

Building blocks for this lecture

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1 Equalities

1. Euclidean norm

$$\|\mathbf{x}\|_2^2 = \mathbf{x}^\top \mathbf{x}.$$

2. Expanding the squared norm of the sum of two vectors

$$\|\mathbf{x} + \mathbf{y}\|_2^2 = \|\mathbf{x}\|_2^2 + 2\mathbf{x}^\top \mathbf{y} + \|\mathbf{y}\|_2^2.$$

3. Singular value decomposition

$$\mathbf{X} = \mathbf{U}\mathbf{S}\mathbf{V}^\top,$$

where \mathbf{U} and \mathbf{V} are orthogonal matrices and \mathbf{S} is diagonal.

4. Orthogonal matrix

$$\mathbf{U}^\top \mathbf{U} = \mathbf{U}\mathbf{U}^\top = \mathbf{I}.$$

5. Trace identity

$$\text{Tr}(\mathbf{A}\mathbf{B}) = \text{Tr}(\mathbf{B}\mathbf{A}).$$

2 Inequalities

6. Any norm $\|\cdot\|$ satisfies

- (a) Positive homogeneity

$$\|a\mathbf{x}\| = |a|\|\mathbf{x}\|.$$

- (b) Triangular inequality

$$\|\mathbf{x}\| - \|\mathbf{y}\| \leq \|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|.$$

- (c) Zero means zero

$$\|\mathbf{x}\| = 0 \quad \Rightarrow \quad \mathbf{x} = \mathbf{0}.$$

(d) Positivity

$$\|\mathbf{x}\| \geq 0.$$

(implied by the positive homogeneity and the triangular inequality).

7. Euclidean norm is dual to itself

$$\mathbf{x}^\top \mathbf{y} \leq \|\mathbf{x}\|_2 \|\mathbf{y}\|_2.$$

8. ℓ_∞ - and ℓ_1 -norms are dual to each other

$$\mathbf{x}^\top \mathbf{y} \leq \|\mathbf{x}\|_\infty \|\mathbf{y}\|_1,$$

where $\|\mathbf{x}\|_\infty = \max_j |x_j|$ and $\|\mathbf{y}\|_1 = \sum_{j=1}^p |y_j|$.

9. Compatibility between ℓ_1 and ℓ_2 (Euclidean norm): if \mathbf{x} is k -sparse (only k non-zero entries), then

$$\|\mathbf{x}\|_1 \leq \sqrt{k} \|\mathbf{x}\|_2.$$

10. Euclidean norm increases when adding two orthogonal vectors: if $\mathbf{x}^\top \mathbf{y} = 0$,

$$\|\mathbf{x}\|_2 \leq \|\mathbf{x} + \mathbf{y}\|_2 \quad \text{and} \quad \|\mathbf{y}\|_2 \leq \|\mathbf{x} + \mathbf{y}\|_2$$

3 Probability theory

11. Linearity of expectation

$$\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y].$$

12. Reproducibility of Gaussian: if $X, Y \sim \mathcal{N}(0, \sigma^2)$,

$$aX + bY \sim \mathcal{N}(0, (a^2 + b^2)\sigma^2).$$

13. Gaussian covariance: if $\mathbf{x} \sim \mathcal{N}(0, \Sigma)$,

$$\mathbb{E}[\mathbf{x}\mathbf{x}^\top] = \Sigma.$$

14. Union bound: the probability of any of the n events E_1, \dots, E_n being true is bounded by the sum of the probabilities:

$$P(\cup_{i=1}^n E_i) \leq \sum_{i=1}^n P(E_i).$$

15. Max of Gaussians: let $z_j \sim \mathcal{N}(0, \sigma_j^2)$ ($j = 1, \dots, p$), then

$$\Pr\left(\max_j |z_j| \geq 2R\sqrt{\log p}\right) \leq \frac{2}{p} \quad \text{where} \quad R := \max_j \sigma_j.$$

In other words, with probability at least $1 - 2/p$, we have

$$\max_j |z_j| \leq 2R\sqrt{\log p}.$$