

Assignment - 1

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Subject: Advanced Data
Science

Q.1 State and Prove Markov's Inequality

→ Statement :-

Let x be a non-negative random variable. Then for $a > 0$,

$$\text{Prob}(x \geq a) \leq \frac{E(x)}{a}$$

Proof :-

For continuous non-negative r.v. x with probability density p ,

$$\begin{aligned} E(x) &= \int_0^{\infty} x p(x) dx \\ &= \int_0^a x p(x) dx + \int_a^{\infty} x p(x) dx \\ &\geq \int_a^{\infty} x p(x) dx \geq a \int_a^{\infty} p(x) dx \\ &= a \text{Prob}(x \geq a) \end{aligned}$$

$$\therefore \boxed{\text{Prob}(x \geq a) \leq \frac{E(x)}{a}}$$

Hence proved.

Q.2 State and prove chebyshov's inequality

→ Statement :-

Let x be a random variable. Then for $c > 0$,

$$P(|x - E(x)| \geq c) \leq \frac{\text{Var}(x)}{c}$$

Proof :-

Here, $P(|x - E(x)| \geq c)$ can also be written as $P(|x - E(x)|^2 \geq c^2)$.

Let, $y = |x - E(x)|^2$.

Note that y is a non-negative random variable & $E(y) = \text{Var}(x)$

So, Markov's inequality can be

$$\begin{aligned} P(|x - E(x)| \geq c) &= P(|x - E(x)|^2 \geq c^2) \\ &\leq \frac{E(|x - E(x)|^2)}{c^2} = \frac{\text{Var}(x)}{c^2} \end{aligned}$$

$$\therefore P(|x - E(x)| \geq c) \leq \frac{\text{Var}(x)}{c}$$

Q.3 State and prove Law of Large Numbers

→ Statement :-

Let x_1, x_2, \dots, x_n be n independent samples of a random var. x , then

$$P\left(\left|\frac{x_1+x_2+\dots+x_n}{n} - E(x)\right| \geq \epsilon\right) \leq \frac{\text{Var}(x)}{n \epsilon^2}$$

Proof :-

By chebyshew's inequality,

$$\begin{aligned} P\left(\left|\frac{x_1+x_2+\dots+x_n}{n} - E(x)\right| \geq \epsilon\right) &\leq \frac{\text{Var}\left(\frac{x_1+x_2+\dots+x_n}{n}\right)}{\epsilon^2} \\ &= \frac{1}{n^2 \epsilon^2} \text{Var}(x_1+x_2+\dots+x_n) \\ &= \frac{1}{n^2 \epsilon^2} (V(x_1)+V(x_2)+\dots+V(x_n)) \\ &= \frac{\text{Var}(x)}{n^2 \epsilon^2} \end{aligned}$$

$$\therefore P\left(\left|\frac{x_1+x_2+\dots+x_n}{n} - E(x)\right| \geq \epsilon\right) \leq \frac{\text{Var}(x)}{n^2 \epsilon^2}$$

Hence proved.

Q.4 Show that most of the volume of unit ball in \mathbb{R}^d is contained in an annulus of width $O(1/d)$ near the boundary if 'd' is large.

- Consider any object A in \mathbb{R}^d . Now shrink A by small amount ϵ to produce new object

$$(1-\epsilon)A = \{(1-\epsilon)x | x \in A\}.$$

Then the following equality holds:

$$\text{Volume}(1-\epsilon)A = (1-\epsilon)^d \text{ volume}(A)$$

To see that this is true, partition A into infinitesimal cubes. Then $(1-\epsilon)A$ is the union of a set of cubes obtained by shrinking the cubes in A by a factor $(1-\epsilon)$.

When we shrink each of 2d sides of a d-dimensional cube by a factor f , its volume shrinks by a factor f^d .

