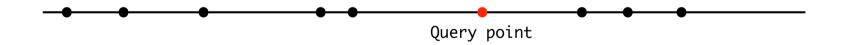
# Approximate Near Neighbor Search: Locality Sensitive Hashing

Inge Li Gørtz

## Nearest Neighbor

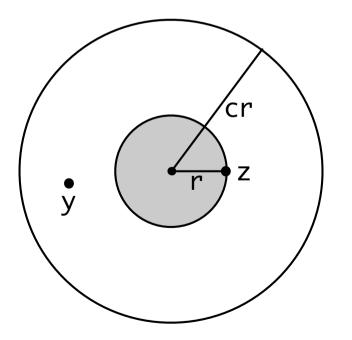
- Nearest Neighbor. Given a set of points P in a metric space, build a data structure which given a query point x returns the point in P closest to x.
- Metric. Distance function d is a metric:
  - 1.  $d(x,y) \ge 0$
  - 2. d(x,y) = 0 if and only if x = y
  - 3. d(x,y) = d(y,x)
  - 4.  $d(x,y) \le d(x,z) + d(z,y)$
- Warmup. 1D: Real line



# Approximate Near Neighbors

• ApproximateNearNeighbor(x): Return a point y such that  $d(x, y) \le c \cdot \min_{z \in P} d(x, z)$ 

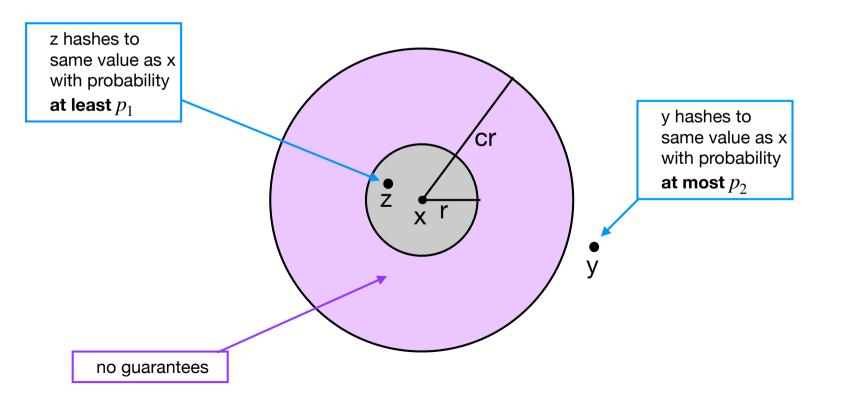
- c-Approximate r-Near Neighbor: Given a point x if there exists a point z in P  $d(x, z) \le r$  then return a point y such that  $d(x, y) \le c \cdot r$ . If no such point z exists return Fail.
- Randomised version: Return such an y with probability  $\delta$ .



# Locality Sensitive Hashing

- Locality sensitive hashing. A family of hash functions H is  $(r, cr, p_1, p_2)$ -sensitive with  $p_1 > p_2$  and c > 1 if:
  - $d(x, y) \le r \implies P[h(x) = h(y)] \ge p_1$  (close points)
  - $d(x, y) \ge cr \implies P[h(x) = h(y)] \le p_2$  (distant points)

for h chosen randomly from H.



#### Hamming Distance

- P set of n bit strings each of length d.
- Hamming distance. the number of bits where x and y differ:

 $d(x, y) = |\{i : x_i \neq y_i\}|$ 

• Example.

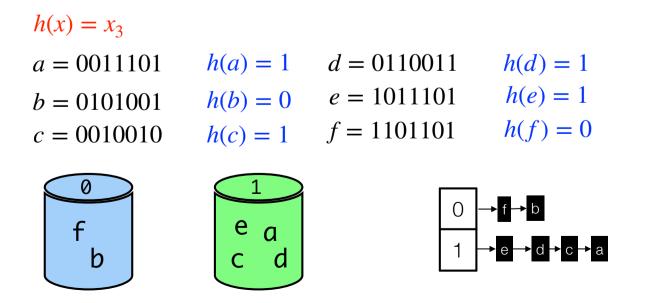
- Hash function. Chose  $i \in \{1, ..., d\}$  uniformly at random and set  $h(x) = x_i$ .
- What is the probability that h(x) = h(y)?

