COMPSCI 514: ALGORITHMS FOR DATA SCIENCE

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University of Massachusetts Amherst. Spring 2020.
Lecture 12

- Problem Set 2 is due this upcoming Sunday 3/8 at 8pm.
- Midterm is next Thursday, 3/12. See webpage for study guide/practice questions.
- I will hold office hours **after class today**.
- Next week office hours will be at the usual time after class Tuesday and also **before class at 10:00am**.

Last Class: Finished Up Johnson-Lindenstrauss Lemma

- Completed the proof of the Distributional JL lemma.
- Showed two applications of random projection: faster support vector machines and k-means clustering.
- Started discussion of high-dimensional geometry.

This Class: High-Dimensional Geometry

- Bizarre phemomena in high-dimensional space.
- Connections to JL lemma and random projection.

What is the largest set of mutually orthogonal unit vectors in d-dimensional space? Answer: d.

What is the largest set of unit vectors in d-dimensional space that have all pairwise dot products $|\langle \vec{x}, \vec{y} \rangle| \leq \epsilon$? (think $\epsilon = .01$) Answer: $2^{\Theta(\epsilon^2 d)}$.

In fact, an exponentially large set of random vectors will be nearly pairwise orthogonal with high probability!

Claim: $2^{\Theta(\epsilon^2 d)}$ random d-dimensional unit vectors will have all pairwise dot products $|\langle \vec{x}, \vec{y} \rangle| \leq \epsilon$ (be nearly orthogonal).

Proof: Let $\vec{x}_1, \ldots, \vec{x}_t$ each have independent random entries set to $\pm 1/\sqrt{d}$.

- What is $\|\vec{x}_i\|_2$? Every $\vec{x}_i$ is always a unit vector.
- What is $\mathbb{E}[\langle \vec{x}_i, \vec{x}_j \rangle]$? $\mathbb{E}[\langle \vec{x}_i, \vec{x}_j \rangle] = 0$
- By a Chernoff bound, $\Pr[|\langle \vec{x}_i, \vec{x}_j \rangle| \geq \epsilon] \leq 2e^{-\epsilon^2 d/6}$.
- If we chose $t = \frac{1}{2} e^{\epsilon^2 d/12}$, using a union bound over all $\binom{t}{2} \leq \frac{1}{8} e^{\epsilon^2 d/6}$ possible pairs, with probability $\geq 3/4$ all will be nearly orthogonal.

Up Shot: In d-dimensional space, a set of $2^{\Theta(\epsilon^2 d)}$ random unit vectors have all pairwise dot products at most ϵ (think $\epsilon = .01$)

$$\|\vec{x}_i - \vec{x}_j\|_2^2 = \|\vec{x}_i\|_2^2 + \|\vec{x}_j\|_2^2 - 2\vec{x}_i^T\vec{x}_j \geq 1.98.$$

Even with an exponential number of random vector samples, we don't see any nearby vectors.

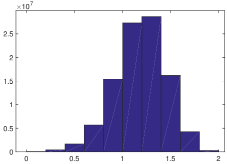
- Can make methods like nearest neighbor classification or clustering useless.

Curse of dimensionality for sampling/learning functions in high-dimensional space – samples are very 'sparse' unless we have a huge amount of data.

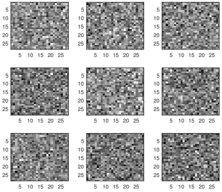
- Only hope is if we lots of structure (which we typically do...)

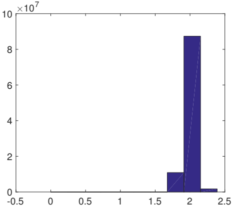
CURSE OF DIMENSIONALITY

Distances for MNIST Digits:



Distances for Random Images:





Another Interpretation: Tells us that random data can be a very bad model for actual input data.