Using the fact that $1-x \leq e^{-x}$, for any object in \mathbb{R}^d we have:

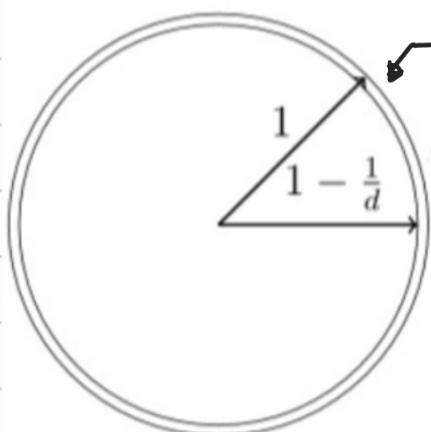
$$\frac{\text{volume } (c(1-\epsilon)A)}{\text{volume } (A)} = c(1-\epsilon)^d \leq \bar{e}^{\epsilon d}$$

Fixing ϵ and letting $d \rightarrow \infty$, the above quantity rapidly approaches 0. This means that nearly all of the volume of A must be in portion of A that does not belong to the region $c(1-\epsilon)A$.

Let S denote the unit ball in d -dimension, that is, the set of points within distance one of the origin.

An immediate implication of above observation is that at least a $1 - \bar{e}^{\epsilon d}$ fraction of volume of unit ball is concentrated in $S/c(1-\epsilon)S$, namely in a small annulus of width ϵ at the boundary.

In particular, most of the volume of the d -dimensional unit ball is contained in an annulus of width $O(1/d)$ near boundary.



Annulus of width $O(1/d)$

Note:- If radius of ball is r , then width of annulus will be $O(r/d)$

Q.5 Derive formulas for the volume and surface area of unit ball in \mathbb{R}^d . Also show that both $\rightarrow 0$ as $d \rightarrow \infty$

→ Volume of the unit ball :-

The volume, $V(d)$, of unit ball in cartesian co-ordinate system is given by

$$V(d) = \int_{x_1=-1}^{x_1=1} \int_{x_2=-\sqrt{1-x_1^2}}^{x_2=\sqrt{1-x_1^2}} \dots \int_{x_d=-\sqrt{1-x_1^2-\dots-x_{d-1}^2}}^{x_d=\sqrt{1-x_1^2-\dots-x_{d-1}^2}} dx_d \dots dx_2 dx_1$$

As, the limits in cartesian co-ordinate system are complicated, we will follow polar co-ordinate system.

$\therefore V(d)$ in polar co-ordinate system is,

$$V(d) = \int_{S^d} \int_{r=0}^1 r^{d-1} dr d\Omega$$

Since variables Ω & r do not interact we can separate integrals.

$$\text{i.e. } V(d) = \int_{S^d} V(d) \int_{r=0}^1 r^{d-1} dr = \frac{1}{d} \int_{S^d} d\Omega$$

∴

$$V(d) = \frac{A(d)}{d}$$

where $A(d)$ is surface area of d -dimensional unit ball.

For instance, for 3-dimensional unit ball ($d=3$) ,

$$A(d) = 4\pi \quad \& \quad V(d) = \frac{4\pi}{3}$$

Surface area of unit ball :-

To calculate $A(d)$, consider diffⁿ integral

$$I(d) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} e^{-(x_1^2 + x_2^2 + \dots + x_d^2)^2} dx_d \dots dx_2 dx_1$$

Including exponential allows integration to infinity rather than stopping at the surface of the sphere.

Thus, $I(d)$ can be computed in both cartesian and polar co-ordinates.

Integrating in polar co-ordinates will relate $I(d)$ to $A(d)$. & Equating 2-results for $I(d)$ allows one to solve for $A(d)$

In cartesian co-ordinate system,

$$I(d) = \left[\int_{-\infty}^{\infty} e^{-x^2} dx \right]^d = (\sqrt{\pi})^d = \pi^{d/2}$$

$$\therefore I(d) = \pi^{d/2} \quad - \textcircled{1}$$

& In polar co-ordinate system,

$$I(d) = \int_{S^d} d\Omega \int_0^{\infty} e^{-r^2} r^{d-1} dr.$$

Here, integral $\int_{S^d} d\Omega$ is integral over entire solid angle and gives surface area $A(d)$ of a unit sphere.