• 
$$d(x, y) \le r \Rightarrow P[h(x) = h(y)] \ge 1 - r/d$$

•  $d(x, y) \ge cr \Rightarrow P[h(x) = h(y)] \le 1 - cr/d$ 

- Pick random index *i* uniformly at random. Let  $h(x) = x_i$ .
- Bucket: Strings with same hash value h(x).
- Insert(x): Insert x in the list A[h(x)]
- NearNeighbour(*x*): Compute Hamming distance from *x* to all bitstrings in A[h(x)] until find one that is at most *cr* away. If no such string found return FAIL.

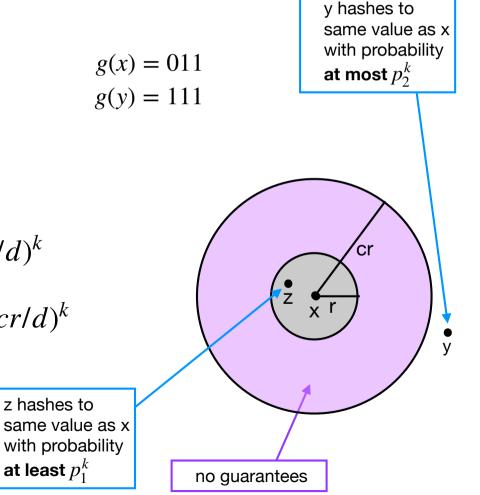
Query time: O(nd).



- Pick k random indexes uniformly and independently at random with replacement:
  - $g(x) = x_{i_1} x_{i_2} \cdots x_{i_k}$
- Example. k = 3.  $g(x) = x_2 x_3 x_6$

X =	1	0	1	0	0	1	0	0
x = y =	0	1	1	0	0	1	1	0

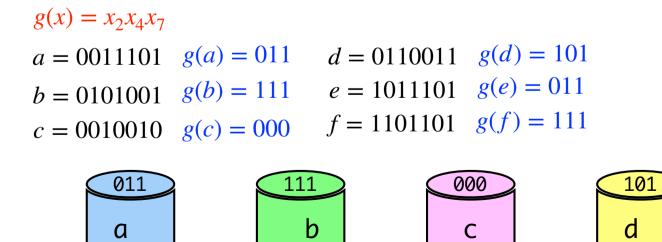
- Probability that g(x) = g(y)?
  - $d(x, y) \le r \Rightarrow P[g(x) = g(y)] \ge (1 r/d)^k$
  - $d(x, y) \ge cr \Rightarrow P[g(x) = g(y)] \le (1 cr/d)^k$



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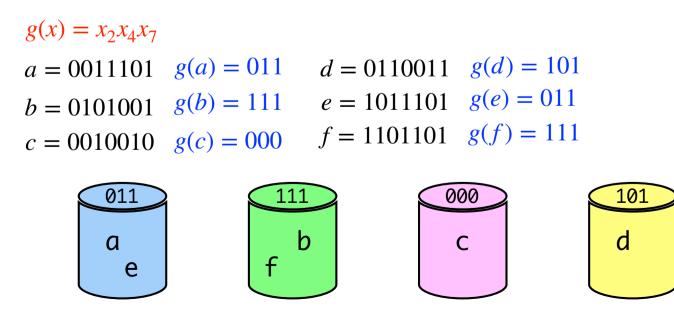
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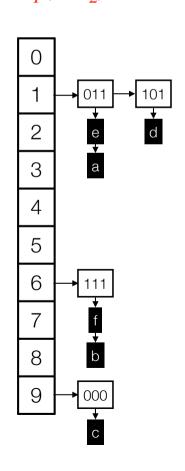
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  - $g(x) = x_{i_1} x_{i_2} \cdots x_{i_k}$
- Bucket: Strings with same hash value g(x).
- Save buckets in a hash table T with hash function  $h_T$ .

