

**Problem 1: (LSH for Angular Similarity)**

For any vectors  $x, y \in \mathbb{R}^d$ , the angular distance is the angle (in radians) between the two vectors – formally,  $d_\theta(x, y) = \cos^{-1} \left( \frac{x \cdot y}{\|x\|_2 \|y\|_2} \right)$  (where  $\cos^{-1}(\cdot)$  returns the principle angle, i.e., angles in  $[0, \pi]$ ). The (normalized) angular similarity is given by  $s_\theta(x, y) = 1 - d_\theta(x, y)/\pi$ .

We now want to construct a LSH for the angular similarity metric. Consider the following family of hash functions: we first choose a random unit vector  $\sigma$  (i.e.,  $\sigma \in \mathbb{R}^d$  with  $\|\sigma\|_2 = 1$ ), and for any vector  $x$ , define  $h_\sigma(x) = \text{sgn}(x \cdot \sigma)$  (i.e., the sign of the dot product of  $x$  and  $\sigma$ ). Argue that for any  $x, y \in \mathbb{R}^d$ , we have:

$$\mathbf{P}[h_\sigma(x) = h_\sigma(y)] = s_\theta(x, y)$$

*Hint: For any pair  $x$  and  $y$  in  $\mathbb{R}^d$ , there is a unique plane passing through the origin containing  $x$  and  $y$  – convince yourself that  $d_\theta(x, y)$  is precisely the angle between  $x$  and  $y$  in this plane. Also, given any vector  $\sigma$ , its dot product with  $x$  and  $y$  only depends on the projection of  $\sigma$  on this plane. Now what can you say about the signs of the dot products of  $x$  and  $y$  with a random unit vector?*

**Solution:** Vectors  $x$  and  $y$  always define a plane, and the angle between them is measured in this plane. Figure (1) is a “top-view” of the plane containing  $x$  and  $y$ .

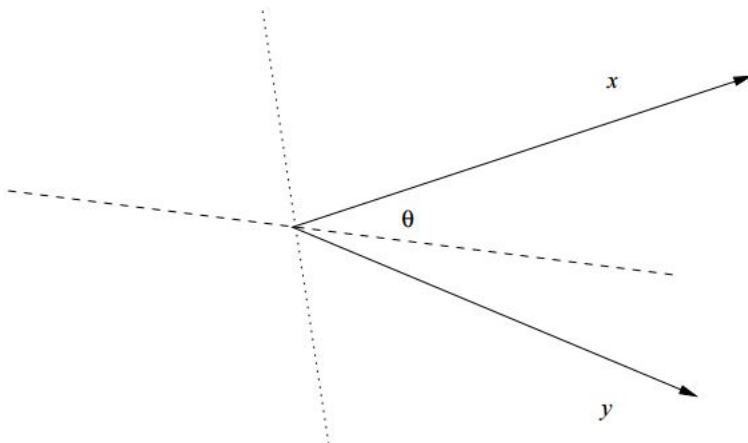


Figure 1: Two vectors make an angle  $\theta$

Suppose we pick a hyperplane through the origin. This hyperplane intersects the plane of  $x$  and  $y$  in a line. Figure (1) suggests two possible hyperplanes, one whose intersection is the dashed line and the other’s intersection is the dotted line. To pick a random hyperplane, we actually pick the normal vector to the hyperplane, say  $\sigma$ . The hyperplane is then the set of points whose dot product with  $\sigma$  is 0.

First, consider a vector  $\sigma$  that is normal to the hyperplane whose projection is represented by the dashed line in Fig. (1); that is,  $x$  and  $y$  are on different sides of the hyperplane. Then the dot products  $\sigma \cdot x$  and  $\sigma \cdot y$  will have different signs. If we assume, for instance, that  $\sigma$  is a vector whose

projection onto the plane of  $x$  and  $y$  is above the dashed line in Fig. (1), then  $\sigma \cdot x$  is positive, while  $\sigma \cdot y$  is negative. The normal vector  $\sigma$  instead might extend in the opposite direction, below the dashed line. In that case  $\sigma \cdot x$  is negative and  $\sigma \cdot y$  is positive, but the signs are still different.

