

1. To show K is a field:

We can say that $a+bi$ and $c+di$ are elements of K , as a and b are rational numbers and so $a+c$ and $b+d$ are rational and so $(a+c) + (b+d)i$ is an element of K .

Furthermore, $(ac-bd)$ and $(ad+bc)$ are rational numbers, so $(ac-bd) + (ad+bc)i$ is an element of K .

Finally, there exists additive and multiplicative inverses, as $-a-bi$ exists. Additionally, we know that the aforementioned identities exist as well.

2. To show that $U \cap W$ and $U+W$ are subspaces of V :

We know based on the description of each that they are non-empty subspaces of V . Additionally, they should contain the zero vector since U and W are subspaces of V .

Considering x_1, x_2 to be elements of $U \cap W$, we can say that x_1 and x_2 belong to U and W . $x_1 + x_2$ belongs to both U and W , and thus, $U \cap W$.

Similarly, u_1 and u_2 being elements of U and w_1 and w_2 being elements of W would be written as $(u_1 + w_1) + (u_2 + w_2)$, which belongs to $U+W$.

Alternatively, we can let k be a scalar and x be an element of U and thus, kx belongs to $U \cap W$. Also, $kU + kW = k(U+W)$ belongs to $U+W$ as U and W are subspaces of V .

Thus, we have proved that $U \cap W$ and $U+W$ are subspaces of V .

3. $\|A\| > 0$ if $A \neq 0$:

- Proof: If $A \neq 0$, then there needs to be at least one element a_{ij} in A that is non-zero. Thus, $\max_j \sum_{i=1}^m |a_{ij}| > 0$ and $\|A\| > 0$.

• $\|\gamma A\| = |\gamma| \cdot \|A\|$ for any scalar γ :

- Proof: Considering $x = \gamma A$, $\|x\| = \max_j \sum_{i=1}^m |\gamma a_{ij}| = |\gamma| \max_j \sum_{i=1}^m |a_{ij}| = |\gamma| \|A\|$

Thus, $\|\gamma A\| = \|x\| = |\gamma| \|A\|$

• $\|A+B\| \leq \|A\| + \|B\|$:

$$\max_j \sum_{i=1}^m |a_{ij} + b_{ij}| \leq \max_j \left(\sum_{i=1}^m |a_{ij}| + \sum_{i=1}^m |b_{ij}| \right) \leq \max_j \sum_{i=1}^m |a_{ij}| + \max_j \sum_{i=1}^m |b_{ij}| = \|A\| + \|B\|$$

Thus, $\|A+B\| \leq \|A\| + \|B\|$. Similarly, we can show that $\|A+B\|_\infty \leq \|A\|_\infty + \|B\|_\infty$.

• $\|AB\| \leq \|A\| \cdot \|B\|$:

- Proof: Considering $C=AB$, $|c_{ij}| = \left| \sum_{k=1}^{nm} a_{ik} b_{kj} \right| \leq \sum_{k=1}^{nm} |a_{ik}| \cdot |b_{kj}| = \max_k \sum_{i=1}^{nm} |a_{ik}| \cdot \max_k \sum_{j=1}^{nm} |b_{kj}|$
 $= \|A\| \cdot \|B\|_\infty$

• $\|Ax\| \leq \|A\| \cdot \|x\|$ for any vector x :

- Proof: $\|Ax\| \leq \|A\| \cdot \|x\|$ iff $\|Ax\|/\|x\| \leq \|A\|$.

Considering $y=Ax$, then $\|y\|/\|x\| = \|Ax\|/\|x\| \leq \max_j \left(\sum_{i=1}^m |a_{ij}| \right) = \|A\|$

Thus, $\|Ax\| \leq \|A\| \cdot \|x\|$. (For $\|A\|$)

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4. a) With x being a column vector:

$$\begin{aligned} x^T(Bx) &= x^T \left(\frac{(B+B^T)}{2} + \frac{(B-B^T)}{2} \right) x \\ &= \frac{x^T(B+B^T)x}{2} + \frac{x^T(B-B^T)x}{2} \end{aligned}$$

- The first term is always going to be non-negative for any vector x , so the second term will be 0.

- B_s being the symmetric part of B , $B_s = \frac{(B+B^T)}{2}$. $B-B^T = 2(B-B_s)$, so

we show that the quadratic form

$x^T(B-B_s)x$ is 0, because $(B-B_s)=0$ and annihilates due to skew-symmetrism.

b) Considering A to be a square matrix, $B = A^T A$ is symmetric. For any vector x , we have:

$$x^T(A^T A)x = (Ax)^T(Ax) = \|Ax\|^2$$

- $B = A^T A$ is non-negative definite because of iff $\|Ax\|^2 \geq 0$ for all $x \neq 0$, which is true because of the norm of any vector being non-negative.

5. The least-squares orthogonality principle states that the residual vector $b - A\hat{x}$ is orthogonal to the column space of A .

Rewriting in terms of the SVD of A , we get $V(SD^T b - DC\hat{x}) = 0$.

We can use the SVD to isolate \hat{x} :

$$\hat{x} = VD^{-1}C^T b$$

Use this value in the least-squares orthogonality principle:

$$\begin{aligned} V(SD^T b - DCVD^{-1}C^T b) &= 0 \\ \cdot V^T & \quad \cdot V^T \end{aligned}$$

$$\begin{aligned} SD^T b - DCVD^{-1}C^T b &= 0 \\ Db - C^T D C \hat{x} &= 0 \end{aligned}$$

$$6. f(x) = -\sum_{i=1}^N T_i x_i + \sum_{i=1}^N x_i \log(x_i)$$

subject to constraint $\sum_{i=1}^N x_i = 1$

We define the Lagrangian as: $L(x, \lambda) = f(x) + \lambda \left(\sum_{i=1}^N x_i - 1 \right)$

$$\frac{\partial L}{\partial x_i} = -T_i + 1 + \log(x_i) + \lambda = 0$$

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We solve for x_i :

$$x_i = \exp(-T_i - 1 + \lambda)$$

Noting that the sum of x_i is 1:

$$\frac{\sum_{i=1}^N \exp(-T_i - 1 + \lambda)}{\sum_{j=1}^N \exp(-T_j - 1 + \lambda)} = 1$$

$$\ln \left[\sum_{i=1}^N \exp(-T_i - 1 + \lambda) \right] = \ln \left[\sum_{j=1}^N \exp(-T_j - 1 + \lambda) \right]$$

The methods of bisection and Newton's can be used to solve for λ .