

Consider \mathbf{A} , an $n \times n$ matrix, where the Rank of $\mathbf{A} = n$.

- Full rank
- Nonsingular
- Linearly independent
- Determinant $\neq 0$
- Can invert \mathbf{A}
- Can solve equations
- Unique solution

Normalizing

If $\underline{\mathbf{a}}' \underline{\mathbf{b}} = a_1 b_1 + a_2 b_2 + \dots + a_n b_n = 0$, then $\underline{\mathbf{a}}$ and $\underline{\mathbf{b}}$ are orthogonal.

If $\underline{\mathbf{a}}' \underline{\mathbf{a}} = 1$, $\underline{\mathbf{a}}$ is normalized.

We can normalize a vector: $\underline{\mathbf{x}}^* = \frac{1}{\sqrt{\underline{\mathbf{x}}' \underline{\mathbf{x}}}} \underline{\mathbf{x}}$.

$$\underline{\mathbf{a}}' \underline{\mathbf{a}} = 1 \rightarrow \left(\frac{1}{\sqrt{\underline{\mathbf{x}}' \underline{\mathbf{x}}}} \underline{\mathbf{x}} \right)' \left(\frac{1}{\sqrt{\underline{\mathbf{x}}' \underline{\mathbf{x}}}} \underline{\mathbf{x}} \right) = \left(\frac{1}{\sqrt{\underline{\mathbf{x}}' \underline{\mathbf{x}}}} \right)^2 \underline{\mathbf{x}}' \underline{\mathbf{x}} = \frac{1}{\underline{\mathbf{x}}' \underline{\mathbf{x}}} \underline{\mathbf{x}}' \underline{\mathbf{x}} = 1$$

Canonical Correlation

$$r = \frac{\text{cov}(x, y)}{\sqrt{\text{var}(x)} \sqrt{\text{var}(y)}} \text{ and } r^2 = \frac{\text{cov}(x, y)^2}{\text{var}(x) \text{var}(y)} = \text{cov}(x, y)^2 \text{var}(x)^{-1} \text{var}(y)^{-1}.$$

$$\text{var}(y)^{-1} \text{cov}(x, y) \text{var}(x)^{-1} \text{cov}(x, y) = S_{yy}^{-1} S_{xy} S_{xx}^{-1} S_{xy}$$

Correlation between a single linear function of the Ys and a single linear function of the Xs.

Canonical correlation squared = λ , eigen value.

Row & Column Rank Equivalence

Consider an $n \times p$ matrix.

The n rows of the matrix are vectors in \mathbb{R}^n , spanning the subspace called row space. The dimension of this space is called row rank.

The p columns of the matrix are vectors in \mathbb{R}^p , spanning the subspace called column space. The dimension of this space is called column rank.

A theorem of matrix algebra proves row rank = column rank = rank.

Rank of an $n \times p$ matrix = rank of largest submatrix where $|\mathbf{A}| \neq 0$.

\mathbf{A} is full rank if $\text{rank}(\mathbf{A}) = \min\{n,p\}$.