Recall: The Johnson Lindenstrauss lemma states that if $\mathbf{\Pi} \in \mathbb{R}^{m \times d}$ is a random matrix (linear map) with $m = O\left(\frac{\log n}{\epsilon^2}\right)$, for $\vec{x}_1, \ldots, \vec{x}_n \in \mathbb{R}^d$ with high probability, for all i, j:

$$(1-\epsilon)\|\vec{x}_i - \vec{x}_j\|_2^2 \leq \|\mathbf{\Pi}\vec{x}_i - \mathbf{\Pi}\vec{x}_j\|_2^2 \leq (1+\epsilon)\|\vec{x}_i - \vec{x}_j\|_2^2.$$

Implies: If $\vec{x}_1, \ldots, \vec{x}_n$ are nearly orthogonal unit vectors in d-dimensions (with pairwise dot products bounded by $\epsilon/8$), then $\frac{\mathbf{\Pi}\vec{x}_1}{\|\mathbf{\Pi}\vec{x}_1\|_2}, \ldots, \frac{\mathbf{\Pi}\vec{x}_n}{\|\mathbf{\Pi}\vec{x}_n\|_2}$ are nearly orthogonal unit vectors in m-dimensions (with pairwise dot products bounded by ϵ).

- Similar to SVM analysis. Algebra is a bit messy but a good exercise to partially work through.

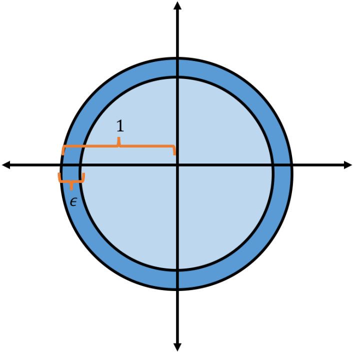
Claim 1: n nearly orthogonal unit vectors can be projected to $m = O\left(\frac{\log n}{\epsilon^2}\right)$ dimensions and still be nearly orthogonal.

Claim 2: In m dimensions, there are at most $2^{O(\epsilon^2 m)}$ nearly orthogonal vectors.

- For both these to hold it might be that $n \leq 2^{O(\epsilon^2 m)}$.
- $2^{O(\epsilon^2 m)} = 2^{O(\log n)} \geq n$. Tells us that the JL lemma is optimal up to constants.
- m is chosen just large enough so that the odd geometry of d-dimensional space still holds on the n points in question after projection to a much lower dimensional space.

Let $\mathcal{B}_d$ be the unit ball in d dimensions. $\mathcal{B}_d = \{x \in \mathbb{R}^d : \|x\|_2 \leq 1\}$.

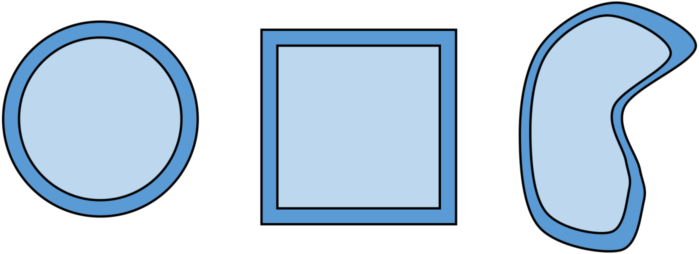
What percentage of the volume of $\mathcal{B}_d$ falls within ϵ distance of its surface? Answer: all but a $(1-\epsilon)^d \leq e^{-\epsilon d}$ fraction. Exponentially small in the dimension d!



Volume of a radius R ball is $\frac{\pi^{\frac{d}{2}}}{(d/2)!} \cdot R^d$.

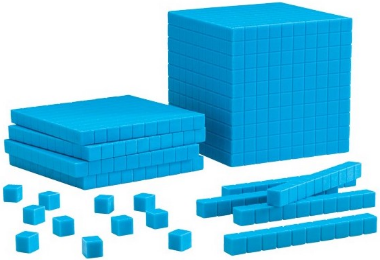
All but an $e^{-\epsilon d}$ fraction of a unit ball's volume is within ϵ of its surface. If we randomly sample points with $\|x\|_2 \leq 1$, nearly all will have $\|x\|_2 \geq 1 - \epsilon$.

- **Isoperimetric inequality**: the ball has the maximum surface area/volume ratio of any shape.



