

1 Representations of ellipsoids

Consider an ellipsoid $\mathcal{E} \subseteq \mathbb{R}^n$ that is centered at the origin, and has nonzero volume. We have seen two representations for such an ellipsoid:

$$\mathcal{E}_1(S) = \{x \in \mathbb{R}^n : x^\top S x \leq 1\} \quad \text{and} \quad \mathcal{E}_2(A) = \{Az : \|z\| \leq 1\},$$

where $S \in \mathbb{R}^{n \times n}$ is symmetric and positive definite, and $A \in \mathbb{R}^{n \times n}$ is nonsingular.

- (a) Given a nonsingular matrix $A \in \mathbb{R}^{n \times n}$, explain how to find a symmetric, positive-definite matrix $S \in \mathbb{R}^{n \times n}$ such that $\mathcal{E}_1(S) = \mathcal{E}_2(A)$. Is there a unique S corresponding to a given A ? If so, explain why; if not, explain why not, and how to find all matrices S corresponding to a given A .
- (b) Given a symmetric, positive-definite matrix $S \in \mathbb{R}^{n \times n}$, explain how to find a nonsingular matrix $A \in \mathbb{R}^{n \times n}$ such that $\mathcal{E}_1(S) = \mathcal{E}_2(A)$. Is there a unique A corresponding to a given S ? If so, explain why; if not, explain why not, and how to find all matrices A corresponding to a given S .

2 Confidence ellipsoids

Consider a measurement model

$$y = Ax + v,$$

where $y \in \mathbb{R}^m$ is a measurement (which is known), $x \in \mathbb{R}^n$ is a vector of unknown parameters (which we want to estimate), $v \in \mathbb{R}^m$ is measurement noise (which is unknown), and $A \in \mathbb{R}^{m \times n}$ describes the measurement system. We will assume that A is skinny and full rank, and v is norm-bounded: that is, there is a known $\alpha > 0$ such that $\|v\| \leq \alpha$.

- (a) First, consider the specific case when

$$A = \begin{bmatrix} 2 \\ -1 \end{bmatrix}, \quad y = \begin{bmatrix} 9 \\ 23 \end{bmatrix}, \quad \text{and} \quad \alpha = 25.$$

We say that the parameter $x \in \mathbb{R}$ is consistent with the model if there exists a noise vector $v \in \mathbb{R}^m$ such that $y = Ax + v$, and $\|v\| \leq \alpha$. Find the set of all parameters x that are consistent with the specific model given above. You can do this by finding the set of all x such that $\|y - Ax\| \leq \alpha$.

- (b) Your friend proposes a different method for determining the set of consistent parameters. Since $y = Ax + v$, and $A^\dagger A = I$ for a skinny and full rank matrix, he argues that

$$\hat{x} = A^\dagger y = A^\dagger (Ax + v) = x + A^\dagger v,$$

and hence that

$$x = \hat{x} - A^\dagger v,$$

where $\hat{x} = A^\dagger y$ is the least-squares estimate of x . Therefore, the set of all parameter vectors x that are consistent with the model is

$$\hat{x} - A^\dagger \{v \in \mathbb{R}^m : \|v\| \leq \alpha\}.$$

- (i) According to your friend's analysis, what is the set of all parameter vectors x that are consistent with the specific model given in (a)? Is the consistent with the result that you derived earlier?
 - (ii) If your friend's analysis does not produce the same answer you derived earlier, why is there a difference? Which do you think is correct: your friend's analysis, or the answer you derived earlier?
- (c) Now consider the general case. Let the singular-value decomposition of A be $A = U\Sigma V^\top$. By "completing the square," show that the set of all parameters $x \in \mathbb{R}^n$ that are consistent with the model is

$$\left\{ \hat{x} + V\Sigma^{-1}z : \|z\| \leq \sqrt{\alpha^2 - \|\hat{\epsilon}\|^2} \right\}.$$

- (d) The file `confidence_ellipsoids_data.m` contains values of A , y , and α . For this example, the vector of parameters has dimension $n = 2$. Plot the set of all parameter vectors x that are consistent with the model.

3 The Frobenius norm

The Frobenius norm of a matrix $A \in \mathbb{R}^{m \times n}$ is defined to be

$$\|A\|_F = \sqrt{\text{tr}(A^\top A)}.$$

- (a) Show that

$$\|A\|_F = \left(\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2 \right)^{\frac{1}{2}}.$$

Thus, the Frobenius norm is simply the Euclidean norm of a matrix, when we think of the matrix as an element of \mathbb{R}^{mn} . Additionally, note that the Frobenius norm is much easier to compute than the spectral norm.

- (b) Show that if $U \in \mathbb{R}^{m \times m}$ and $V \in \mathbb{R}^{n \times n}$ are orthogonal, then

$$\|UA\|_F = \|AV\|_F = \|A\|_F.$$

Thus, multiplication by orthogonal matrices on the left or right does not change the Frobenius norm.

- (c) Show that

$$\|A\|_F = \sqrt{\sigma_1^2 + \cdots + \sigma_r^2},$$

where $\sigma_1, \dots, \sigma_r$ are the nonzero singular values of A . Use this result to deduce that

$$\sigma_{\max}(A) \leq \|A\|_F \leq \sqrt{r} \sigma_{\max}(A).$$

In particular, we have that $\|Ax\| \leq \|A\|_F \|x\|$ for all $x \in \mathbb{R}^n$.