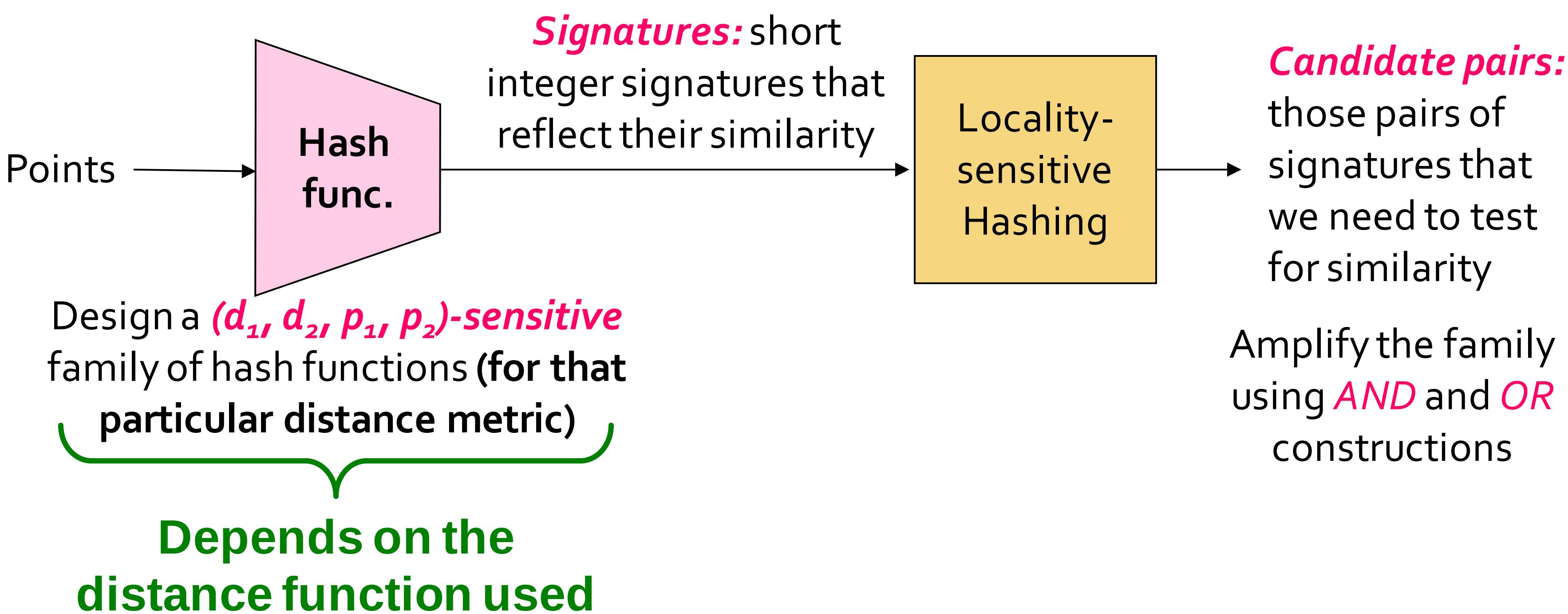
Summary

- Pick any two distances $d_1 < d_2$
- Start with a $(d_1, d_2, (1- d_1), (1- d_2))$-sensitive family
- Apply constructions to **amplify** (d_1, d_2, p_1, p_2)-sensitive family, where p_1 is almost 1 and p_2 is almost 0
- **The closer to 0 and 1 we get, the more hash functions must be used!**