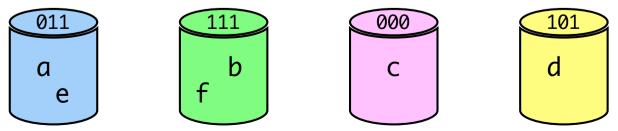
 $h_T(011_2) = 1$   $h_T(111_2) = 6$   $h_T(000_2) = 9$  $h_T(101_2) = 1$ 



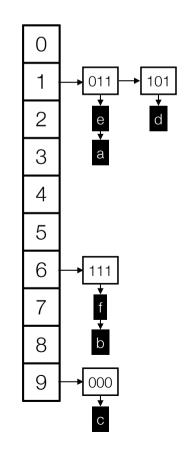


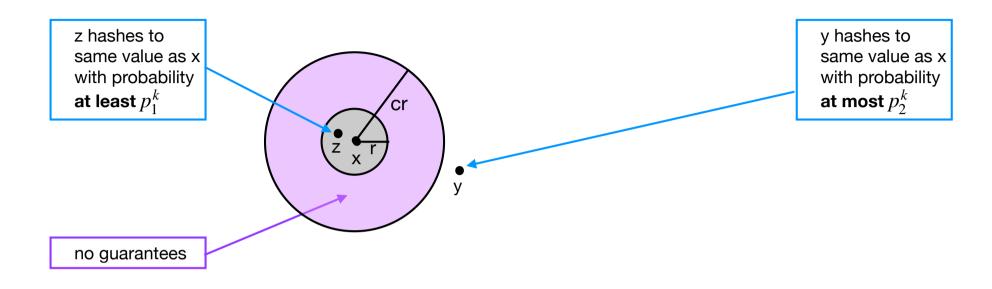
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- Insert(x): Insert x in the list of g(x) in T.
- NearNeighbour(*x*): Compute Hamming distance from *x* to all bitstrings in g(x) until find one that is at most *cr* away. If no such string found return FAIL.

 $g(x) = x_2 x_4 x_7$   $a = 0011101 \quad g(a) = 011 \qquad d = 0110011 \quad g(d) = 101$   $b = 0101001 \quad g(b) = 111 \qquad e = 1011101 \quad g(e) = 011$  $c = 0010010 \quad g(c) = 000 \qquad f = 1101101 \quad g(f) = 111$ 

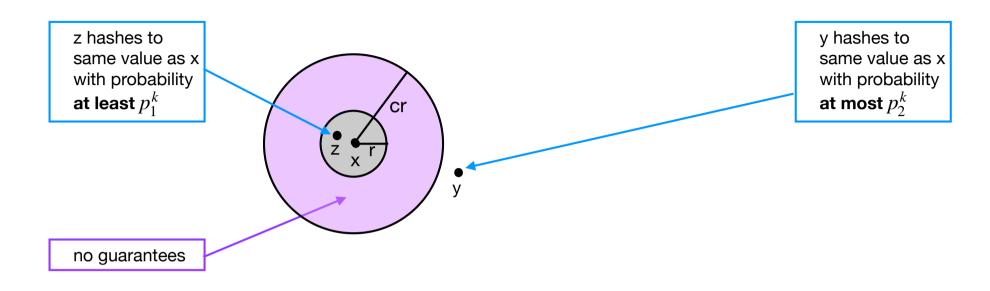


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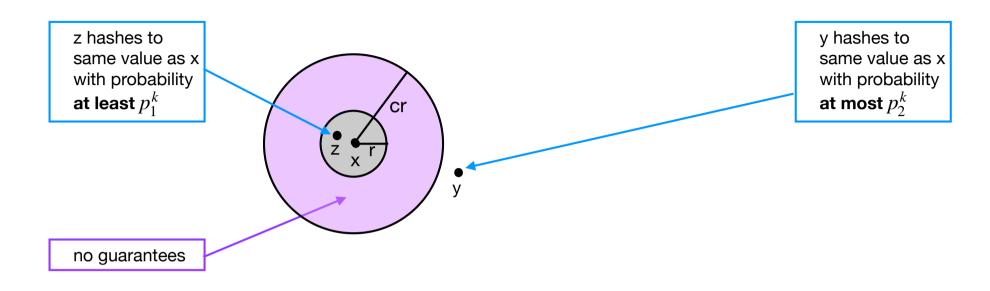




