

Exercise P3

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1 P3.1

Problem 1 Prove the following Cauchy-Schwarz inequality $|\langle v, w \rangle| \leq \|v\| \|w\|$

1.1 Solution

$$\begin{aligned}\cos \theta &= \frac{\langle v, w \rangle}{\|v\| \|w\|} \\ \implies |\cos \theta| &= \frac{|\langle v, w \rangle|}{\|v\| \|w\|} \\ \implies \frac{|\langle v, w \rangle|}{\|v\| \|w\|} &\leq 1\end{aligned}$$

Hence, $|\langle v, w \rangle| \leq \|v\| \|w\|$

2 P3.2

Problem 2 Prove the Triangle inequality $\|v\| - \|w\| \leq \|v + w\| \leq \|v\| + \|w\|$

2.1 Solution

$$\begin{aligned}(\|v\| - \|w\|)^2 &= \langle v, v \rangle + \langle w, w \rangle - 2\|v\| \|w\| \leq \langle v, v \rangle + \langle w, w \rangle + 2\langle v, w \rangle \\ &= \langle v, v + w \rangle + \langle w + v, w \rangle = \langle v + w, v + w \rangle = \|v + w\|^2\end{aligned}$$

Hence $\|v\| - \|w\| \leq \|v + w\|$

Similarly:

$$\begin{aligned}(\|v\| + \|w\|)^2 &= \langle v, v \rangle + \langle w, w \rangle + 2\|v\| \|w\| \geq \langle v, v \rangle + \langle w, w \rangle + 2\langle v, w \rangle \\ &= \langle v, v + w \rangle + \langle w + v, w \rangle = \langle v + w, v + w \rangle = \|v + w\|^2\end{aligned}$$

Hence $\|v\| + \|w\| \geq \|v + w\|$

3 P3.3

Problem 3 Prove the Parallelogram law $\|v+w\|^2 + \|v-w\|^2 = 2(\|v\|^2 + \|w\|^2)$

3.1 Solution

$$\|v\|^2 + \|w\|^2 + 2\langle v, w \rangle = \langle v, v \rangle + \langle v, w \rangle + \langle w, w \rangle + \langle w, v \rangle = \langle v+w, v+w \rangle = \|v+w\|^2$$

Similarly:

$$\|v\|^2 + \|w\|^2 - 2\langle v, w \rangle = \langle v, v \rangle - \langle v, w \rangle + \langle w, w \rangle - \langle w, v \rangle = \langle v-w, v-w \rangle = \|v-w\|^2$$

Adding up 2 equations together:

$$\|v+w\|^2 + \|v-w\|^2 = 2(\|v\|^2 + \|w\|^2)$$

4 P3.4

Problem 4 Prove the Polarization identity: $\langle v, w \rangle = \frac{1}{2}(\|v+w\|^2 - \|v\|^2 - \|w\|^2)$

4.1 Solution

It is proven that:

$$\|v\|^2 + \|w\|^2 + 2\langle v, w \rangle = \langle v, v \rangle + \langle v, w \rangle + \langle w, w \rangle + \langle w, v \rangle = \langle v+w, v+w \rangle = \|v+w\|^2$$

Hence

$$\begin{aligned} 2\langle v, w \rangle &= \|v+w\|^2 - \|v\|^2 - \|w\|^2 \\ \implies \langle v, w \rangle &= \frac{1}{2}(\|v+w\|^2 - \|v\|^2 - \|w\|^2) \end{aligned}$$

5 P3.5

Problem 5 Find the distance from a point $\mathbf{w} = (w_x, w_y, w_z)^\top$ to the plane H_n normal to $\mathbf{n} = (a, b, c)^\top$ and translated from the origin by vector $\mathbf{p} = (x_0, y_0, z_0)^\top$. Show that it is the smallest distance to any point in H_n

5.1 Solution

Given $H_n : \forall v \in V : \langle v - p, n \rangle = 0$

Denote w_H an orthogonal projection of w on H

Hence

$$\begin{aligned} w - w_H &= kn \\ \implies w_H &= w - kn \end{aligned}$$

Also $w_H \in H$

$$\implies \langle w_H - p, n \rangle = 0$$

$$\implies \langle w - kn - p, n \rangle = 0 \implies k = \frac{\langle w - p, n \rangle}{\|n\|^2}$$

Hence the distance is :

$$d = k\|n\| = \frac{\langle w - p, n \rangle}{\|n\|}$$

6 P3.6

Problem 6 Prove that $w_p = \text{proj}_{V_k}(w)$ is the vector in subspace V_k *closest* to w using 2 approaches:

6.1 Solution

Denote w_V the orthogonal projection of w on V_k .

