

L7: Locality Sensitive Hashing

+ Distances for Distributions

Data Mining
Sep 15, 2026

Jeff M. Phillips



Min Hashing

$h_a \sim \mathcal{H}$
↳ salt

two sets S, S'

$$\Pr_{h \sim \mathcal{H}} [h(s) = h(s')] = JS(S, S')$$

$$\mathbb{E}_{h \sim \mathcal{H}} [\mathbb{1}(h(s) = h(s'))] = JS(S, S')$$

indicator

1 if true
0 if false

many hashes
 $h_1, h_2, \dots, h_t \sim \text{iid } \mathcal{H}$

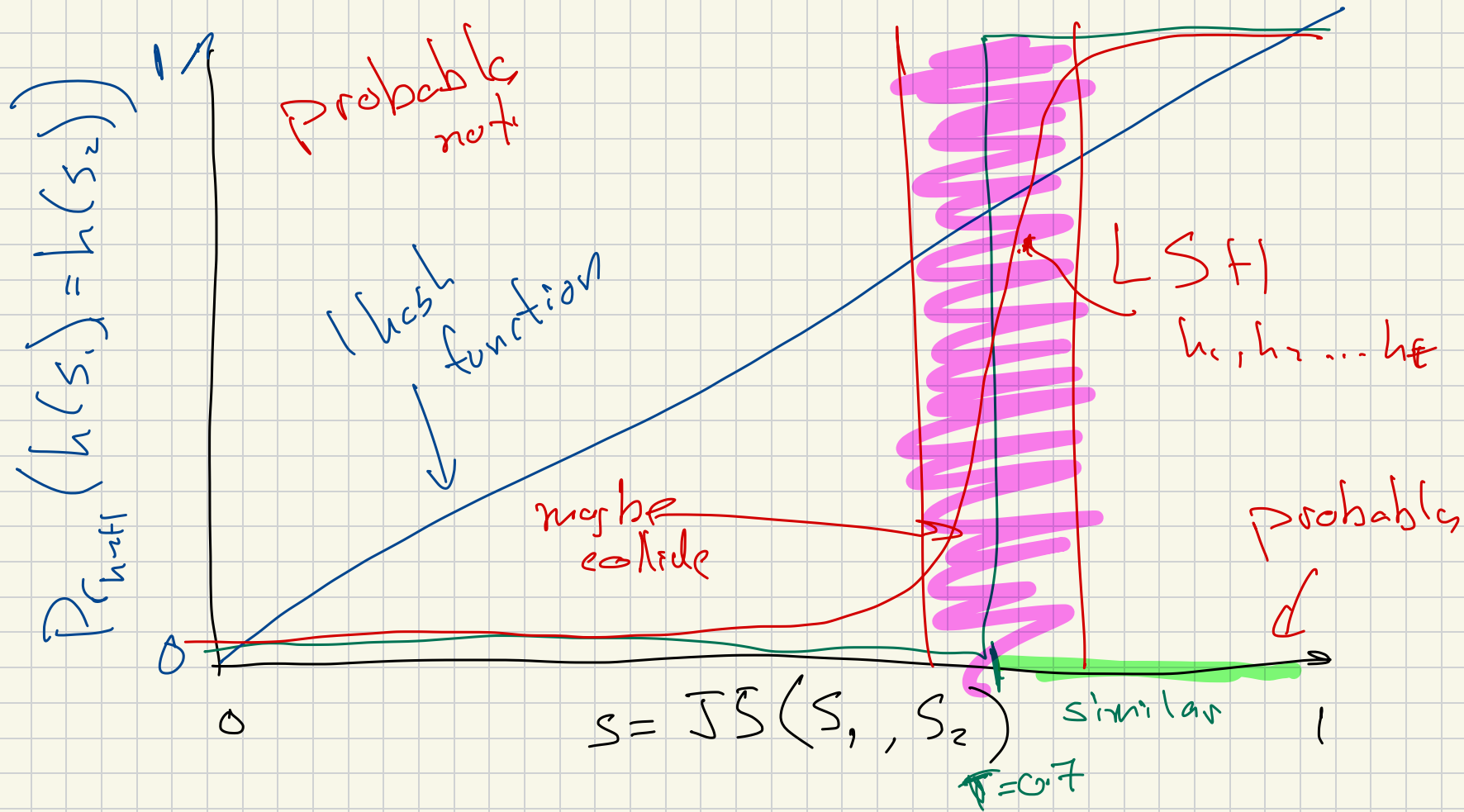
$t \approx 100, \dots, 1000$

$$\hat{JS}(S, S') = \frac{1}{t} \sum_{i=1}^t \mathbb{1}(h_i(s) = h_i(s'))$$

$$\mathbb{E}[\hat{JS}(S, S')] = JS(S, S')$$

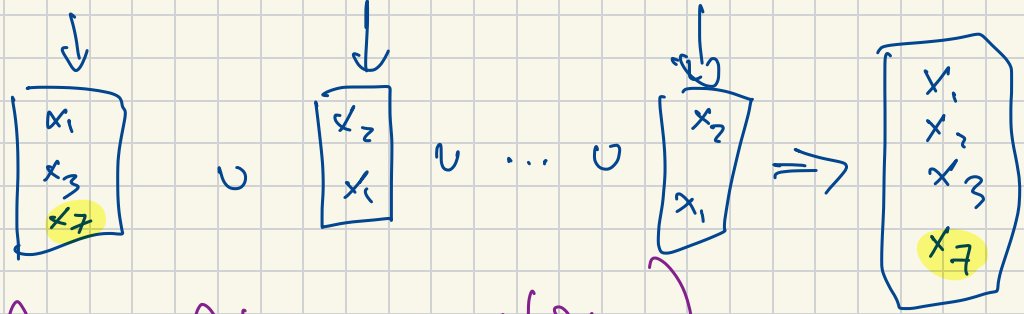
CLT

as $t \rightarrow \infty$
better estimate.



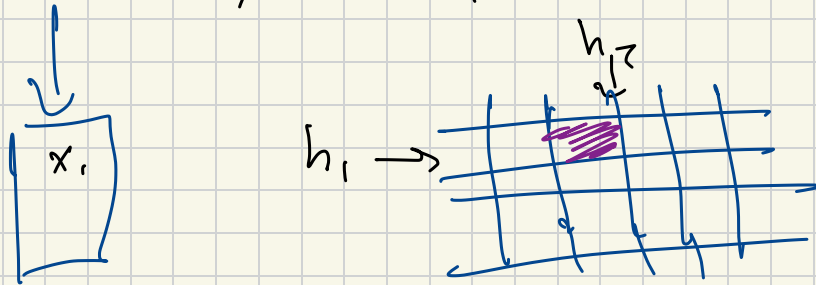
① Aggressive (few false negatives)

query $q \rightarrow h_1(q), h_2(q), \dots, h_t(q)$



② Conservative (few false positives)

concatenation $[h_1(q), h_2(q), \dots, h_t(q)] \rightarrow \mathbb{R}^t$



Banding

