Chapter 2

Random Vectors in High Dimensions

- concentration of the norm
- Isotropy
- Similarity of Normal and Spherical
- Sub-Gaussian and Subexponential random vectors.

Two main results we'll prove:

1) Sub-Gaussian vectors concentrate around a sphere.
2) Two independent isotropic subGaussian random vectors are nearly orthogonal in high dimensions.

We next investigate the behavior of random vectors in high dimensions

Concentration of the norm

Let $X = (X_1, \dots, X_d) \in \mathbb{R}^d$ have independent σ-subGaussian coordinates with

$$\mathbb{E} X_i = 0 \quad \text{and} \quad \mathbb{E} X_i^2 = 1$$

What can we expect from

$$\|X\|_2^2 \quad \text{and} \quad \|X\|_2$$

Lemma: Suppose y is σ-subGaussian. Then y^2 is $(\sigma^2, 4\sigma^2)$ subexponential

pf sketch:

Step 1: Estimate $\mathbb{E}[|y|^r] \le r\, 2^{r/2} \sigma^r \Gamma(\frac{r}{2})$

using $\mathbb{E}[|y|^r] = \int_0^\infty \mathbb{P}[|y| > t^{1/r}]\, dr$

Step 2: Use Taylor Expansion

$$\mathbb{E}[e^{\lambda(y^2 - \mathbb{E}y^2)}] \le 1 + \sum_{r=2}^\infty \lambda^r 2^{r+1} \sigma^{2r} \le 1 + \frac{8\lambda^2\sigma^4}{1 - 2\lambda\sigma^2}$$

$$\le \exp(\cdots) \quad \square$$

Cor: Let $X=(X_1,\dots,X_d)\in\mathbb{R}^d$ have independent σ-subGaussian coordinates with

$$\mathbb{E}X_i=0 \quad\text{and}\quad \mathbb{E}X_i^2=1$$

Then $\mathbb{P}\left[\,\left|\|X\|_2^2-d\right|\ge td\right]\le 2\exp\left(-\frac{d}{4\sigma^2}(t\wedge t^2)\right)$

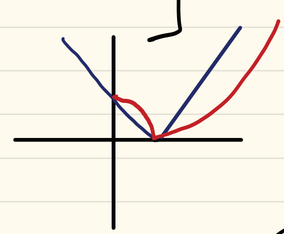
$$\mathbb{P}\left[\,\left|\|X\|_2-\sqrt{d}\right|\ge t\sqrt{d}\right]\le 2\exp\left(\frac{-dt^2}{4\sigma^2}\right)$$

pf: $\|X\|_2^2=\sum_{i=1}^{d} X_i^2 \Rightarrow \begin{cases}\mathbb{E}\|X\|_2^2=d\\ \|X\|_2^2 \text{ is } (\sigma\sqrt{d},4\sigma^2) \text{ subexponential.}\end{cases}$

Bernstein $\Rightarrow$

$$\mathbb{P}\left[\left|\frac{1}{d}\|X\|_2^2-1\right|\ge t\right]\le 2\exp\left[-\frac{d}{4\sigma^2}(t\wedge t^2)\right]$$

Observation: for any $z\ge 0$, have



$$|z-1|\ge t \Rightarrow |z^2-1|\ge t\vee t^2$$

So $\mathbb{P}\left[\left|\frac{1}{\sqrt{d}}\|X\|_2-1\right|\ge t\right]\le \mathbb{P}\left[\left|\frac{1}{d}\|X\|_2^2-1\right|\ge t\vee t^2\right]$

$$\le 2\exp\left(\frac{-dt^2}{4\sigma^2}\right) \qquad \square$$

Isotropic Vectors

Recall for $X \in \mathbb{R}^d$, covariance

$$\mathrm{cov}(X) = \mathbb{E}\left((X-\mu)(X-\mu)^T\right)$$

where $\mu = \mathbb{E}X$.