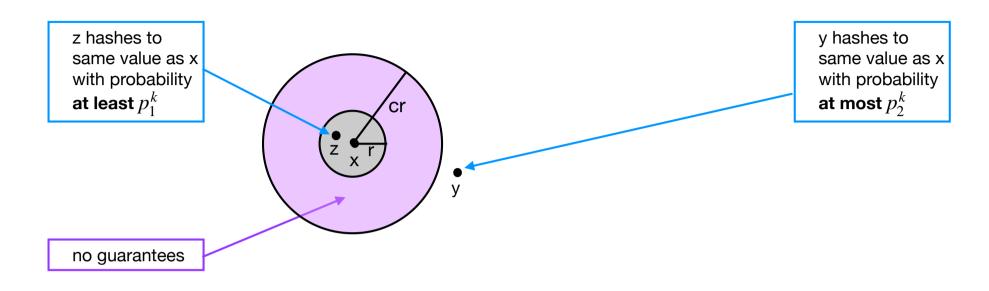
- What happens when we increase k?
  - Far away strings:



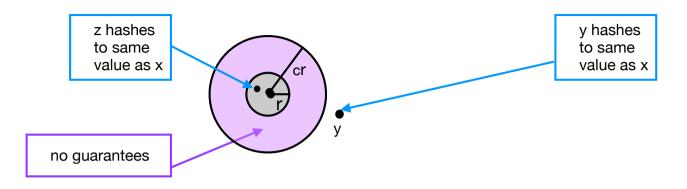
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  - Close strings:



- What happens when we increase k?
  - Far away strings: Probability that a far away string hashes to the same bucket as x decrease.
  - Close strings: Probability that a close string hashes to the same as x decrease.



- Expected number of far away strings that hashes to same bucket as x:
  - $F = \{y : d(x, y) > cr\}.$
- For  $y \in F$  we want  $P[g(y) = g(x)] \le 1/n$ :

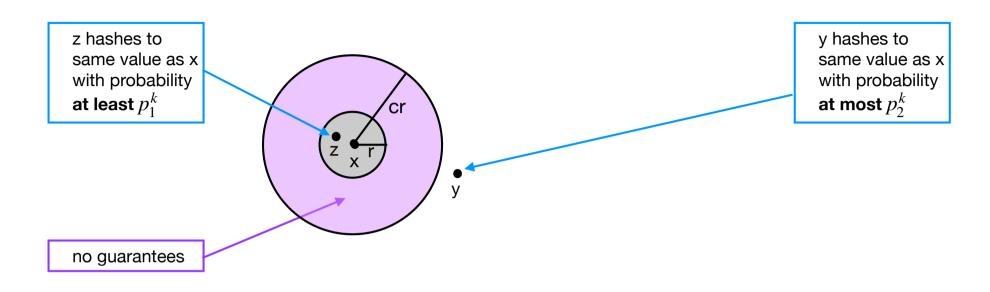
• Set 
$$k = \lg n / \lg(1/p_2)$$

• 
$$X_y = \begin{cases} 1 & y \text{ collides with } x \\ 0 & \text{otherwise} \end{cases}$$

• #far away strings colliding with x:  $X = \sum_{y \in F} X_y$ 

• 
$$E[X] = \sum_{y \in F} E[X_y] = \sum_{y \in F} 1/n \le 1.$$

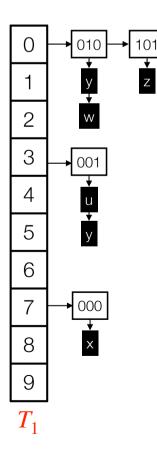
• Markov:  $P[X > 6] < E[X]/6 \le 1/6$ .

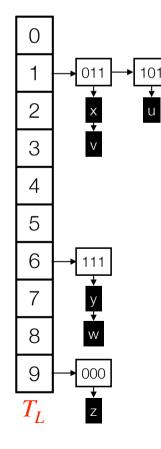


- What happens when we increase k?
  - Probability that a far away string hashes to the same bucket as x decrease.
    - $k = \lg n / \lg(1/p_2) \implies$  with probability  $\ge 5/6$  at most 6 far away strings hashes to x's bucket.
  - Probability that a close string hashes to the same as x decrease.

# LSH with Hamming Distance: Solution 3 (Amplification)

- Construct *L* hash tables  $T_j$ . Each table  $T_j$  has its own independently chosen hash function  $h_j$  and its own independently chosen locality sensitive hash function  $g_j$ .
- Insert(x): For all  $1 \le j \le L$  insert x in the list of  $g_j(x)$  in  $T_j$ .
- Query(x): For all 1 ≤ j ≤ L check each element in bucket g<sub>j</sub>(x) in T<sub>j</sub>. Return the one closest to x.