$\left[\begin{array}{c} h_1 \\ h_2 \\ \vdots \\ h_b \end{array} \right]$

$$H_1 = \text{concat}(h_1, \dots, h_b)$$

$\left[\begin{array}{c} h_{b+1} \\ \vdots \\ h_{2b} \\ h_{2b+1} \\ \vdots \\ h_t \end{array} \right]$

$$H_2 = \text{concat}(h_{b+1}, \dots, h_{2b})$$

$\vdots$

h_t

$$H_r = \text{concat} \dots h_t$$

$$t = b \cdot r$$

$\swarrow$ size of band

$\nwarrow$ # bands

Return union
collections on

$$H_1(g) \cup H_2(g) \dots \cup H_r(g)$$

LSH b (size of band) and r (number of bands)

Probability of found collision = $1 - (1 - s^b)^r$

$$\Pr(D_1 \equiv D_2)$$

$$\text{JS}(D_1, D_2) = s$$

$s = \text{JS}(D_1, D_2)$ is probability $h(D_1) = h(D_2)$:

s^b = probability all hashes collide in 1 band

$(1 - s^b)$ = probability not all collide in 1 band

$(1 - s^b)^r$ = probability that in no band, do all hashes collide

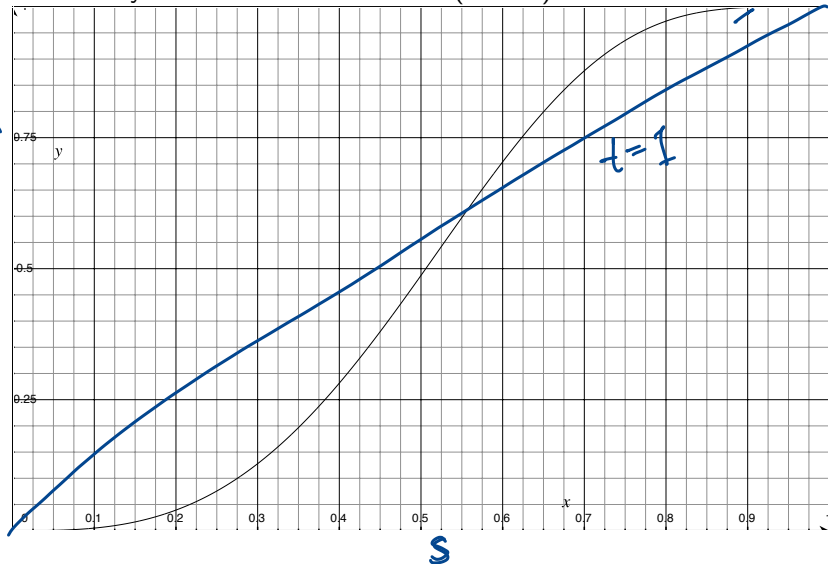
$1 - (1 - s^b)^r$ = probability all hashes collide in at least 1 band