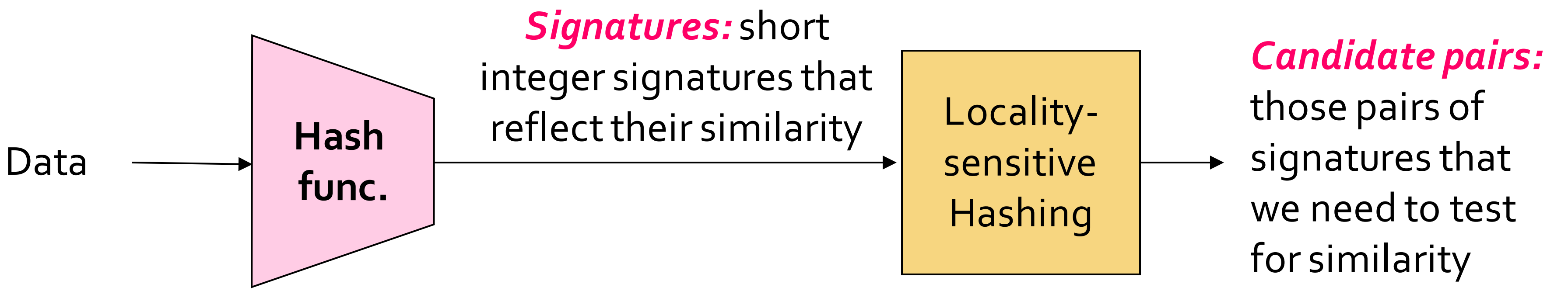
LSH for other distance metrics

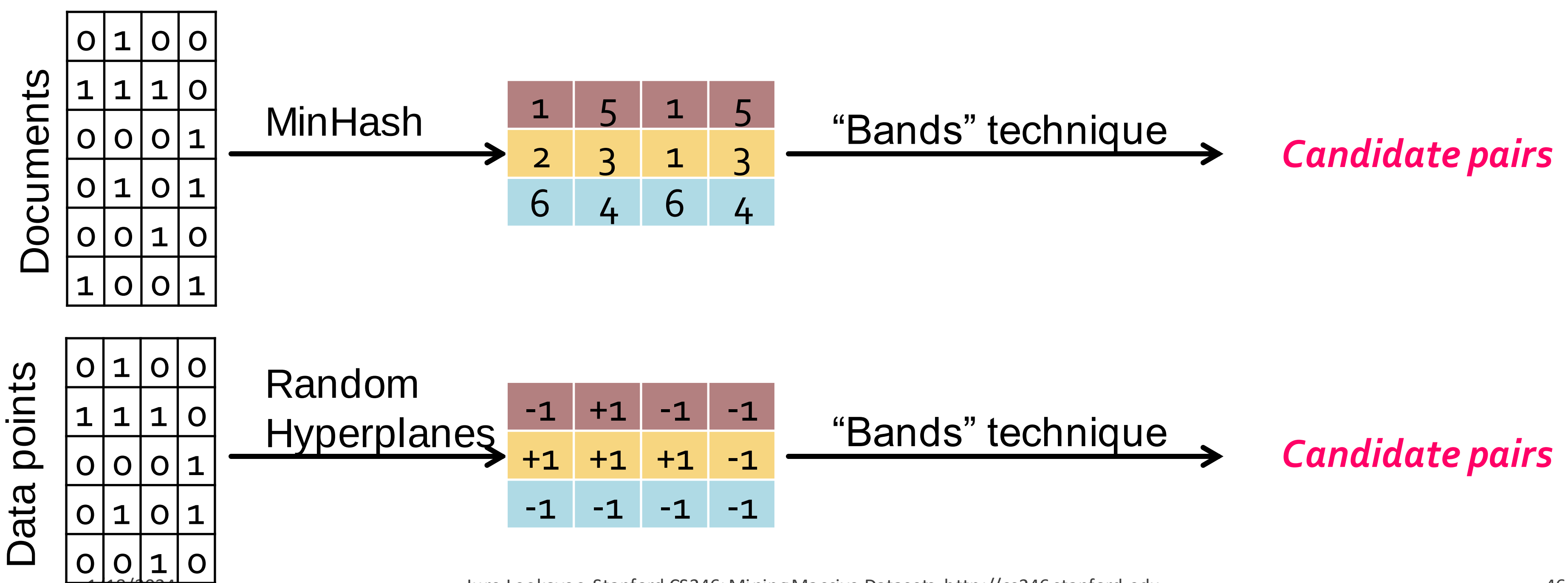
LSH for other Distance Metrics

- **LSH methods for other distance metrics:**
  - **Cosine distance: Random hyperplanes**
  - **Euclidean distance: Project on lines**