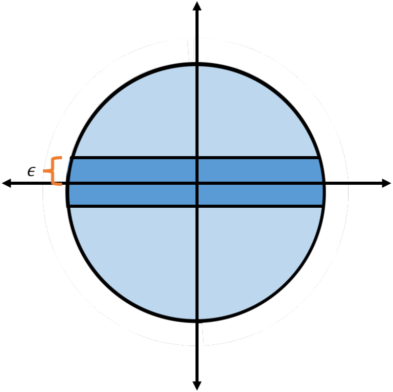
- If we randomly sample points from any high-dimensional shape, nearly all will fall near its surface.
- 'All points are outliers.'

What fraction of the cubes are visible on the surface of the cube?



$$\frac{10^3 - 8^3}{10^3} = \frac{1000 - 512}{1000} = .488.$$

What percentage of the volume of $\mathcal{B}_d$ falls within ϵ distance of its equator? Answer: all but a $2^{\Theta(-\epsilon^2 d)}$ fraction.

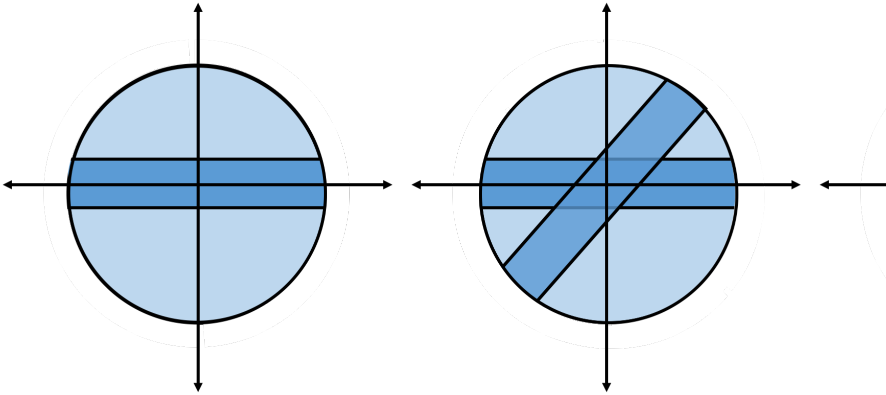


Formally: volume of set $S = \{x \in \mathcal{B}_d : |x(1)| \leq \epsilon\}$.

By symmetry, all but a $2^{\Theta(-\epsilon^2 d)}$ fraction of the volume falls within ϵ of any equator! $S = \{x \in \mathcal{B}_d : |\langle x, t \rangle| \leq \epsilon\}$

Claim 1: All but a $2^{\Theta(-\epsilon^2 d)}$ fraction of the volume of a ball falls within ϵ of any equator.

Claim 2: All but a $2^{\Theta(-\epsilon d)}$ fraction falls within ϵ of its surface.



How is this possible? High-dimensional space looks nothing like this

Claim: All but a $2^{\Theta(-\epsilon^2 d)}$ fraction of the volume of a ball falls within ϵ of its equator. I.e., in $S = \{x \in \mathcal{B}_d : |x(1)| \leq \epsilon\}$.

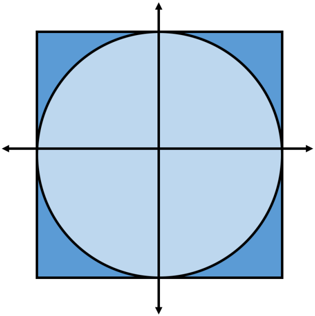
Proof Sketch:

- Let x have independent Gaussian $\mathcal{N}(0,1)$ entries and let $\bar{x} = \frac{x}{\|x\|_2}$. $\bar{x}$ is selected uniformly at random from the surface of the ball.
- Suffices to show that $\Pr[|\bar{x}(1)| > \epsilon] \leq 2^{\Theta(-\epsilon^2 d)}$. Why?
- $\bar{x}(1) = \frac{x(1)}{\|x\|_2}$. What is $\mathbb{E}[\|x\|_2^2]$?$\mathbb{E}[\|x\|_2^2] = \sum_{i=1}^d \mathbb{E}[x(i)^2] = d$.
  $\Pr[\|x\|_2^2 \leq d/2] \leq 2^{-\Theta(d)}$
- Conditioning on $\|x\|_2^2 \geq d/2$, since $x(1)$ is normally distributed,

$$\begin{aligned}\Pr[|\bar{x}(1)| > \epsilon] &= \Pr[|x(1)| > \epsilon \cdot \|x\|_2] \\ &\leq Pr[|x(1)| > \epsilon \cdot \sqrt{d/2}] = 2^{\Theta(-(\epsilon\sqrt{d/2})^2)} = 2^{\Theta(-\epsilon^2 d)}.\end{aligned}$$