LSH $b = 3$ and $r = 5$

$$r \cdot b = 15$$

Probability of found collision = $1 - (1 - s^b)^r$

$$P_r(s=s)$$

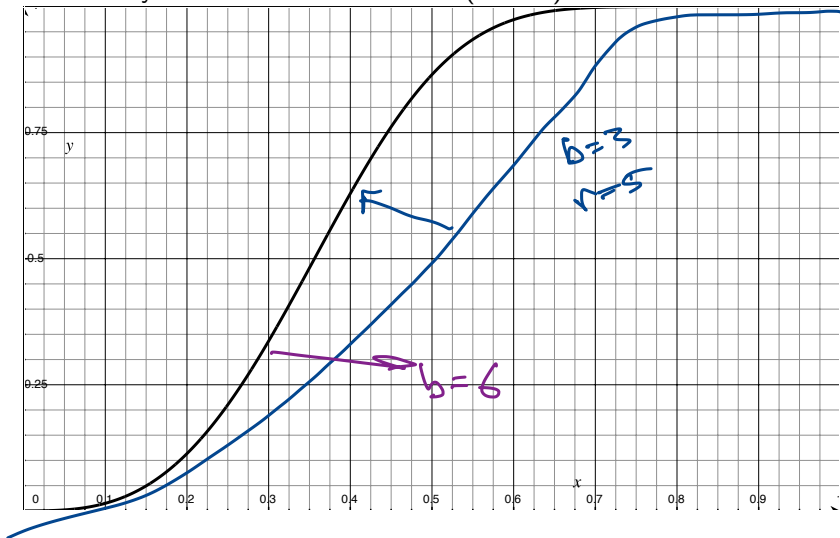


LSH $b = 3$ and $r = 15$

Probability of found collision $= 1 - (1 - s^b)^r$

LSH $b = 3$ and $r = 15$

Probability of found collision = $1 - (1 - s^b)^r$



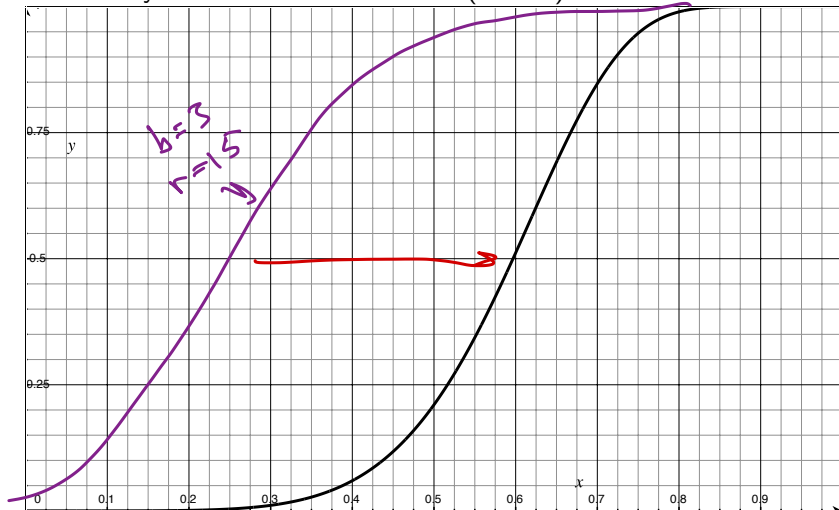
LSH $b = 6$ and $r = 15$

Probability of found collision $= 1 - (1 - s^b)^r$

LSH $b = 6$ and $r = 15$

$$b \cdot r \cdot b = 90$$

Probability of found collision = $1 - (1 - s^b)^r$