Summary of what we will learn

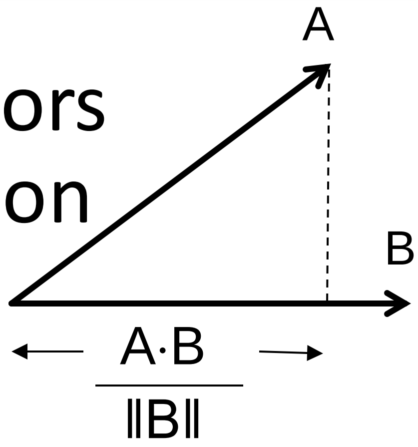




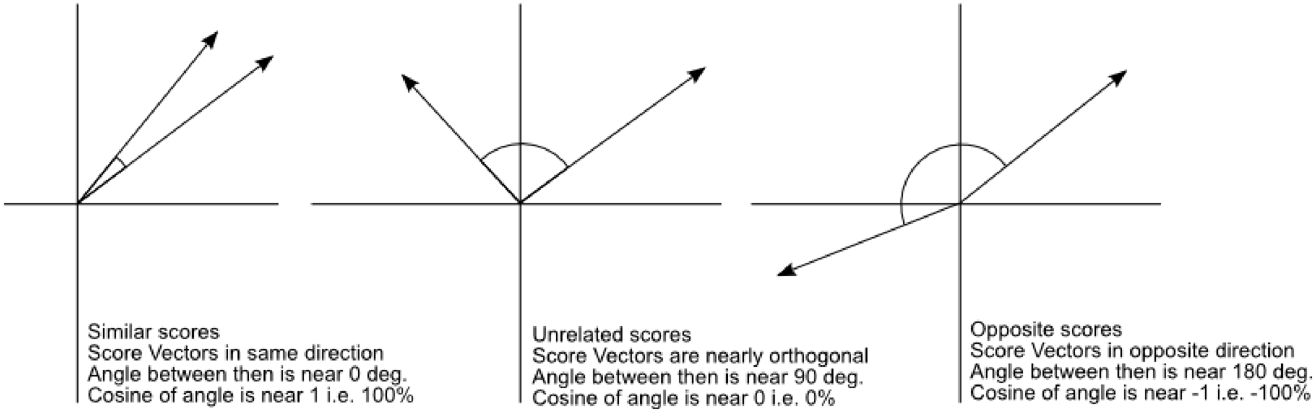
LSH for Cosine Distance

Cosine Distance

- ***Cosine distance*** = angle between vectors from the origin to the points in question
  $d(A, B) = \theta = \arccos(A \cdot B / \|A\| \cdot \|B\|)$
  - Has range $[\mathbf{0}, \boldsymbol{\pi}]$ (equivalently $[0,180°]$)
  - Can divide θ by $\boldsymbol{\pi}$ to have distance in range [0,1]



- **Cosine similarity = 1-d(A,B)**
  - But often defined as **cosine sim:** $\cos(\theta) = \dfrac{A \cdot B}{\|A\| \|B\|}$



- Has range -1…1 for general vectors
- Range 0..1 for non-negative vectors (angles up to 90°)

LSH for Cosine Distance

- For **cosine distance**, there is a technique called **Random Hyperplanes**
  - Technique similar to Min-Hashing
- **Random Hyperplanes** method is a ***$(d_1, d_2, (1-d_1/\pi), (1-d_2/\pi))$**-sensitive* family for any $\boldsymbol{d_1}$ and $\boldsymbol{d_2}$
- **Reminder:** (d_1, d_2, p_1, p_2)*-sensitive*
  1. If $d(x,y) \leq d_1$, then prob. that $h(x) = h(y)$ is at least p_1
  2. If $d(x,y) \geq d_2$, then prob. that $h(x) = h(y)$ is at most $\mathbf{p_2}$

Random Hyperplanes

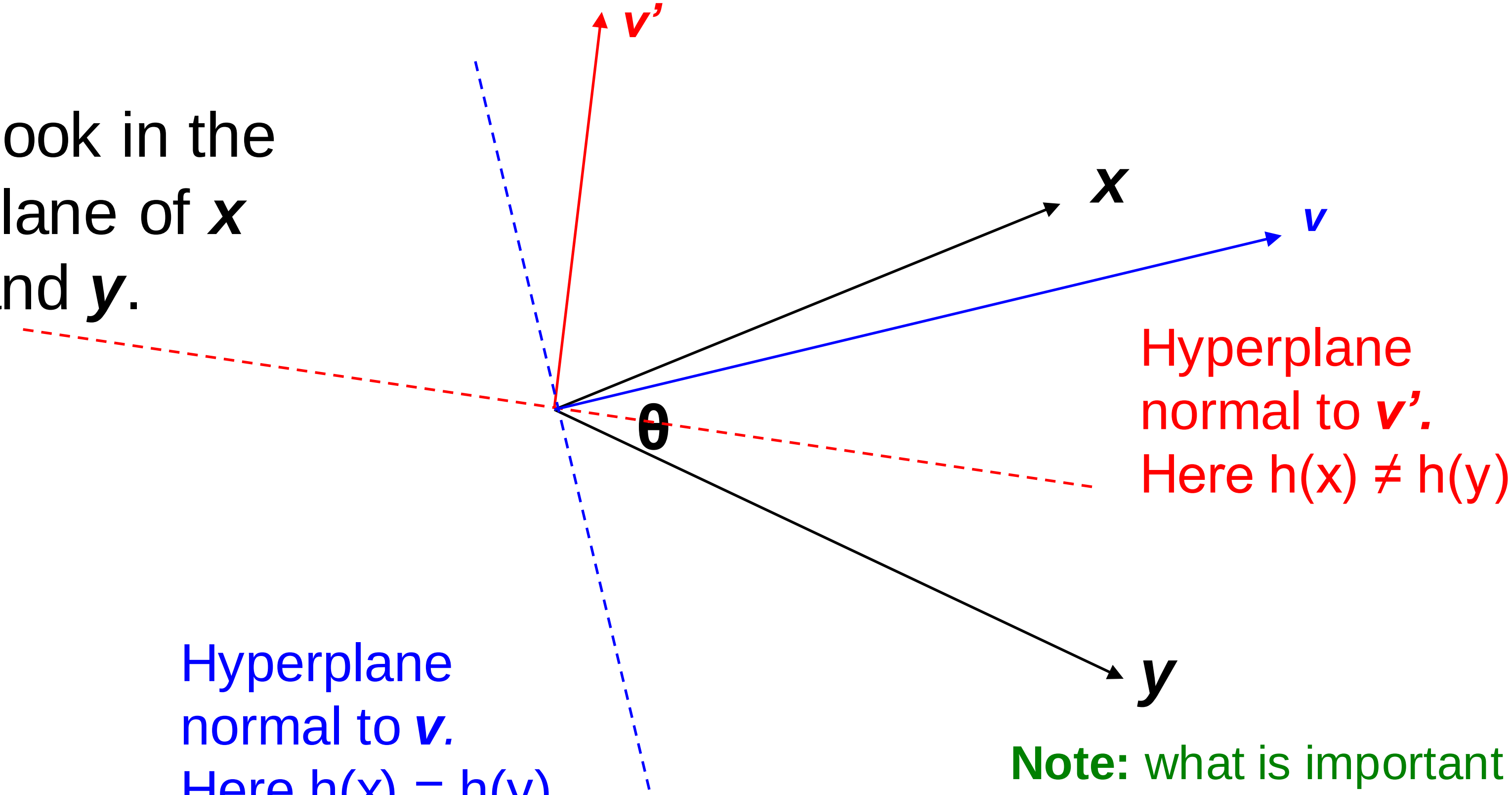
- Each vector $\boldsymbol{v}$ determines a hash function $\boldsymbol{h_v}$ with two buckets
- $\mathbf{h_v(x) = +1}$ if $\mathbf{v \cdot x \geq 0}$; $\mathbf{= -1}$ if $\mathbf{v \cdot x < 0}$
- LS-family $\boldsymbol{H}$ = set of all functions derived from any vector
- **Claim:** For points **x** and **y**,