On the other hand, the randomly chosen vector  $\sigma$  could be normal to a hyperplane like the dotted line in Fig. (1). In that case, both  $\sigma \cdot x$  and  $\sigma \cdot y$  have the same sign. If the projection of  $\sigma$  extends to the right, then both dot products are positive, while if  $\sigma$  extends to the left, then both are negative.

What is the probability that the randomly chosen vector is normal to a hyperplane that looks like the dashed line rather than the dotted line? All angles for the line that is the intersection of the random hyperplane and the plane of  $x$  and  $y$  are equally likely. Thus, the hyperplane will look like the dashed line with probability  $\theta/\pi$  and will look like the dotted line otherwise.

### Problem 2: (Choosing LSH Parameters for Nearest Neighbors)

An important routine in many clustering/machine learning algorithms is the  $(c, R)$ -Nearest-Neighbors (or  $(c, R)$ -NN) problem: given a set of  $n$  points  $V$  and a distance metric  $d$ , we want to store  $V$  in order to support the following query:

*Given a query point  $q$ , if there exists  $x \in V$  such that  $d(x, q) \leq R$  then, with probability at least  $1 - \delta$ , we must output a point  $x' \in V$ , such that  $d(x', q) \leq cR$ .*

We now show how to solve this problem using LSH. Assume that we are given a  $(R, cR, p_1, p_2)$ -sensitive hash family  $H$ <sup>1</sup>. As in class, we can amplify the probabilities by first taking the AND of  $r$  such hash functions to get a new family  $H_{AND}$ ; next, we can take the OR of  $b$  hash functions from  $H_{AND}$  to get another family  $H_{OR-AND}$ .

Given the set  $V$ , we hash each element using a single hash function  $g$  from  $H_{OR-AND}$  (which corresponds to  $b \times r$  hash functions from  $H$ ). Now given a query point  $q$ , we hash  $q$  using our cascaded hash-function  $g$ , and find all  $y \in V$  such that  $g(y) = g(q)$  – let this set be denoted  $Y_q$ . Finally, we can check  $d(q, y)$  for each  $y$  in  $Y_q$ , and return those  $y$  for whom  $d(q, y) < cR$ .

#### Part (a)

If there exists  $x \in V$  such that  $d(x, q) \leq R$  then, argue that we output  $x$  with probability  $1 - (1 - p_1^r)^b$ . On the other hand, also show that the expected number of false positives (i.e., points  $x' \in V$  such that  $d(x', q) > cR$ ) that we consider per hash function in  $H_{AND}$  is at most  $np_2^r$ .

**Solution:** From the definition of a  $(R, cR, p_1, p_2)$ -sensitive hash family, we know that for any  $x \in V$  such that  $d(x, q) \leq R$ , the probability that there is a collision is at least  $p_1$  – hence the probability that all the hash functions *do not* collide is  $1 - p_1^r$ . Now since we are taking the OR of  $b$  such hash functions from the family  $H_{AND}$ , the probability that *none of them* output  $x$  is at most  $1 - (1 - p_1^r)^b$ .

On the other hand, for any  $x \in V$  such that  $d(x, q) \geq cR$ , we know that for any composite hash function in  $H_{AND}$ , a false collision occurs with probability at most  $p_2^r$ . Now to bound the expected

<sup>1</sup>Recall in class we defined a  $(d_1, d_2, p_1, p_2)$ -sensitive hash family – for convenience, we are setting the distances to  $R$  and  $cR$

number of false positives, note that the number of elements  $x$  such that  $d(x, q) \geq cR$  is bounded by  $|V| = n$  – thus the expected number of false positives is at most  $np_2^r$ .

**Part (b)**

Note that since we check for false positives, we never output one – however, we have  $O(1)$  runtime cost for each false positive (to check its distance). Choose  $r$  to ensure that the expected number of false-positives per hash function in  $H_{AND}$  is 1. Using this choice of  $r$ , show that for the guarantee we desire for the  $(c, R)$ -NN problem, we need to choose  $b = n^\rho \ln(1/\delta)$ , where  $\rho = \frac{\ln(1/p_1)}{\ln(1/p_2)}$ .