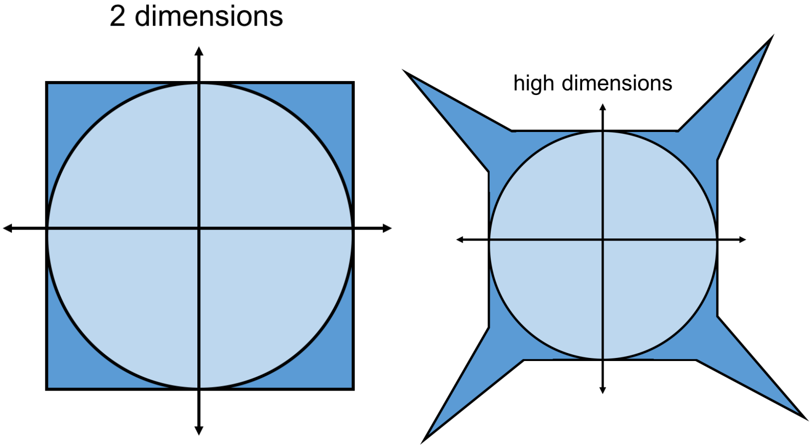
Let $\mathcal{C}_d$ be the d-dimensional cube: $\mathcal{C}_d = \{x \in \mathbb{R}^d : |x(i)| \leq 1 \; \forall \; i\}$.

In low-dimensions, the cube is not that different from the ball.



But volume of $\mathcal{C}_d$ is 2^d while volume of $\mathcal{B}^d$ is $\frac{\pi^{\frac{d}{2}}}{(d/2)!} = \frac{1}{d^{\Theta(d)}}$. A huge gap! So something is very different about these shapes...

HIGH-DIMENSIONAL CUBES

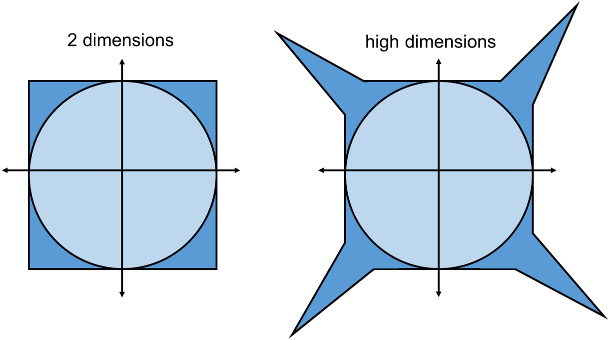


Corners of cube are $\sqrt{d}$ times further away from the origin than the surface of the ball.

HIGH-DIMENSIONAL CUBES

Data generated from the ball $\mathcal{B}_d$ will behave very differently than data generated from the cube $\mathcal{C}_d$.

- $x \sim \mathcal{B}_d$ has $\|x\|_2^2 \leq 1$.
- $x \sim \mathcal{C}_d$ has $\mathbb{E}[\|x\|_2^2] = ?d/3$, and $\Pr[\|x\|_2^2 \leq d/6] \leq 2^{-\Theta(d)}$.
- Almost all the volume of the unit cube falls in its corners, and these corners lie far outside the unit ball.



- High-dimensional space behaves very differently from low-dimensional space.
- Random projection (i.e., the JL Lemma) reduces to a much lower-dimensional space that is still large enough to capture this behavior on a subset of n points.
- Need to be careful when using low-dimensional intuition for high-dimensional vectors.
- Need to be careful when modeling data as random vectors in high-dimensions.