$$\mathbf{Pr[h(x) = h(y)] \;=\; 1 - d(x,y) / \pi}$$

Proof of Claim: Points x and y

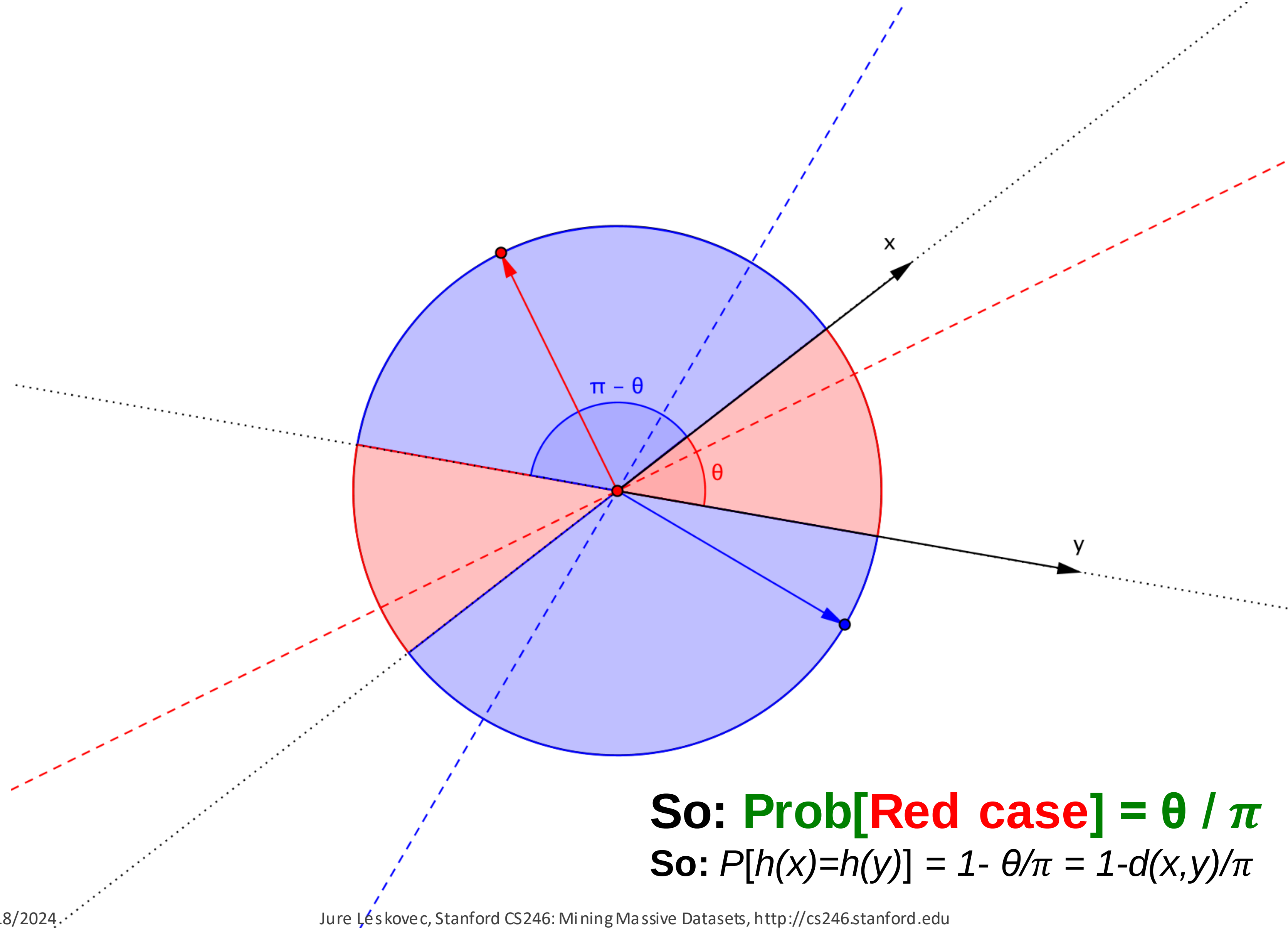
- Consider points ***x*** and ***y***
- Let's analyze hyperplanes ***v*** and ***v'***