#### LSH with Hamming Distance

Let 
$$k = \frac{\lg n}{\lg(1/p_2)}$$
,  $\rho = \frac{\lg(1/p_1)}{\lg(1/p_2)}$ , and  $L = \lceil 2n^{\rho} \rceil$ , where  $p_1 = 1 - r/d$  and  $p_2 = 1 - cr/d$ .

- Claim 1. If there exists a string z\* in P with d(x,z\*) ≤ r then with probability at least 5/6 we will return some z in P for which d(x,z) ≤ r.
- Probability that z\* collides with x:

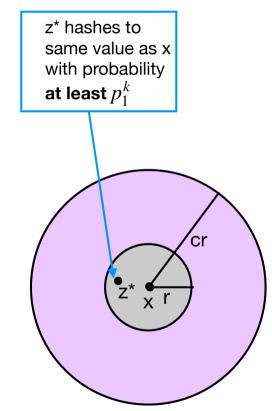
• 
$$P[\exists i : g_i(x) = g_i(z^*)] = 1 - P[g_i(x) \neq g_i(z^*) \text{ for all } i]$$
  

$$= 1 - \prod_{i=1}^{L} P[g_i(x) \neq g_i(z^*)]$$

$$= 1 - \prod_{i=1}^{L} \left(1 - P[g_i(x) = g_i(z^*)]\right)$$

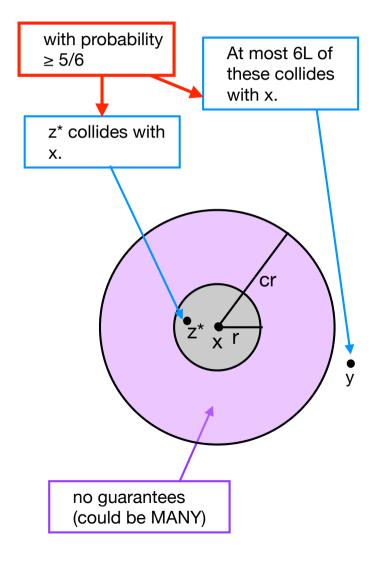
$$\ge 1 - \prod_{i=1}^{L} (1 - p_1^k) = 1 - (1 - p_1^k)^L \ge 1 - e^{-Lp_1^k}$$

$$\ge 1 - \frac{1}{e^2} \ge 1 - \frac{1}{6} = \frac{5}{6}$$



# LSH with Hamming Distance

- Expected query time is O(L): Can show that the expected number of far away strings that collides with x is L.
- Claim. The expected number of far away strings that collides with x is L.



# Locality Sensitive Hashing

- Locality sensitive hash function. A family of hash functions  $\mathscr{H}$  is  $(r, cr, p_1, p_2)$ -sensitive with  $p_1 > p_2$  and c > 1 if:
  - $d(x, y) \le r \implies P[h(x) = h(y)] \ge p_1$  (close points)
  - $d(x, y) \ge cr \implies P[h(x) = h(y)] \le p_2$  (distant points)
- Amplification.
  - Choose *L* hash functions  $g_j(x) = h_{1,j}(x) \cdot h_{2,j}(x) \cdots h_{k,j}(x)$ , where  $h_{i,j}$  is chosen independently and uniformly at random from  $\mathscr{H}$ .
- Locality sensitive hashing scheme.
  - Construct L hash tables  $T_i$ .
  - Insert(x): For all  $1 \le j \le L$  insert x in the list of  $g_i(x)$  in  $T_j$ .
  - Query(x): For all 1 ≤ j ≤ L check each element in bucket g<sub>j</sub>(x) in T<sub>j</sub>. Return the one closest to x.

