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Problem 1.

- (a) We are given two sets P, N with n unit vectors on opposite sides of a hyperplane through the origin. $\langle a, x \rangle = 0$. Moreover, the distance of each point from the hyperplane is at least ε . Let $S = \{0, a\} \cup P \cup N \cup P' \cup N'$ with P', N' being their respective points reflected across the origin. We want to show it is possible to represent the points in S in lower dimension $O(\log n/\varepsilon^2)$ with distances being preserved up to a $1 \pm (\varepsilon/10)$.
 - This is possible with the JL Lemma. The JL Lemma states that for n points in d dimensions, it is possible to represent these points in $m = O(\log n/\varepsilon^2)$ dimensions. If we plug into our lemma (n = 4n and $\varepsilon = \varepsilon/10$), we end up with a bound of $m = O(100 \log 4n/\varepsilon^2)$ with distances being preserved up to $1 \pm (\varepsilon/10)$. With Big-O notation, we can simplify $m = O(100 \log 4n/\varepsilon^2) = O(\log n/\varepsilon^2)$.
- (b) We want to show that the margin for the above transformation is still preserved up to $\varepsilon/2$. To do so, we will use the identity $< a, x > = \frac{\|a+x\|^2 \|a-x\|^2}{4}$. From this, we have the following:

From the JL-Lemma, we have that $T(a) = (1 \pm \frac{\epsilon}{10}) \times a$ and that $T(x) = (1 \pm \frac{\epsilon}{10}) \times x$. Since we want to find the lower bound, we can push the bounds as far as we can go. This nets us:

$$(1 - \frac{\varepsilon}{10})^2 ||a + x||^2 - (1 + \frac{\varepsilon}{10})^2 ||a - x||^2 \stackrel{?}{\geq} 2\varepsilon$$

$$(1 - \frac{\varepsilon}{10})^2 ||a + x||^2 - (1 + \frac{\varepsilon}{10})||a + x||^2 - (1 + \frac{\varepsilon}{10})^2 ||a - x||^2 + (1 + \frac{\varepsilon}{10})||a + x||^2 \stackrel{?}{\geq} 2\varepsilon$$

$$\left[(1 - \frac{\varepsilon}{10})^2 - (1 + \frac{\varepsilon}{10})^2 \right] ||a + x||^2 + (1 + \frac{\varepsilon}{10})^2 \left[||a + x||^2 - ||a - x||^2 \right] \stackrel{?}{\geq} 2\varepsilon$$

We can examine this expression piecewise. First, we know that $a^2 - b^2 = (a + b)(a - b)$.

$$\left[(1 - \frac{\varepsilon}{10})^2 - (1 + \frac{\varepsilon}{10})^2 \right] ||a + x||^2 = (\frac{-4\varepsilon}{10}) ||a + x||^2$$

Next we know that $||a + x||^2 - ||a - x||^2 = 4\varepsilon$. We know this because of the identity $\langle a, x \rangle = \frac{||a + x||^2 - ||a - x||^2}{4}$.

$$(1 + \frac{\varepsilon}{10})^2 \left[||a + x||^2 - ||a - x||^2 \right] = 4\varepsilon (1 + \frac{\varepsilon}{10})^2$$

If combine these expressions, shuffle terms around, and add back in the $\frac{1}{\|T(a)\|}$ from earlier, we get the following:

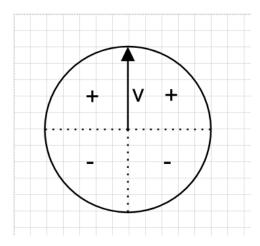
$$(1 + \frac{\varepsilon}{10})(4\varepsilon) \stackrel{?}{\geq} 2\varepsilon + \frac{(\frac{4\varepsilon}{10})||a + x||^2}{1 + \frac{\varepsilon}{10}}$$

Even if we stretch $||a+x||^2$ as far as it can go, which is 4, the RHS is bounded by 4ε . Meanwhile, the LHS is $4\varepsilon + (\frac{\varepsilon}{10})(4\varepsilon)$. As such, we are done, and we have proved that the margin is still preserved up to $\varepsilon/2$.

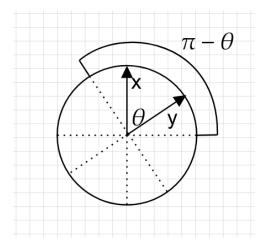
Problem 2.

(a) We are designing an LSH family as follows: A hash function is to pick a random unit vector v from the unit sphere, and then h(x) is the sign of $\langle v, x \rangle$. If $\langle v, x \rangle = 0$, then the hash value is 1. We want to express the probability that two unit vectors x and y shared the same hash value (they collide) as a function of r, the distance between x and y.