Look in the plane of ***x*** and ***y***.



Note: what is important is that hyperplane is outside the angle, not that the vector is inside.

Proof of Claim



So: Prob[Red case] = θ / π

So: $P[h(x)=h(y)] = 1- \theta/\pi = 1-d(x,y)/\pi$

Signatures for Cosine Distance

- Pick some number of random vectors, and hash your data for each vector
- The result is a signature (*sketch*) of **+1**'s and **–1**'s for each data point
- Can be used for LSH like we used the Min-Hash signatures for Jaccard distance
- Amplify using **AND/OR** constructions

How to pick random vectors?

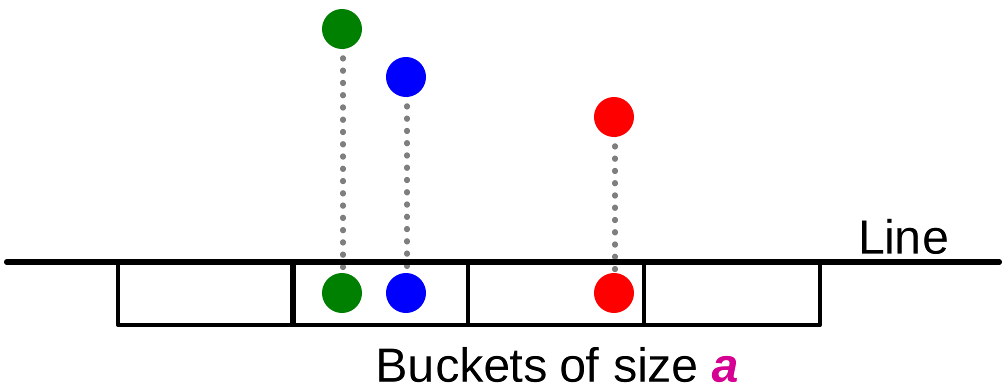
- Expensive to pick a random vector in ***M*** dimensions for large ***M***
  - Would have to generate ***M*** random numbers
- **A more efficient approach**
  - It suffices to consider only vectors ***v*** consisting of +1 and –1 components
    - **Why?** Assuming data is random, then vectors of +/-1 cover the entire space evenly (and does not bias in any way)

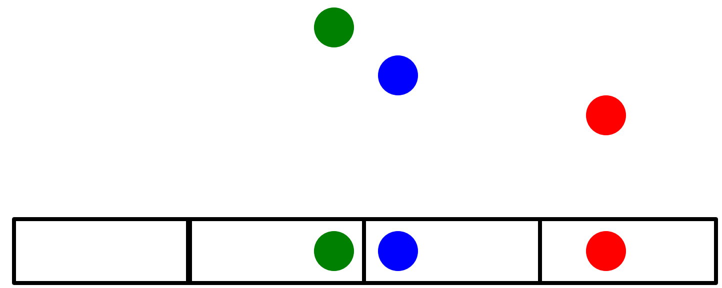
LSH for Euclidean Distance

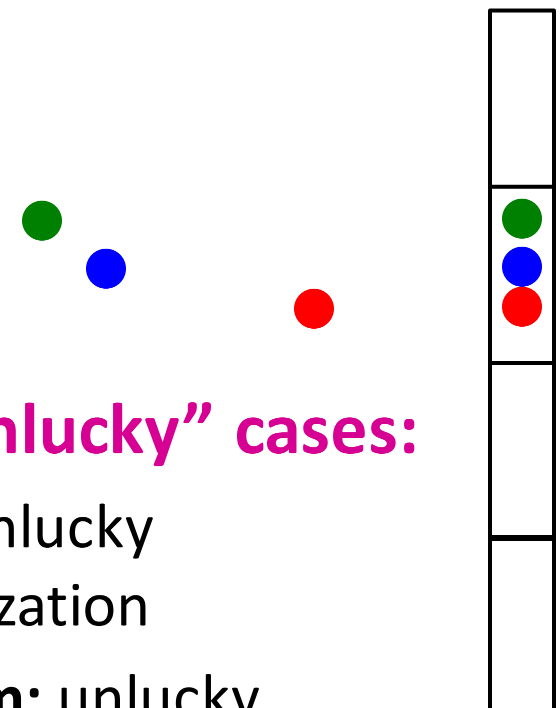
LSH for Euclidean Distance

- **Idea: Hash functions correspond to lines**
- Partition the line into buckets of size ***a***
- **Hash each point to the bucket containing its projection onto the line**
  - An element of the "Signature" is a bucket id for that given projection line
- **Nearby points are always close**;
  distant points are rarely in same bucket