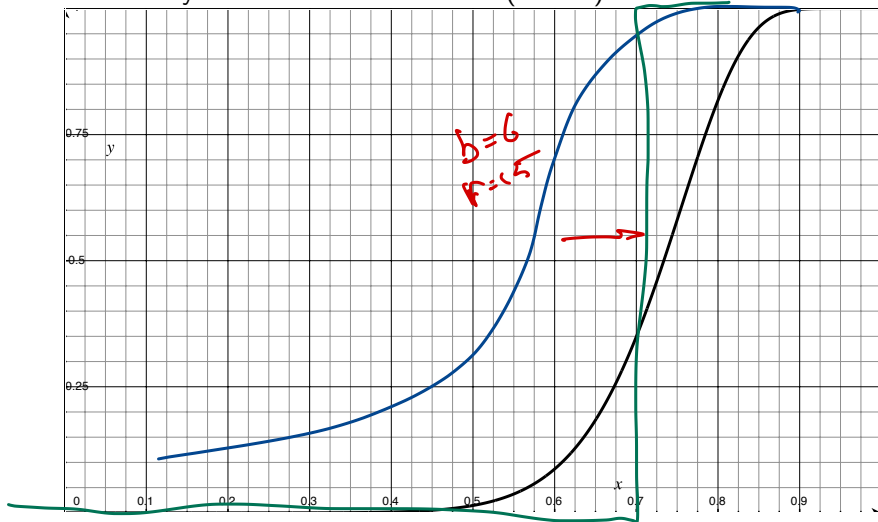
LSH $b = 10$ and $r = 15$

$$\text{Probability of found collision} = 1 - (1 - s^b)^r$$

LSH $b = 10$ and $r = 15$

$t = 150$

Probability of found collision = $1 - (1 - s^b)^r$



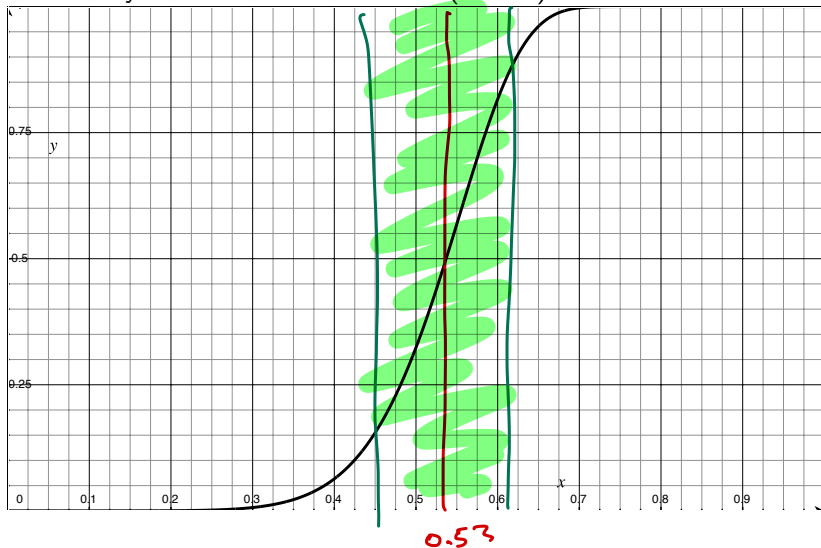
LSH $b = 8$ and $r = 100$

$$\text{Probability of found collision} = 1 - (1 - s^b)^r$$

LSH $b = 8$ and $r = 100$

1-800

Probability of found collision = $1 - (1 - s^b)^r$

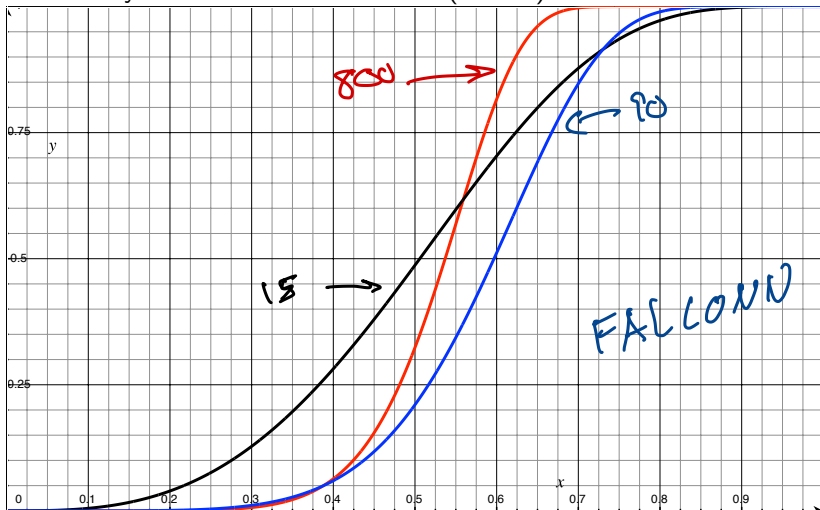


LSH ($b = 3, r = 5$) & ($b = 6, r = 15$) & ($b = 8, r = 100$)