**Solution:** To ensure that on average we have at most one false positive, we can choose  $r$  such that  $np_2^r = 1$  – thus  $r = \ln n / \ln(1/p_2)$  – thus  $(1/p_1)^r = \exp(\ln(1/p_1) \ln n / \ln(1/p_2)) = n^\rho$ . Now suppose we choose  $b = n^\rho \ln(1/\delta)$  – then we have:

$$\begin{aligned} 1 - (1 - p_1^r)^b &= 1 - \left(1 - \frac{1}{n^\rho}\right)^{n^\rho \ln(1/\delta)} \\ &\geq 1 - e^{-\ln(1/\delta)} \\ &= 1 - \delta, \end{aligned}$$

where we have used  $(1 - x) < e^{-x}$ . Thus, we have that for this choice of  $b$  and  $r$ , any  $x \in V$  such that  $d(x, q) \geq cR$  is returned with probability at least  $1 - \delta$ , while we return on average one  $x' \in V$  such that  $d(x', q) \leq cR$ .

**Problem 3: (More on the Morris' Counter)**

Recall in class we saw the basic Morris counter, wherein we initiated the counter to 1 when one item arrived, and upon each subsequent arrival, incremented the counter with probability  $1/2^X$ . We also showed that after  $n$  items have arrived,  $\mathbf{E}[2^X] = n + 1$ .

**Part (a)**

Prove that the variance of the counter is given by:

$$\text{Var}(2^{X_n}) = \frac{n^2 - n}{2}$$

Using this, find the probability that the average of  $k$  Morris counters is less than  $n + 1 - \epsilon n$  after  $n$  items have passed.

*Hint: Use induction for  $\mathbf{E}[2^{2X}]$ .*

**Solution:** Let counter's state after seeing  $n$  items be  $X_n$  – recall that we showed in class that  $\mathbf{E}[2^{X_n}] = n + 1$ . Since, we want to prove that  $\text{Var}(2^{X_n}) = \frac{n^2 - n}{2}$ , this is equivalent to showing:

$$\mathbf{E}[2^{2X_n}] = \text{Var}(2^{X_n}) + (\mathbf{E}[2^{X_n}])^2 = \frac{n^2 - n}{2} + (n + 1)^2 = \frac{3}{2}n^2 + \frac{3}{2}n + 1.$$

We will now show this by induction. Clearly for  $X_0 = 1$ , we have  $\mathbf{E}[2^{2^1}] = \frac{3}{2}(1)^2 + \frac{3}{2}(1) + 1 = 4$ . For the inductive step, we have:

$$\begin{aligned} \mathbf{E}[2^{2^{X_n}}] &= \sum_{j=0}^{\infty} \mathbf{P}(2^{X_{n-1}} = j) \cdot \mathbf{E}[2^{2^{X_n}} | 2^{X_{n-1}} = j] \\ &= \sum_{j=0}^{\infty} \mathbf{P}(2^{X_{n-1}} = j) \cdot \left[ \frac{1}{j} \cdot 4j^2 + \left(1 - \frac{1}{j}\right) \cdot j^2 \right] \\ &= \sum_{j=0}^{\infty} \mathbf{P}(2^{X_{n-1}} = j) \cdot (j^2 + 3j) \\ &= \mathbf{E}[2^{2^{X_{n-1}}}] + 3 \cdot \mathbf{E}[2^{X_{n-1}}] = \frac{3}{2}(n-1)^2 + \frac{3}{2}(n-1) + 1 + 3n \\ &= \frac{3}{2}n^2 + \frac{3}{2}n + 1. \end{aligned}$$

Now, assume we have  $k$  Morris counters  $X_1, \dots, X_k$ , and  $Z = \frac{1}{k} \sum_{j=1}^k 2^{X_j}$ . Then, by independence:

$$\text{Var}(Z) = \frac{1}{k^2} \text{Var} \left( \sum_{j=1}^k 2^{X_j} \right) = \frac{n^2 - n}{2k}.$$

By Chebyshev's inequality:

$$\mathbf{P}(Z < n + 1 - \epsilon n) \leq \mathbf{P}(|Z - (n + 1)| > \epsilon n) \leq \frac{\text{Var}(Z)}{(\epsilon n)^2} = \frac{n - 1}{2kn\epsilon^2}.$$

### Part (b)

Next, suppose we modify the counter as follows: we still initialize counter  $Y$  to 1 when the first item arrives, but on every subsequent arrival, we increment the counter by 1 with probability  $1/(1+a)^Y$ , for some  $a > 0$ . Let  $Y_n$  be the counter-state after  $n$  items have arrived – choose constants  $b, c$  such that  $b \cdot (1+a)^{Y_n} + c$  is an unbiased estimator for the number of items (i.e.,  $\mathbf{E}[b \cdot (1+a)^{Y_n} + c] = n$ ).