Thus,

$$I(d) = A(d) \int_0^{\infty} e^{-r^2} r^{d-1} dr. \quad - \textcircled{2}$$

Now,

$$\text{let, } I = \int_0^{\infty} e^{-r^2} r^{d-1} dr.$$

limits.

$$\text{put } r^2 = t \Rightarrow r = \sqrt{t}$$

$$\frac{r}{t} \begin{array}{|c|c|} \hline 0 & \infty \\ \hline 0 & 0 \\ \hline \end{array}$$

$$\therefore dr = \frac{1}{2\sqrt{t}} dt$$

$$\therefore I = \int_0^{\infty} e^{-t} t^{\frac{d-1}{2}} \left(\frac{1}{2\sqrt{t}}\right) dt$$

$$\therefore I = \frac{1}{2} \int_0^{\infty} e^{-t} t^{\frac{d}{2}-1} dt$$

$$\therefore I = \frac{1}{2} \Gamma\left(\frac{d}{2}\right)$$

\therefore eqⁿ ② becomes,

$$I(d) = A(d) \times \frac{1}{2} \Gamma\left(\frac{d}{2}\right) \quad -③$$

Solving eqⁿ ① & ③ we get,

$$A(d) = \frac{2 \pi^{\frac{d}{2}}}{\Gamma\left(\frac{d}{2}\right)}$$

&

$$\therefore V(d) = \frac{A(d)}{d}$$

$$\therefore V(d) = \frac{2 \pi^{\frac{d}{2}}}{d \Gamma\left(\frac{d}{2}\right)}$$

from formulas, it can be seen that as $d \rightarrow \infty$, both $A(d)$ & \sqrt{cd} $\rightarrow 0$ because,

as d increases; the denominator term gets bigger & bigger than the numerator term & Hence the ratio approaches to zero.

Q.6 Show that most of the volume of unit ball in \mathbb{R}^d is near equator, if d is large.

→ Consider a high-dimensional unit ball & fix north pole on the x_1 -axis at $x_1=1$. Divide the ball in half by intersecting it with plane $x_1=0$. The intersection of the plane with ball forms a region of one lower dimension, namely $\{\mathbf{x} \mid \|\mathbf{x}\| \leq 1, x_1=0\}$ which we call equator. The intersection is a sphere of dimension $d-1$ and has volume $V(d-1)$. In 3-dimensions this region is circle, in four dimensions the region is a 3-dimensional sphere/ball, etc.

In general, the intersection is a ball of ' $d-1$ '-dimension.

It turns out that essentially all of the mass of upper hemisphere lies between the plane $x_1=0$ & a parallel plane $x_1=\epsilon$, that is slightly higher. For what value of ϵ does essentially all the mass lie between $x_1=0$ & $x_1=\epsilon$?

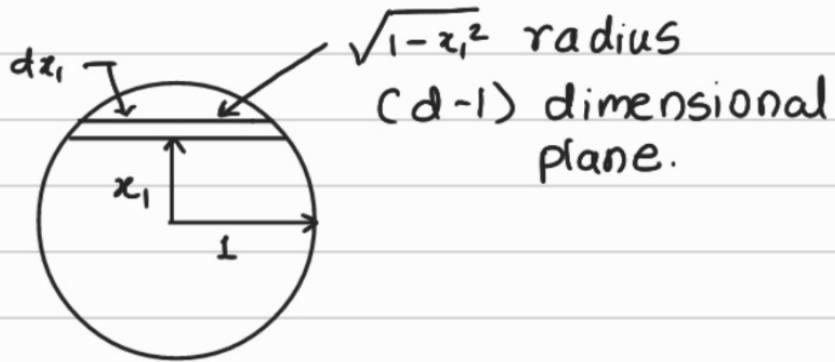
The answer depends on the dimension.

For dimension d it is $O(1/\sqrt{d-1})$. To see this, calculate the volume of portion of the ball above the slice lying between $x_1=0$ & $x_1=\epsilon$.

Let $T = \{\mathbf{x} \mid \|\mathbf{x}\| \leq 1, x_1 \geq \epsilon\}$ be the portion of the sphere above the slice. To calculate volume of T , integrate over x_1 from ϵ to 1.