Probability of found collision = $1 - (1 - s^b)^r$

LSH ($b = 3, r = 5$) & ($b = 6, r = 15$) & ($b = 8, r = 100$)

Probability of found collision = $1 - (1 - s^b)^r$



Cosine Similarity

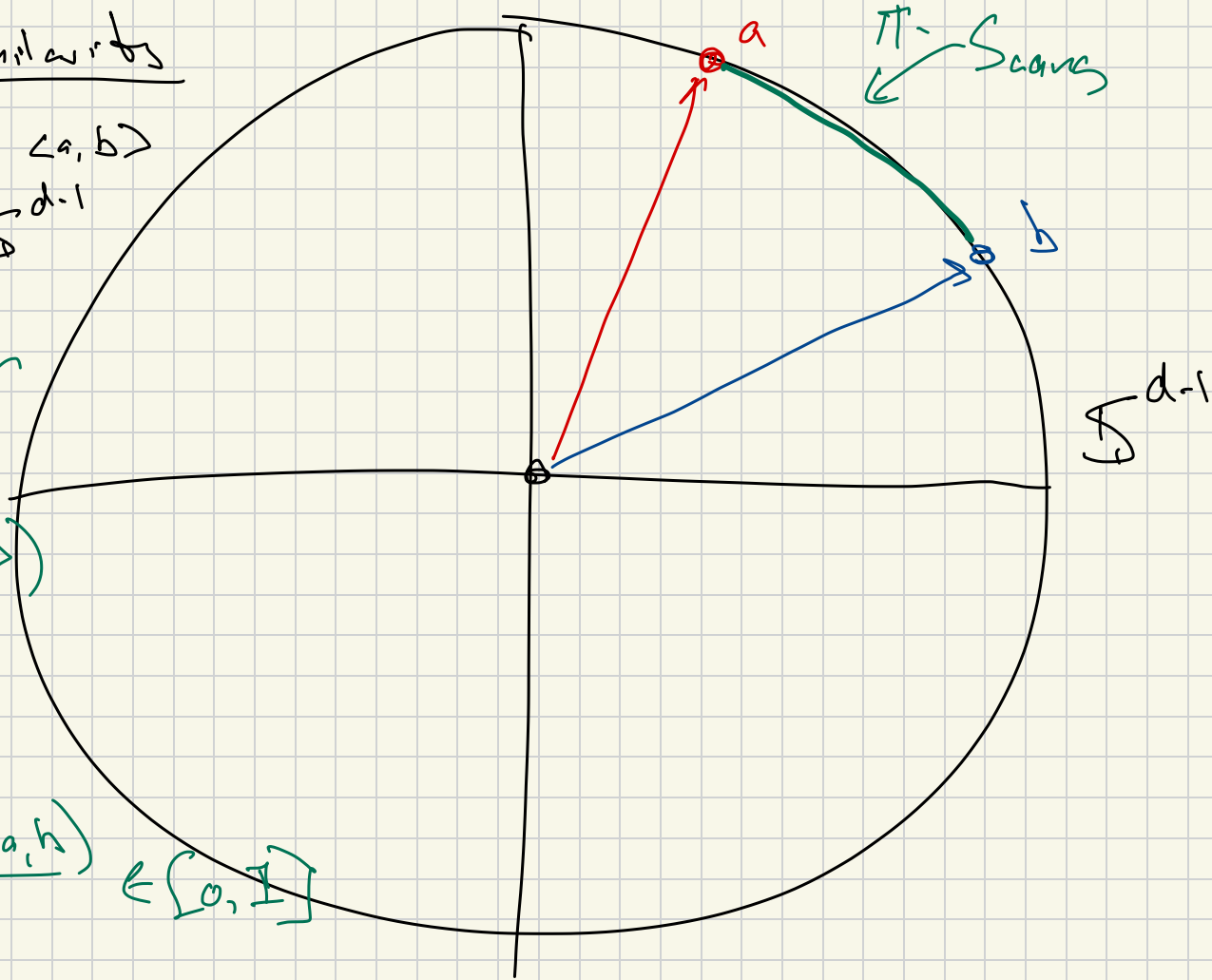
$$S_{\cos}(a, b) = \langle a, b \rangle$$