Projection of Points

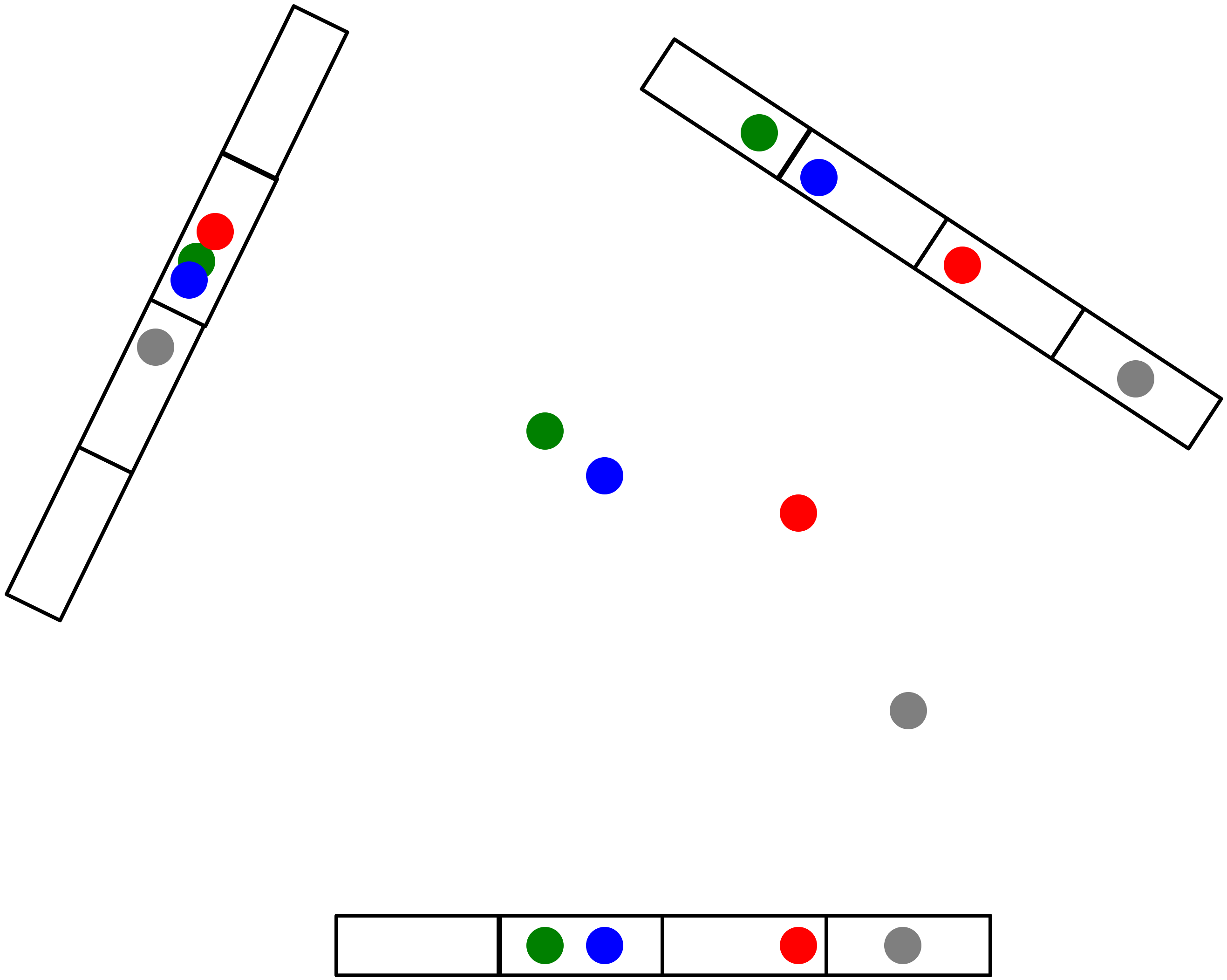




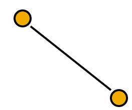


- **"Lucky" case:**
  - Points that are close hash in the same bucket
  - Distant points end up in different buckets
- **Two "unlucky" cases:**
  - **Top:** unlucky quantization
  - **Bottom:** unlucky projection