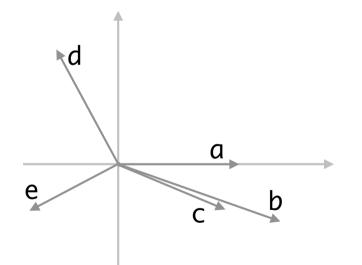
#### Jaccard distance and Min Hash

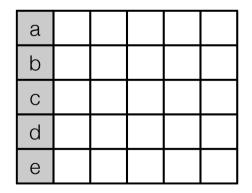
- Jaccard distance. Jaccard similarity:  $Jsim(A, B) = \frac{|A \cap B|}{|A \cup B|}$ 
  - Jaccard distance: 1- Jsim(A,B).
  - Hash function: *Min Hash*. (exercise)



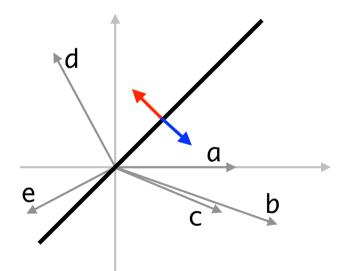
- Collection of vectors.
- Distance between two vectors is the angular distance between them  $dist(u, v) = \angle (u, v) / \pi$ .
  - Assume u and v are unit vectors. Then  $u \cdot v = \cos(\angle(u, v))$
- Hash function: Sim Hash.
  - Random projection: Take a random vector r and set  $h_r(u) = \operatorname{sign}(r \cdot u)$

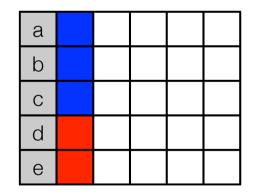
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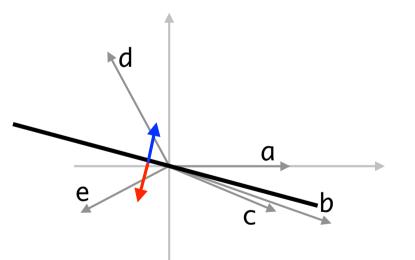


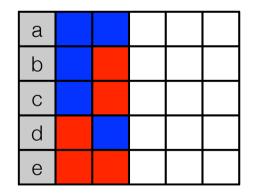
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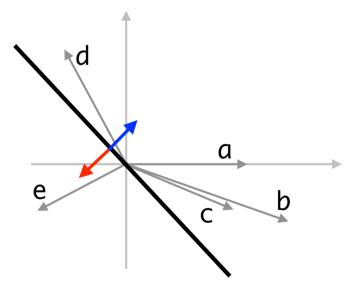


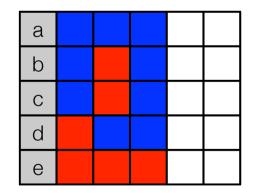
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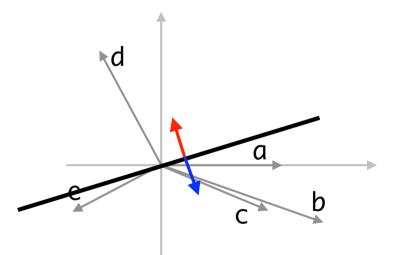


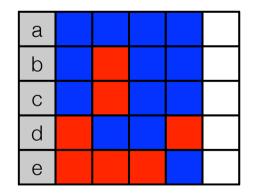
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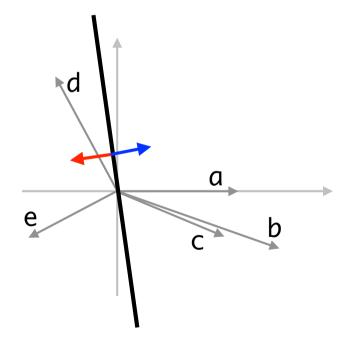


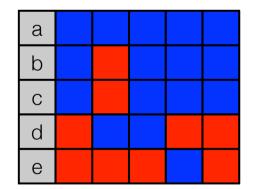
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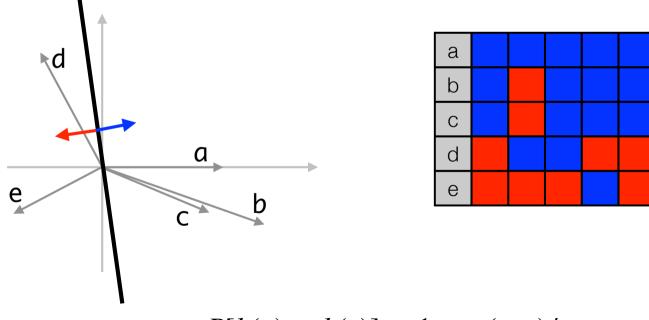


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• Can show that  $P[h(u) = h(v)] = 1 - \angle (u, v) / \pi$ .