$a, b \in \mathbb{S}^{d-1}$

Angular Sim

$$S_{\text{ang}}(a, b) = 1 - \arccos(\langle a, b \rangle)$$

$$\hat{S}_{\text{ang}}(a, b) = \frac{S_{\text{ang}}(a, b)}{\pi} \in [0, 1]$$



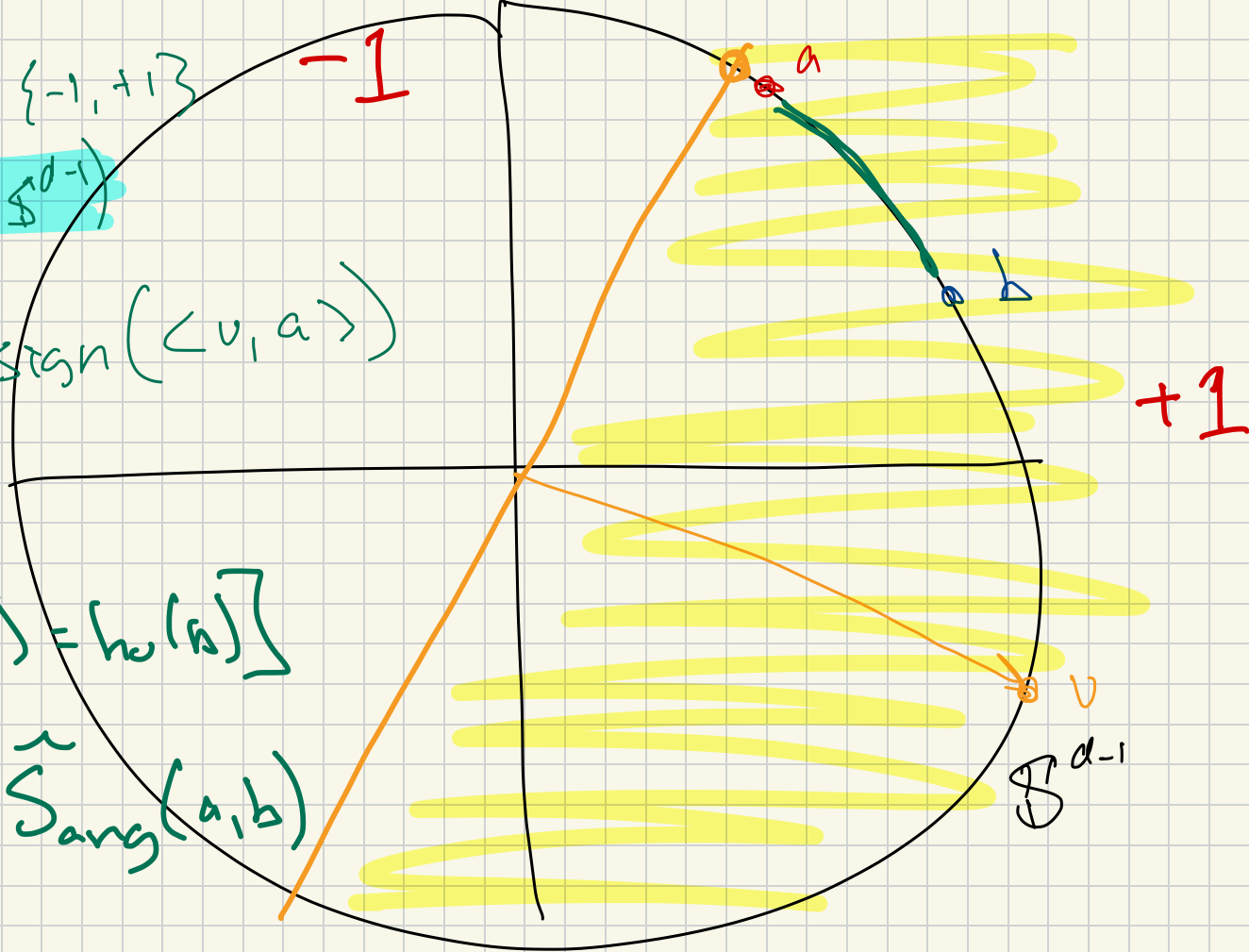
$$h_v: \mathbb{S}^{d-1} \rightarrow \{-1, +1\}$$

$$v \sim \text{Unif}(\mathbb{S}^{d-1})$$

$$h_v(a) = \text{sign}(\langle v, a \rangle)$$

$$\Pr_{v \sim \mathbb{S}^{d-1}} [h_v(a) = h_v(b)]$$

$$= \hat{S}_{\text{ang}}(a, b)$$



$$v \sim \text{Unif}(\mathbb{S}^{d-1})$$

proposal

$$x \in \left(\text{Unif}[-1, +1], \text{Unif}[-1, +1], \dots, \text{Unif}[-1, +1] \right)^d$$