We can do this by focusing on the 2-dimensional space spanned by x and y. The reasoning for this is because we can project v onto this plane and that will the primary decider on the hash value. The first thing we want to define is collision. In this case, two vectors x and y collide when $\langle v, x \rangle$ and $\langle v, y \rangle$ share the same sign. And in terms of v, the regions of $\langle v, x \rangle$ are defined below:



Thus, in order for $\langle v, x \rangle$ and $\langle v, y \rangle$ to share the same sign, x and y must fall into same sign regions. The region that v is allowed to be in can be expressed as a function of θ , the angle between vectors x and y. This angle of this region is $\pi - \theta$, and can be visualized below:



Thus, the probability of collision can be expressed in terms of θ . We double the region size, since we the signs can either be both + or both –, and then divide over the entire circle.

$$\Pr[\text{collision}] = \frac{2(\pi - \theta)}{2\pi} = 1 - \frac{\theta}{\pi}$$

To get theta from r, we can use the law of cosines:

$$r^{2} = ||x||^{2} + ||y||^{2} + 2||x||||y||\cos\theta$$

$$r^{2} = 1 + 1 + 2\cos\theta$$

$$2 - r^{2} = 2\cos\theta$$

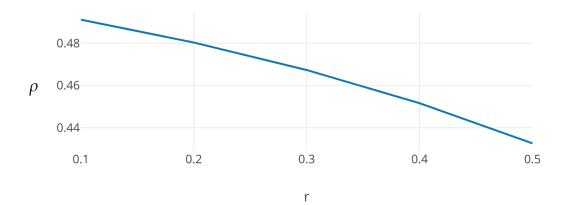
$$\cos\theta = 1 - \frac{r^{2}}{2}$$

$$\theta = \arccos\left(1 - \frac{r^{2}}{2}\right)$$

And so, the final probability is:

$$\Pr[\text{collision}] = 1 - \frac{\arccos\left(1 - \frac{r^2}{2}\right)}{\pi}$$

(b) We would like to evaluate the parameter ρ for the approximate near neighbor problem with c=2. If we let $p_1=\Pr[\text{collision for r}]$ and $p_2=\Pr[\text{collision for 2r}]$ and $\rho=\frac{\log p_1}{\log p_2}$, we get the following graph:



Problem 3.

Followed the instructions at: https://www.youtube.com/watch?v=H7qMMudo3e8

```
from PIL import Image
from matplotlib.image import imread
import matplotlib.pyplot as plt
import numpy as np
# Import image
A = imread('images/sf-gray.jpg')
# SVD computations
U, S, VT = np.linalg.svd(A,full_matrices=False)
S = np.diag(S)
j = 1
for k in (50, 60, 70, 80, 90, 100):
    # appr image
    X = U[:,:k] @ S[0:k,:k] @ VT[:k,:]
    plt.figure(j)
    img = plt.imshow(X)
    img.set_cmap('gray')
    plt.title('k = ' + str(k))
    plt.show()
    j += 1
# Best Approximation
k = 90
B = U[:,:k] @ S[0:k,:k] @ VT[:k,:]
img = plt.imshow(B)
img.set_cmap('gray')
plt.axis('off')
plt.savefig('images/sf-compressed.jpg')
```

Original Image:



Compressed Image (at rank 90):



Problem 4.

(a) We are given $A = U\Sigma V^T$ with singular values $\sigma_1 \ge \sigma_2 \ge ... \ge \sigma_n$. We would like to find a matrix B of at most rank k such that $\|A - B\|_2 \le \frac{\|A\|_F}{\sqrt{k}}$.

We can define *B* similarly to *A*, but at rank *k*:

$$B = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \sigma_k & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}^T$$

Thus, the result of $||A - B||_2$ can be expressed as follows:

$$||A - B||_2 = \sigma_{k+1}$$

$$\sigma_{k+1} \stackrel{?}{\leq} \frac{||A||_F}{\sqrt{k}}$$

$$\sigma_{k+1} \stackrel{?}{\leq} \frac{\sqrt{\sum_i \sigma_i^2}}{\sqrt{k}}$$

$$\sigma_{k+1}^2 \stackrel{?}{\leq} \frac{\sum_i \sigma_i^2}{k}$$

$$k\sigma_{k+1}^2 \stackrel{?}{\leq} \sum_i \sigma_i^2$$

The last statement is true because $\sigma_1 \ge \sigma_2 \ge ... \sigma_k \ge \sigma_{k+1} \ge ...$ Since there are k singular values from σ_1 to σ_{k+1} , the following is true:

$$k\sigma_{k+1}^2 \le \sum_i \sigma_i^2 \checkmark$$

(b) We want to find a matrix C that is a good approximate for A, such that the margin of error is $||(A-C)x||_2 \le \varepsilon ||A||_F ||x||_2$. If we define C like we defined B as in Part A, but with rank $k = \frac{1}{\varepsilon^2}$, we have the following:

$$C = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \sigma_k & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}^T$$

We can also prove the bounds:

$$||(A - C)x||_{2} = ||A - C||_{2}||x||_{2}$$

$$\leq \frac{||A||_{F}}{\sqrt{k}}||x||_{2}$$

$$\leq \frac{||A||_{F}}{1/\varepsilon}||x||_{2}$$

$$\leq \varepsilon ||A||_{F}||x||_{2}$$

The reason we want to approximate *A* with *C* is for performance reasons. The runtime for using *A* is $O(n^2)$. We can do better with *C*, which has a runtime of O(nk) or $O(\frac{n}{\varepsilon^2})$.