**Solution:** First, since  $Y_0 = 0$ , hence  $\mathbf{E}[(1+a)^{Y_n}] = 1$ . Now as in the previous analysis, we have:

$$\begin{aligned} \mathbf{E}[(1+a)^{Y_n}] &= \sum_{j=0}^{\infty} \mathbf{P}(Y_{n-1} = j) \mathbf{E}[(1+a)^{Y_n} | Y_{n-1} = j] \\ &= \sum_{j=0}^{\infty} \mathbf{P}(Y_{n-1} = j) \left( \frac{1}{(1+a)^j} (1+a)^{j+1} + \left(1 - \frac{1}{(1+a)^j}\right) (1+a)^j \right) \\ &= \mathbf{E}[(1+a)^{Y_{n-1}}] + a. \end{aligned}$$

Thus, we have that  $\mathbf{E}[(1+a)^{Y_n}] = 1 + na$ . Thus, if we choose  $b = 1/a, c = -1/a$ , we get:

$$\mathbf{E}[b \cdot (1+a)^{Y_n} + c] = \frac{1+na}{a} - \frac{1}{a} = n.$$

**Part (c) (OPTIONAL)**

Now suppose you are restricted to use a single Morris counter, but can choose  $a$  as above. Find the variance of the estimator, and using Chebyshev, find the required  $a$  to ensure that the estimate is within  $n \pm \epsilon n$  with probability at least  $1 - \delta$ . What is the expected storage required by this counter?

**Problem 4: (Dyadic Partitions and the Count-Min Sketch)**

In this problem, we modify the Count-Min sketch to give estimates for range queries and heavy-hitters. For this, we first need an additional definition. For convenience, assume  $n = 2^k$ ; the dyadic partitions of the set  $[n]$  are defined as follows:

$$\begin{aligned} \mathcal{I}_0 &= \{\{1\}, \{2\}, \dots, \{n\}\} \\ \mathcal{I}_1 &= \{\{1, 2\}, \{3, 4\}, \dots, \{n-1, n\}\} \\ \mathcal{I}_2 &= \{\{1, 2, 3, 4\}, \{5, 6, 7, 8\}, \dots, \{n-3, n-2, n-1, n\}\} \\ &\vdots \\ \mathcal{I}_k &= \{\{1, 2, \dots, n\}\} \end{aligned}$$

**Part (a)**

Let  $\mathcal{I} = \mathcal{I}_0 \cup \mathcal{I}_1 \cup \dots \cup \mathcal{I}_k$  be the set of all dyadic intervals. Show that  $|\mathcal{I}| \leq 2n$ . Moreover, show that any interval  $[a, b] = \{a, a+1, \dots, b\}$  can be written as a disjoint union of at most  $2 \log_2 n$  sets from  $\mathcal{I}$ . (For example, for  $n = 16 = 2^4$ , the set  $[6, 15]$  can be written as  $\{6\} \cup \{7, 8\} \cup \{9, 10, 11, 12\} \cup \{13, 14\} \cup \{15\}$ , which is less than  $2 \times 4 = 8$  sets.)

**Solution:** By definition of the dyadic intervals, we have that for any  $i \in \{0, 1, \dots, k\}$ , we have that  $|\mathcal{I}_i| = n/2^i$ . Thus the number of dyadic intervals is given by  $|\mathcal{I}| = \sum_{i=0}^k n2^{-i} \leq n \sum_{i=0}^{\infty} 2^{-i} = 2n$ .