$$v = \frac{x}{\|x\|}$$

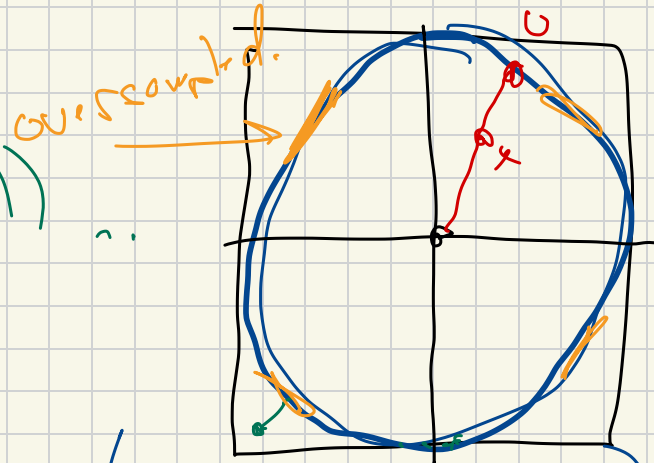
correct

$$g \in (\text{Norm}(0, 1), \text{Norm}(0, 1), \dots)$$

$$g_i \sim \mathcal{N}(0, 1)$$

$$v = \frac{g}{\|g\|}$$

$$\begin{array}{l} \uparrow \\ \text{BoxMuxrr} (x, x^* \sim \text{Unif}(0, 1)) \\ g, g^* \sim \mathcal{N}(0, 1) \end{array}$$



LSH for Euclidean



$f_u \mathbb{R}^d$
 σ Similar threshold

$$h(a) = (a - \beta) \bmod \sigma$$

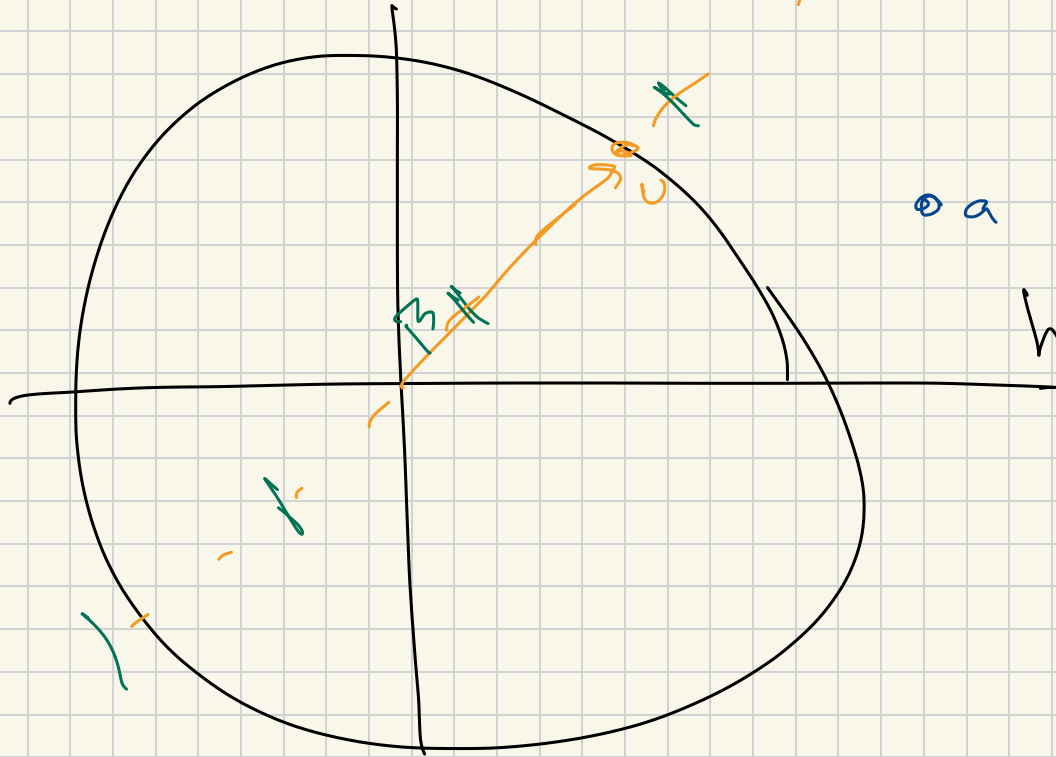
$$\Pr(h(a) = h(b)) = \begin{cases} 1 - \frac{\|a - b\|}{\sigma} & \text{if } \|a - b\| < \sigma \\ 0 & \text{otherwise} \end{cases}$$