Defn: A random vector $X \in \mathbb{R}^d$ with $\mathbb{E}X = 0$ is isotropic if

$$\Sigma(X) := \mathbb{E}XX^T = I_d$$

Remark: If $\Sigma = \Sigma(X)$ is invertible, then

$$Z := \Sigma^{-1/2}(X-\mu) \text{ is isotropic.}$$

Lemma: X is isotropic iff

$$\mathbb{E}\langle X, y\rangle^2 = \|y\|_2^2 \quad \forall y \in \mathbb{R}^d$$

pf: X is isotropic iff $\mathbb{E}XX^T = I$

iff $y^T \mathbb{E}XX^T y = y^T y$

iff $\mathbb{E}y^T X X^T y = \|y\|_2^2$

iff $\mathbb{E}\langle X, y\rangle^2 = \|y\|_2^2$ $\square$

Thus if $\mathbb{E}X=0$, then X isotropic iff marginal $\langle X, \frac{y}{\|y\|} \rangle$ has unit variance $\forall y \in \mathbb{R}^d$

Lemma: Let $X \in \mathbb{R}^d$ be isotropic. Then

$$\mathbb{E}\|X\|_2^2 = d.$$

Moreover, if X and Y are two independent isotropic vectors, then

$$\mathbb{E}\langle X, Y \rangle^2 = d$$

pf: First

$$\|X\|_2^2 = X^T X = \mathrm{trace}(XX^T)$$

$$\Rightarrow \mathbb{E}\|X\|_2^2 = \mathrm{trace}(I_d) = d.$$

Next $\mathbb{E}\langle X, Y \rangle^2 = \mathbb{E}_Y\left[\mathbb{E}_X \langle X, Y \rangle^2 \mid Y\right]$

$$= \mathbb{E}_Y \|Y\|_2^2 = d \quad \boxtimes$$

Let X and Y be independent and isotropic

Then $\|X\| \sim \sqrt{d}$
$\|Y\| \sim \sqrt{d}$ and $\left\langle \frac{X}{\|X\|}, \frac{Y}{\|Y\|} \right\rangle \sim \frac{1}{\sqrt{d}}$.

$\therefore$ Almost orthogonal.

Can be made rigorous by assuming light tails.

Examples of isotropic RV:

1) Spherical $X \sim \text{Unif}(\sqrt{d}\, S^{d-1})$ $\boxed{HW}$

2) Symmetric Bernoulli: $X \sim \text{Unif}(\{-1,1\}^d)$

3) Any vector $X=(X_1,\dots,X_d)$, where X_i are independent, zero mean, unit variance.

4) Coordinate $\text{Unif}(\{\sqrt{d}\, e_i\}_{i=1}^d)$

5) Gaussian $g=(g_1,\dots,g_d) \sim N(0,I_d)$

Recall this means g_i are i.i.d. $N(0,1)$

$\Rightarrow$ Density
$$p(x)=\prod_{i=1}^d p_i(x)=\prod_{i=1}^d \frac{1}{\sqrt{2\pi}} e^{-x_i^2/2} = \frac{1}{(2\pi)^{n/2}} e^{-\|x\|_2^2/2}.$$

$\Rightarrow N(0,I_d)$ is rotation invariant.

Exercise:

Let $g \sim N(0,I_d)$. Then
$$r := \|g\|_2 \quad \text{and} \quad \theta = \frac{g}{\|g\|_2}$$
are independent random variables and
$$\theta \sim \text{Unif}(S^{d-1})$$

Defn: X in $\mathbb{R}^d$ is σ-subGaussian if
$\langle X, u \rangle$ is σ-subGaussian $\forall_{u \in S^{d-1}}$

Ex: Let $X = (X_1, \dots, X_d)$ be RV
with independent σ-subGaussian X_i'.
Then X is σ-subGaussian.

Ex: 1) $N(0, I_d)$ is 1-subGaussian
2) $\mathrm{Unif}(\{-1, 1\}^d)$ is 1-subGaussian
3) $\mathrm{Unif}(\{\sqrt{d}\, e_i\}_{i=1}^d)$ is σ-subGaussian
with $\sigma \simeq \sqrt{\frac{d}{\log(d)}}$

Way too big to be useful

4) $\mathrm{Unif}(\sqrt{d}\, S^{d-1})$ is c-subGaussian
for a constant c.

Q: How to get high probability bound on
$\| X - \mathbb{E}X \|$?

Idea: $\| X - \mathbb{E}X \| = \sup_{y \in B^*} \langle X - \mathbb{E}X, y \rangle$