Matrix Norm

- One of the main concerns in matrix algorithms is the sensitivity of a system to its coefficients. To do so, we need to measure the size of errors. The measurement is done by the notion of *norm*.
- We have already seen some examples of vector norms. Mathematically, a vector norm is a function $\| \cdots \| : \mathbb{R}^n \longrightarrow \mathbb{R}$ that satisfies:
 - 1. $x \neq 0 \Longrightarrow ||x|| > 0$,
 - 2. $\|\alpha x\| = |\alpha| \|x\|$,
 - 3. $||x + y|| \le ||x|| + ||y||.$
- Matrix norms are defined in analogy with vector norms because a matrix in $\mathbb{R}^{n \times n}$ can be thought of as a vector in \mathbb{R}^{n^2} . There are additional properties (and often confusing), however, in matrix norms.
 - \diamond We say a matrix norm $\|\cdot\|$ is *consistent* if it satisfies

$$||AB|| \le ||A|| ||B|| \tag{0.1}$$

whenever AB is defined.

▷ Not all matrix norms are consistent. For example, if we define $||A|| = \max_{i,j} |a_{ij}|$ like the sup-norm for vectors, we find

$$\left\| \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \right\| = 2,$$
$$\left\| \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \right\| \left\| \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \right\| = 1$$

while

$$\left\| \left[\begin{array}{cc} 1 & 1 \\ 1 & 1 \end{array} \right] \right\| \left\| \left[\begin{array}{cc} 1 & 1 \\ 1 & 1 \end{array} \right] \right\| = 1.$$

 \diamond The *induced* norm

$$||A|| := \max_{x \neq 0} \frac{||Ax||_{(m)}}{||x||_{(n)}} \tag{0.2}$$

where $\|\cdot\|_{(m)}$ and $\|\cdot\|_{(n)}$ are fixed vector norms is a consistent matrix norm.