The incremental volume is a disk of width dx_1 , whose face is a sphere of dimension $d-1$ of radius $\sqrt{1-x_1^2}$ & therefore, the surface area of disk is

$$(1-x_1^2)^{\frac{d-1}{2}} V(d-1)$$



volume of cross sectional slab
of a d -dimensional ball

Thus,

$$\begin{aligned} \text{Volume}(T) &= \int_E^1 (1-x_1^2)^{\frac{d-1}{2}} V(d-1) dx_1 \\ &= V(d-1) \int_E^1 (1-x_1^2)^{\frac{d-1}{2}} dx_1 \end{aligned}$$

Note that $V(d)$ denotes the volume of the d -dimensional unit ball. For the volume of other sets such as the set T , we use the notation $\text{Volume}(T)$ for the volume. The above integral is difficult to evaluate so we use some approximations.

First, we use the inequality $1+x \leq e^x$ for all real x & change the upper bound on integral to be infinity. Since x_1 always greater than ε over the region of integration we can insert x_1/ε in the integral. This gives,

$$\begin{aligned} \text{Volume}(CT) &\leq \sqrt{(d-1)} \int_{\varepsilon}^{\infty} e^{-\frac{d-1}{2}x_1^2} dx_1 \\ &\leq \sqrt{(d-1)} \int_{\varepsilon}^{\infty} \frac{x_1}{\varepsilon} e^{-\frac{(d-1)}{2}\left(\frac{x_1}{\varepsilon}\right)^2} dx_1 \end{aligned}$$

Now,

$$\int x_1 e^{-\frac{d-1}{2}x_1^2} dx_1 = -\frac{1}{d-1} e^{-\frac{d-1}{2}x_1^2} \quad \text{hence,}$$

$$\text{Volume}(CT) \leq \frac{1}{\varepsilon(d-1)} e^{-\frac{d-1}{2}\varepsilon^2} \sqrt{(d-1)}$$

Next, we lower bound the volume of the entire upper hemisphere. Clearly the volume of upper hemisphere is at least the volume between the slabs $x_1=0$ &

$x_1 = \frac{1}{\sqrt{d-1}}$, which is at least the volume of cylinder of radius $\sqrt{1-\frac{1}{d-1}}$ & height

$$\frac{1}{\sqrt{d-1}}.$$

The volume of cylinder is $\frac{1}{\sqrt{d-1}}$ times the $d-1$ dimensional volume of the disk

$$R = \{x \mid \|x\| \leq 1; x_1 = \pm \frac{1}{\sqrt{d-1}}\}.$$

Now, R is a $d-1$ -dimensional ball

of radius $\sqrt{1 - \frac{1}{d-1}}$ and so its volume is,

$$\text{Volume}(R) = \pi^{(d-1)/2} \left(1 - \frac{1}{d-1}\right)^{(d-1)/2}$$

Using $(1-x)^\alpha \geq 1 - \alpha x$,

$$\therefore \text{Volume}(R) \geq \pi^{(d-1)} \left(1 - \frac{1}{d-1} \cdot \frac{d-1}{2}\right)$$

$$\therefore \boxed{\text{Volume}(R) \geq \frac{1}{2} \pi^{(d-1)}}$$

Thus, the volume of upper hemisphere

is at least $\frac{1}{2\sqrt{d-1}} \pi^{(d-1)}$. The fraction of

the volume above the plane $x_1 = \varepsilon$ is upper bounded by the ratio of upper bound on the volume of the hemisphere above the plane $x_1 = \varepsilon$ to the lower bound on the total volume. This ratio is

$$\frac{2}{\varepsilon\sqrt{d-1}} e^{-\left(\frac{d-1}{2}\right)\varepsilon^2}$$

$$\text{Now, substitute, } \varepsilon = \frac{c}{\sqrt{d-1}}$$

\therefore The ratio becomes $\frac{2}{c} e^{-c^2/2}$.

Now, for $c \geq 2$, the fraction of the volume of the hemisphere above

$$x_1 = \frac{c}{\sqrt{d-1}} \text{ is less than } \bar{e}^2 \approx 0.14$$

& for $c \geq 4$, the fraction is less than $0.5 \times \bar{e}^8 \approx 0.0003$.

This essentially means, all the mass as well as volume of ball in Rd is in a narrow slice at the equator.