For the second claim, we can use induction on  $k = \log_2 n$ . The base case of  $k = 1$  ( $n = 2$ ) is easy to check. Now suppose that for  $k - 1$  we have that any sub-interval can be represented as a disjoint union of  $2(k - 1)$  dyadic intervals. Now given a sub-interval  $[a, b] = \{a, a + 1, \dots, b\}$  of  $[2^k]$ , if either  $a > 2^{k-1} = n/2$  or  $b \leq 2^{k-1} = n/2$ , then we are done by the inductive hypothesis. To complete the proof, we need to show that if  $a < n/2 < b$ , then we can write  $[a, b]$  as a disjoint union of  $2k$  dyadic intervals.

We first show that for any  $a \in [2^{k-1}]$ , we can write the set  $\{1, 2, \dots, a\}$  as a disjoint union of at most  $k - 1$  dyadic intervals. This again we can see by induction. Again the base case is easy to check. Moreover, for any  $a \in [2^{k-1}]$ , we have two cases: *i*) if  $a \leq 2^{k-2}$ , then by induction we need  $\leq k - 2$  intervals, and *ii*) if  $a > 2^{k-2}$ , then by induction we need  $\leq 1 + k - 2 = k - 1$  intervals.

Now by symmetry, we also have that for any interval  $\{b, b + 1, \dots, 2^{k-1}\}$  we can write it as a disjoint union of at most  $k - 1$  dyadic intervals (just reverse the sets!). Returning to the main proof, given  $a < n/2 < b$ , we can write  $[a, b] = [a, n/2] \cup [n/2, b]$  – from the above claims, each can be written as a disjoint union of  $k - 1$  dyadic intervals, and hence we have  $[a, b]$  can be written using  $2k - 2 < 2k$  intervals, which completes the proof.

**Part (b)**

In class, given a stream of  $m$  elements, we saw how to construct a Count-Min sketch for the frequencies of items  $i \in [n]$ , and how to use it for point queries (i.e., to estimate  $f_i$  for some  $i \in [n]$ ). We now extend this to *range queries* – estimating  $F_{[a,b]} = \sum_{i=a}^b f_i$  for given  $a, b$ .

Note first that the basic Count-Min sketch can be interpreted as constructing a sketch for frequencies of set-membership for the sets in  $I_0$ . We have also seen how to make hash functions for general set-membership (for example, the Bloom filter!) – we can thus extend the Count-Min sketch to include an estimate for the frequencies of all the dyadic intervals. Using this new sketch, show that for a given range query  $[a, b]$ , we can use a Count-Min sketch with  $R = \log(1/\delta)$  rows and  $B = 2/\epsilon$  columns to get an estimate  $F_{[a,b]}$  satisfying:

$$\mathbf{P} \left[ F_{[a,b]} < \sum_{i \in [a,b]} f_i + 2m\epsilon \log^2 n \right] \geq 1 - \delta$$

**Solution:** (Note: Correction in the above expression - the RHS of the bound on  $F_{[a,b]}$  should be  $\log^2 n$ , not  $\log n$  as was given in the problem.)

First, note that the size of the Count-Min data-structure did not depend on the number of elements  $[n]$  – thus, we can adapt the Count-Min sketch to store counts  $F_I$  for all sets  $I \in \mathcal{I}$ . Note however that each  $i \in [n]$  belongs to  $\log_2 n$  dyadic intervals – thus instead of counting  $m$  items, we are counting  $m \log_2 n$  items.

Next, from the previous part, we know that any interval  $[a, b]$  can be written as the disjoint union of  $\leq 2 \log_2 n$  dyadic intervals – let us denote this set as  $\mathcal{I}_{[a,b]}$ . Thus we have  $F_{[a,b]} = \sum_{I \in \mathcal{I}_{[a,b]}} F_I$ . Moreover, note that each  $F_I \leq m$ .

Now from the performance bounds for the Count-Min sketch (with  $R = \log(1/\delta)$  rows and  $B = 2/\epsilon$  columns, and  $m \log_2 n$  items in the stream) we saw in class, we know that for any  $I \in \mathcal{I}$ , we have:

$$\mathbf{P} \left[ F_I < \sum_{i \in [a,b]} f_i + (m \log_2 n) \epsilon \right] \geq 1 - \delta$$

Since we are adding  $2 \log_2 n$  such counts for  $F_{[a,b]}$ , we get that:

$$\mathbf{P} \left[ F_{[a,b]} < \sum_{i \in [a,b]} f_i + 2m\epsilon \log^2 n \right] \geq 1 - \delta$$

**Part (c)**

The  $\phi$ -heavy-hitters (or  $\phi$ -HH) query is defined as follows:

Given stream  $\{x_1, x_2, \dots, x_m\}$  with  $x_i \in [n]$ , and some constant  $\phi \in [0, 1]$ , we want to output a subset  $L \subset [n]$  such that, with probability at least  $1 - \delta$ ,  $L$  contains all  $i \in [n]$  such that  $f_i \geq \phi m$ , and moreover, every  $i \in L$  satisfies  $f_i \geq \phi m/2$ .