Denote w_i a point on a hyperplane V_k

$$\implies w - w_i = (w - w_V) + (w_V - w_i)$$

Since $(w - w_V)$ and $(w_V - w_i)$ are perpendicular ($w_V - w_i \in V_k$ and $w - w_V \perp V_k$), applying the Pythagorean theorem:

$$\|w - w_i\|^2 = \|w - w_V\|^2 + \|w_V - w_i\|^2 \implies \|w - w_i\| \geq \|w - w_V\|$$

Hence, the shortest distance is the distance between a vector w and its projection in subspace V_k

7 P3.7

Problem 7 Least squares solution of $A\mathbf{x} = \mathbf{b}$ is $\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{b} - A\mathbf{x}\|$. By column view of matrix multiplication, $A\hat{\mathbf{x}}$ is the orthogonal projection of \mathbf{b} onto the column space $\text{Col}(A)$ of matrix A . Thus we must have $(\mathbf{b} - A\hat{\mathbf{x}}) \perp \text{Col}(A)$. Write down matrix form for this and solve for $\hat{\mathbf{x}}$, given that A is full rank. Show that the orthogonal projection operator of \mathbf{b} onto $\text{Col}(A)$ is: $P_{\text{Col}(A)} = A(A^T A)^{-1} A^T$

$$(\mathbf{b} - A\hat{\mathbf{x}}) \perp \text{Col}(A)$$

$$\iff A^T(\mathbf{b} - A\hat{\mathbf{x}}) = 0$$

$$\iff A^T \mathbf{b} = A^T A \hat{\mathbf{x}} \quad (1)$$

Since $A^T A$ is square and full rank ($\text{rank}(A^T A) = \text{rank}(A)$), it is invertible

Hence (1)

$$\iff \hat{\mathbf{x}} = (A^T A)^{-1} A^T \mathbf{b}$$

$$\implies A(A^T A)^{-1} A^T \mathbf{b} = A\hat{\mathbf{x}} \quad (2)$$

From (2) we can see that \mathbf{b} is transformed into the orthogonal projection of \mathbf{b} in hyperplane $\text{Col}(A)$. Hence, the matrix representation of orthogonal projection of \mathbf{b} onto $\text{Col}(A)$ is $P_{\text{Col}(A)} = A(A^T A)^{-1} A^T$

8 P3.8

Problem 8 Show that the generalized dot product $\langle \mathbf{x}, \mathbf{y} \rangle_M = \mathbf{x}^T M \mathbf{y}$ with $M \in R^{n \times n}$ a symmetric positive definite matrix satisfies all 3 requirements of a proper inner product.

8.1 Solution

We prove that the dot product satisfies the following 3 requirements:

-Symmetry:

$$\langle y, x \rangle = y^T M x = (x^T M^T y)^T = x^T M y$$

(because M is symmetric)

-Linearity:

$$\begin{aligned} & \langle a\mathbf{x} + b\mathbf{y}, c\mathbf{z} + d\mathbf{t} \rangle \\ &= (a\mathbf{x} + b\mathbf{y})^T M (c\mathbf{z} + d\mathbf{t}) \\ &= a\mathbf{x}^T M c\mathbf{z} + a\mathbf{x}^T M d\mathbf{t} + b\mathbf{y}^T M c\mathbf{z} + b\mathbf{y}^T M d\mathbf{t} \end{aligned}$$

-Positive definiteness:

$$\begin{aligned} &= ac\langle \mathbf{x}, \mathbf{z} \rangle + ad\langle \mathbf{x}, \mathbf{t} \rangle + bc\langle \mathbf{y}, \mathbf{z} \rangle + bd\langle \mathbf{y}, \mathbf{t} \rangle \\ &\langle x, x \rangle = x^T M x > 0 \end{aligned}$$

(since M is positive definite)

Hence, the inner product $\langle x, y \rangle = x^T M y$ is a proper inner product.

9 P3.9

Problem 9 Prove that the null space and the row space of a matrix are orthogonal, i.e. every vector in null space is orthogonal to every vector in row space (zero dot product)

9.1 Solution

Given a vector $x \in N(A)$, where $\text{rank}(A) = r$, we have:

$$Ax = \vec{0}$$

Applying elementary row operation on both side to reduce A to row-echelon form

$$\begin{aligned} & \implies EAx = \vec{0} \\ \iff & \begin{bmatrix} \langle \mathbf{e}_1^T, x \rangle \\ \langle \mathbf{e}_2^T, x \rangle \\ \vdots \\ \langle \mathbf{e}_n^T, x \rangle \end{bmatrix} = \vec{0} \end{aligned}$$

As it can be seen here , x must be perpendicular to every row in EA. However, after reducing A to row echelon form, we can ensure that first r rows form a basis that span $Row(A)$, hence, x must be orthogonal to $Row(A)$. Therefore the null space of A and the row space of A are orthogonal.

10 P3.10

Problem 10 *What is the distance from a vector to a line? Recall from lecture 1, a line through v in direction of u : $L_1 = \{w \in V : w = v + tu, \forall t \in R, u, v \in V\}$*

10.1 Solution

Denote w_l an orthogonal projection of w on L_1 . Hence $w_l = v + t_l u$. We also have that:

$$\begin{aligned}\langle w - w_l, u \rangle &= 0 \\ \iff w - v - t_l u, u \langle &= 0 \\ \iff t_l &= \frac{\langle w - v, u \rangle}{\|u\|^2}\end{aligned}$$

The distance from w to L_1 is :

$$\begin{aligned}d = \|w - w_l\| &= \|w - v - t_l u\| = \|w\|^2 + \|v\|^2 + t_l^2 \|u\|^2 - 2t_l \langle w - v, u \rangle = \|w\|^2 + \|v\|^2 - t_l^2 \|u\|^2 \\ &= \|w\|^2 + \|v\|^2 - \frac{\langle w - v, u \rangle^2}{\|u\|^2}\end{aligned}$$