Q.7 State and prove Gaussian annulus th^m.

Statement :-

For a d-dimensional spherical Gaussian with unit variance in each direction, for any $\beta \leq \sqrt{d}$, all but at most $3e^{-c\beta^2}$ of probability mass lies within the annulus

$$\sqrt{d} - \beta \leq |x| \leq \sqrt{d} + \beta, \text{ where}$$

c is a fixed positive constant.

Proof :-

Let $x = (x_1, x_2, \dots, x_d)$ be a point selected from a unit variance Gaussian centered at the origin, and let $r = |x|$.

$\sqrt{d} - \beta \leq |y| \leq \sqrt{d} + \beta$ is equivalent to

$|r - \sqrt{d}| \geq \beta$. If $|r - \sqrt{d}| \geq \beta$, then multiplying both sides by $r + \sqrt{d}$ gives,

$$|r^2 - d| \geq \beta(r + \sqrt{d}) \geq \beta\sqrt{d}$$

so, it suffices to bound the probability that $|r^2 - d| \geq \beta\sqrt{d}$.

$$\begin{aligned} \text{Rewrite } r^2 - d &= (x_1^2 + \dots + x_d^2) \\ &= (x_1^2 - 1) + \dots + (x_d^2 - 1) \end{aligned}$$

and perform a change of variables

$$\text{as } y_i = x_i^2 - 1.$$

We want to bound the probability that $|y_1 + \dots + y_d| \geq \beta\sqrt{d}$.

Notice that $E(y_i) = E(x_i^2) - 1 = 0$.

To apply tails theorem, we need to bound the s^{th} moment of y_i .

For $|x_i| \leq 1$, $|y_i|^s \leq 1$ and for $|x_i| \geq 1$, $|y_i|^s \leq |x_i|^{2s}$.

Thus,

$$|E(y_i^s)| = E(|y_i|^s)$$

$$\leq E(1+x_i^{2s}) = 1 + E(x_i^{2s})$$

$$= 1 + \sqrt{\frac{2}{\pi}} \int_0^\infty x^{2s} e^{-x^2/2} dx.$$

Using the substitution $2z = x^2$,

$$|E(y_i^s)| = 1 + \frac{1}{\sqrt{\pi}} \int_0^\infty 2^s z^{s-(1/2)} e^{-z} dz$$

$$\leq 2^s \cdot s!$$

/ using Gamma integral inequality

Since $E(y_i) = 0$, $\text{Var}(y_i) = E(y_i^2) \leq 2^2 \cdot 2 = 8$.

Unfortunately, we do not have

$|E(y_i; s)| \leq 8s!$ as required by tail's theorem. To fix this problem, perform one more change of variables, using

$\omega_i = y_i / 2$. Then $\text{var}(\omega_i) \leq 2$ and

$|E(\omega_i; s)| \leq 2s!$ and our goal is now to bound the probability that $|\omega_1 + \dots + \omega_d| \geq \beta\sqrt{d}/2$.

Applying tails theorem, where $\sigma^2 = 2$ and $n=d$ this occurs with probability less than or equal to $3e^{-\beta^2/96}$.

Q.8

Explain in detail random projection theorem.

Statement :-

Let v be a fixed vector in \mathbb{R}^d and let $f: \mathbb{R}^d \rightarrow \mathbb{R}^k$. There exists constant $C > 0$ such that for $\epsilon \in (0, 1)$,

$$\text{Prob}\left(\left| \|f(v)\| - \sqrt{k} \|v\| \right| \geq \epsilon \sqrt{k} \|v\|\right) \leq 3e^{-Ck\epsilon^2}$$

where the probability is taken over the random draws of vectors u_i used to construct f .

Proof :-

By scaling both sides of the inner inequality by $\|v\|$, we may assume that $\|v\| = 1$.

The sum of independent normally distributed real variables is also normally distributed where the mean and variance are the sum of individual means and variances.