LSH

Euclidean

in

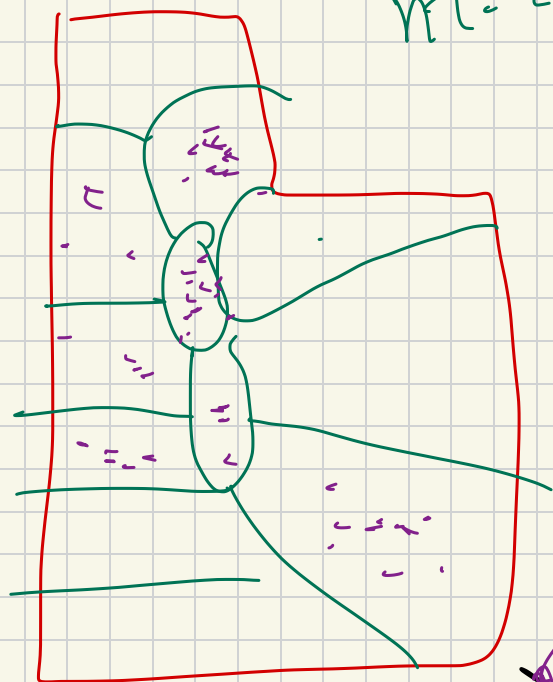
$\mathbb{R}^d$



$$h_{u, \beta}(a) = \lfloor -\beta + \langle a, u \rangle \rfloor$$

Distances for Distribution

$m=29$ counters



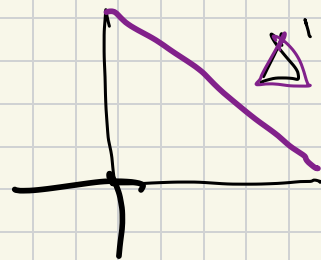
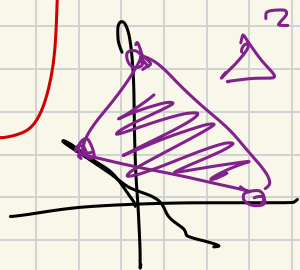
Map counters to coordinates
vector $x \in \mathbb{R}^{29=m}$

$c_1, c_2, \dots, c_m$ counts

$x_i = \frac{c_i}{N}$ N total number $m=29$

$$x \in \Delta^{m-1} = \Delta^{28}$$

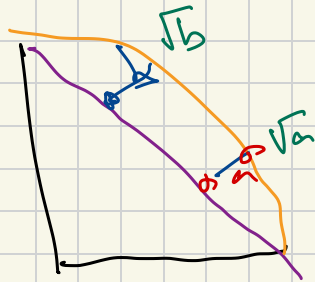
$$x_i \in [0, 1] \quad \sum x_i = 1$$



$$\underline{X, X' \in \Delta^{m-1}}$$

Kullback-Leibler Divergence

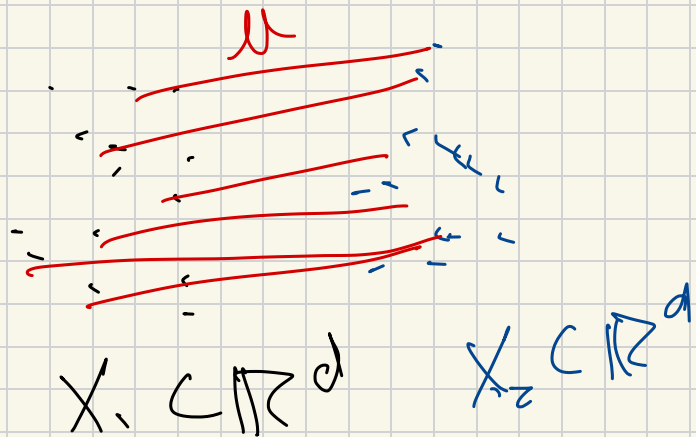
$$\begin{aligned} D_{KL}(a, b) &= D_{KL}(a \parallel b) \\ &= \sum_{i=1}^m a_i \ln \left(\frac{a_i}{b_i} \right) \end{aligned}$$



Hellinger Dist

$$D_H(a, b) = \frac{1}{\sqrt{2}} \sqrt{\sum_{j=1}^m (\sqrt{a_j} - \sqrt{b_j})^2}$$

Data X_1 X_2



EMD

Wasserstein W_1

$$\min_u \frac{1}{n} \sum_{x_i \in X_1} \|x_i - u(x_i)\|_1$$

$$= W_1(X_1, X_2)$$

$$W_2 = \min_u \frac{1}{n} \sqrt{\sum_{x_i} \|x_i - u(x_i)\|^2}$$