We now adapt the above sketch for the  $\phi$ -HH problem. First, using the union bound, argue that if we choose  $\delta = \gamma/2n$ , then we have that for *all* dyadic intervals  $I \in \mathcal{I}$ , we have that the frequency estimate  $F_I$  obeys:  $\mathbf{P} [F_I < \sum_{i \in I} f_i + m\epsilon] \geq 1 - \gamma$ . Thus, argue that if we use  $\epsilon < \phi/2$ , then the set of all  $i \in [n]$  such that  $F_{\{i\}} > \phi m$  is a solution to the  $\phi$ -HH problem.

**Solution:** (Note: There was a typo in the probability bound – it should be  $1 - \gamma$ , not  $1 - \delta$ .) Suppose we choose  $\delta = \gamma/2n$ . Then, from the union bound, we have that:

$$\begin{aligned} \mathbf{P} \left[ \bigcup_{I \in \mathcal{I}} \left\{ F_I > \sum_{i \in I} f_i + m\epsilon \right\} \right] &\leq 2n \mathbf{P} \left[ \left\{ F_I > \sum_{i \in I} f_i + m\epsilon \right\} \right] \\ &\leq 2n\delta = \gamma \end{aligned}$$

Now, if we use  $\epsilon = \phi/2$ , then we have that:

- For any  $i \in [n]$  such that  $f_i \geq \phi m$ , then  $F_{\{i\}}$  is also  $\geq \phi m$  (recall that the Count-Min sketch always overestimates frequencies!).
- For any  $i \in [n]$  such that  $f_i < \phi m/2$ , then with probability  $\geq 1 - 2\gamma$ , we have that  $F_{\{i\}}$  is also  $\leq \phi m$ .

Thus, if we use  $\epsilon < \phi/2$ , then the set of all  $i \in [n]$  such that  $F_{\{i\}} > \phi m$  is a solution to the  $\phi$ -HH problem (with  $\gamma$  instead of  $\delta$  as the probability bound).

### Part (d)

Note though that the brute force way to find all  $i \in [n]$  such that  $F_{\{i\}} > \phi m$  requires  $n$  point queries. Briefly argue how you can use the frequency estimates  $F_I$  for the dyadic intervals to find the same using  $O(\log n/\phi)$  queries.

*Hint: Consider a binary tree defined by the dyadic intervals, with the root as  $I_{\log n} = \{[n]\}$ , and the leaves as  $I_0 = \{\{1\}, \{2\}, \dots, \{n\}\}$ . Argue that for every heavy-hitter node  $i$ , every parent node in the tree has  $F_I > \phi m$ . Also, at any level  $j$ , how many sets  $I \in \mathcal{I}_j$  can have  $F_I > \phi m$ ?*

**Solution:** The main idea is that if  $f_i > \phi m$ , then  $f_I > \phi m$  for any dyadic interval  $I$  that contains  $i$ . Thus, we can start from the top of the tree of dyadic intervals, and at each stage, only expand dyadic intervals  $I$  such that  $F_I > \phi m$ . Now note that at any level of the tree, the dyadic intervals form a partition of  $[n]$  – thus their frequencies must add up to  $m$ . By a counting argument, we see that the number of intervals  $I \in \mathcal{I}_j, i \in \{0, 1, \dots, \log_2 n\}$  such that  $f_I > \phi m$  is  $O(1/\phi)$  (moreover, with high probability, the number of intervals such that  $F_I > \phi m$  is  $O(1/\phi)$ ). Finally, the depth of the tree is  $\log n$ . Thus, in  $O(\log n/\phi)$  time, we can find all  $i$  such that  $F_i > \phi m$ .