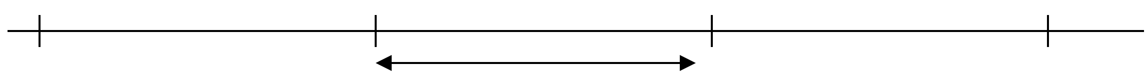
Multiple Projections



Projection of Points (1)

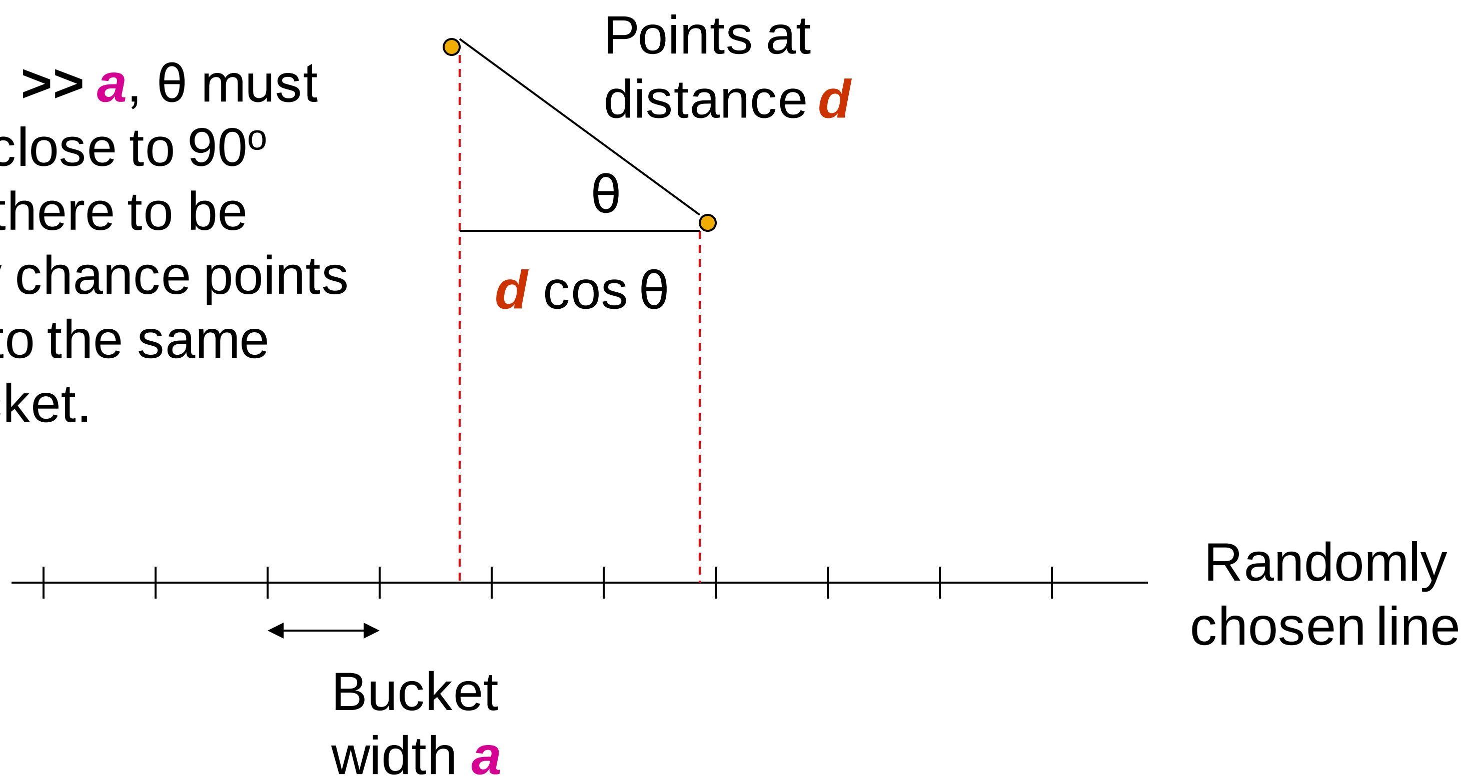


If ***d*** << ***a***, then the chance the points are in the same bucket is at least **1 – *d*/*a***.



Projection of Points (2)