Since $u_i \cdot v = \sum_{j=1}^d u_{ij} \cdot v_j$, the random variable

$u_i \cdot v$ has Gaussian density with zero mean and unit variance. In particular,

$$\text{Var}(u_i \cdot v) = \text{Var}\left(\sum_{j=1}^d u_{ij} \cdot v_j\right)$$

$$= \sum_{j=1}^d v_j^2 \cdot \text{Var}(u_{ij})$$

$$= \boxed{\sum_{j=1}^d v_j^2 = 1}$$

Since $u_1 \cdot v, u_2 \cdot v, \dots, u_k \cdot v$ are independent Gaussian random variables, $f(v)$ is a L -dimensional random vector from a k -dimensional spherical Gaussian with unit variance in each coordinate, and so the ℓ^m follows from the Gaussian Annulus theorem with d replaced by k .

The random projection theorem establishes that the probability of the length of projection of a single vector differing significantly from its expected value is exponentially small in k , the dimension of the target subspace. By a union bound, the probability that any of $O(n^2)$ pairwise differences $|v_i - v_j|$ among n vectors v_1, \dots, v_n differs significantly from their expected values is small, provided $k \geq (3/\epsilon^2) \ln(n)$. Thus, this random projection preserves all relative pairwise distances between points in a set of n -points with high probability. This is the content of Johnson-Lindenstrauss Lemma.

Q.9

Explain the statement and proof of the Johnson-Lindenstrauss lemma.

Statement :-

For any $0 < \epsilon < 1$ and any integer n , let $K \geq \frac{3}{C\epsilon^2} \ln n$. with C as fixed positive

constant. For any set of ' n ' points in \mathbb{R}^d , the random projection $f: \mathbb{R}^d \rightarrow \mathbb{R}^K$ defined above has the property that for all pairs of points v_i and v_j , with probability at least $1 - (3/n)$,

$$(1-\epsilon) \sqrt{K} |v_i - v_j| \leq |f(v_i) - f(v_j)|$$

$$\leq (1+\epsilon) \sqrt{K} |v_i - v_j|$$

Proof :-

Applying the random projection f for any fixed v_i and v_j , the probability that $|f(v_i) - f(v_j)|$ is outside the range

$$[(1-\epsilon) \sqrt{K} |v_i - v_j|, (1+\epsilon) \sqrt{K} |v_i - v_j|]$$

is at most $3e^{CK\epsilon^2} \leq 3/n^3$ for

$K \geq (3 \ln n)/C\epsilon^2$. Since there are

$\binom{n}{2} < n^2/2$ pairs of points, by the union bound, the probability that any pair has a large distortion is less than $(3/n)$.

It is important to note that the conclusion of above theorem asserts for all v_i and v_j , not just for most of them. The weaker assertion for most $v_i \neq v_j$ is typically less useful since our algorithm for a problem such as nearest-neighbour search might return one of the bad points. A remarkable aspect of the theorem is that the number of dimensions in projection is only dependent logarithmically on n . Since k is often much less than d , this is called dimension reduction technique. In applications, the dominant term is typically the $1/\epsilon^2$ term.

For nearest neighbour problem, if the database has n_1 points and n_2 queries are expected during the lifetime of algorithm take $n = n_1 + n_2$ & project database to random k -dimensional space, for k as in above theorem. On receiving a query, project the query to same subspace & compute nearby database points. The Johnson-Lindenstrauss Lemma says that with high probability this will yield the right answer whatever the query.

Note that the exponentially small in k -probability was useful here in making k only dependent on $\ln n$, rather than n .

Q.10 Derive in detail the algorithm for separating points from 2-gaussians in \mathbb{R}^d if d is large by calculating pairwise distances between them.

Algorithm :-

Calculate all pairwise distances between points. The cluster of smallest pairwise distances must come from single Gaussian. Remove these points. The remaining points come from second Gaussian.

Derivation :-

First consider just one spherical unit-variance Gaussian centered at origin. From Gaussian annulus theorem, most of its probability mass lies on an annulus of width O(1) at radius \sqrt{d} . Also

$$e^{-\|x\|^2/2} = \prod_i e^{-x_i^2/2} \text{ and almost all of the}$$

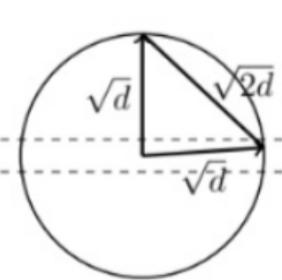
mass is within the slab $\{|x_i| - c \leq x_i \leq c\}$ for $c \in O(1)$. Pick a point x from this Gaussian. After picking x , rotate the coordinate system to make the first axis align with x . Independently pick a second point y from this Gaussian.