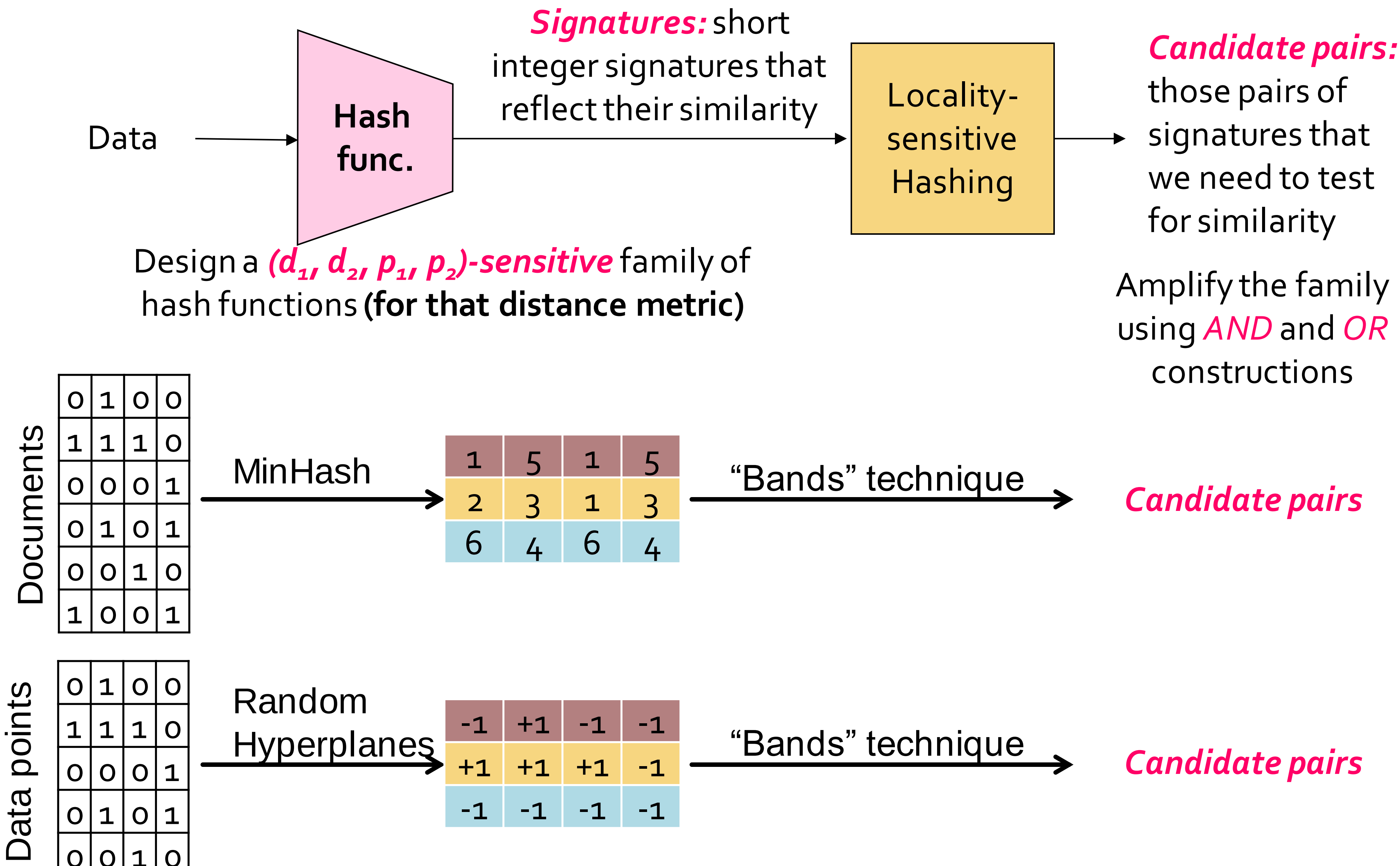
If ***d*** **>>** ***a***, θ must be close to 90° for there to be any chance points go to the same bucket.



A LS-Family for Euclidean Distance

- If points are distance $d \leq a/2$, prob. they are in same bucket $\geq 1 - d/a = ½$
- If points are distance $d \geq 2a$ apart, then they can be in the same bucket only if $d \cos \theta \leq a$
  - $\cos \theta \leq ½$
  - $60 \leq \theta \leq 90$, i.e., at most 1/3 probability
- Yields a ***(a/2, 2a, 1/2, 1/3)****-sensitive* family of hash functions for any ***a***
- **Amplify using AND-OR cascades**

Summary



Data
Hash func.
Signatures: short integer signatures that reflect their similarity
Locality-sensitive Hashing
Candidate pairs: those pairs of signatures that we need to test for similarity
Design a (d_1, d_2, p_1, p_2)-sensitive family of hash functions (for that distance metric)
Amplify the family using AND and OR constructions
Documents
0 1 0 0
1 1 1 0
0 0 0 1
0 1 0 1
0 0 1 0
1 0 0 1
MinHash
1 5 1 5
2 3 1 3
6 4 6 4
"Bands" technique
Candidate pairs
Data points
0 1 0 0
1 1 1 0
0 0 0 1
0 1 0 1
0 0 1 0
Random Hyperplanes
-1 +1 -1 -1
+1 +1 +1 -1
-1 -1 -1 -1
"Bands" technique
Candidate pairs

Two Important Points

- Property $P(h(C_1)=h(C_2))=sim(C_1,C_2)$ of hash function h is the essential part of LSH, without which we can't do anything

- LS-hash functions transform data to signatures so that the bands technique (AND, OR constructions) can then be applied