The fact that almost all of probability mass of the Gaussian is within the

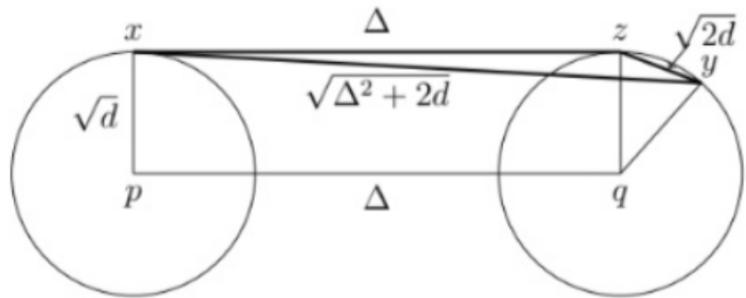
Slab $\{x \mid -c \leq x_i \leq c, c \in O(1)\}$ at equator implies that y 's component along x 's dirⁿ is $O(1)$ with high probability. Thus, y is nearly perpendicular to x .

So,

$$\|x - y\| \approx \sqrt{\|x\|^2 + \|y\|^2}$$



(a)



(b)

(a) indicates that two randomly chosen points in high dimension are surely almost nearly orthogonal.

(b) Indicates the distance between a pair of random points from two different unit balls approximating the annuli of 2-Gaussians.

More precisely, since co-ordinate system has been rotated so that x is at north pole, $x = (\sqrt{d} \pm O(1), 0, \dots, 0)$. Since y is almost on the equator, further rotate the co-ordinate system so that the component of y that is perpendicular to the axis of north pole is in the 2nd co-ordinate.

Then $y = (O(1), \sqrt{d} \pm O(1), 0, \dots, 0)$.

Thus,

$$(x-y)^2 = d \pm O(\sqrt{d}) + d \pm O(\sqrt{d})$$

$$\therefore (x-y)^2 = 2d \pm O(\sqrt{d})$$

and $|x-y| = \sqrt{2d} \pm O(1)$ with high probability.

Consider 2-spherical unit variance Gaussians with centers p & q separated by a distance Δ . The distance between a randomly chosen point x from the first Gaussian and randomly chosen point y from second is close to $\sqrt{\Delta^2 + 2d}$, since

$x-p$, $p-q$ & $q-y$ are nearly mutually \perp .

Pick x & rotate the co-ordinate system so that x is at north pole. Let z be the North Pole of ball approximating the second Gaussian.

Now pick y . Most of the mass of 2nd Gaussian is within $O(1)$ of the equator $z-q$. Also most of the mass of each Gaussian is within distance $O(1)$ of the respective equators \perp to line $q-p$. Thus,

$$|x-y|^2 \approx \Delta^2 + |z-q|^2 + |q-y|^2$$

$$\therefore |x-y|^2 = \Delta^2 + 2d \pm O(\sqrt{d})$$

To ensure that the distance 2-points picked from same Gaussian are closer to each other than two points picked from different Gaussians requires that the upper limit of distance between a pair of points from the same Gaussian is at most the lower limit of distance between points from different Gaussians. This requires that

$$\sqrt{2d} + O(1) \leq \sqrt{2d+D^2} - O(1)$$

or

$$2d + O(\sqrt{d}) \leq 2d + D^2$$

which holds when $D \in \omega(d^{1/4})$.

Thus, mixtures of spherical Gaussians can be separated in this way, provided their centers are separated $\omega(d^{1/4})$.

If we have n points and want to correctly separate all of them with high probability we need our individual high-probability statements to hold with probability

$1 - 1/\text{poly}(n^3)$, which means our $O(1)$ terms from Gaussian annulus theorem become $O(\sqrt{\log n})$. So we need to include an extra $O(\sqrt{\log n})$ term in the separation distance.