

Homework Week #4

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AI Math Foundations: Abstract Vector Spaces

CENTER OF TALENT IN AI

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Section P

P3.1

Cauchy-Schwarz inequality: $|\langle v, w \rangle| \leq \|v\| \|w\|$

Beside the solution in Terence Tao's note, we can prove it intuitively as follows. We have the following:

$$\begin{aligned} |\langle v, w \rangle| &\leq \|v\| \|w\| \\ \Leftrightarrow (\langle v, w \rangle)^2 &\leq \|v\|^2 \|w\|^2 \\ \Leftrightarrow (\|v\| \|w\| \cos(v, w))^2 &\leq \|v\|^2 \|w\|^2 \\ \Leftrightarrow \|v\|^2 \|w\|^2 \cos^2(v, w) &\leq \|v\|^2 \|w\|^2 \end{aligned}$$

As $-1 \leq \cos(v, w) \leq 1$, we have proved the above inequality.

P3.2

Triangle inequality: $\|v\| - \|w\| \leq \|v + w\| \leq \|v\| + \|w\|$

We have the following:

$$\begin{aligned} \|v\| - \|w\| &\leq \|v + w\| \leq \|v\| + \|w\| \\ \Leftrightarrow \sqrt{\langle v, v \rangle} - \sqrt{\langle w, w \rangle} &\leq \sqrt{\langle v + w, v + w \rangle} \leq \sqrt{\langle v, v \rangle} + \sqrt{\langle w, w \rangle} \\ \Leftrightarrow \langle v, v \rangle - 2\sqrt{\langle v, v \rangle \langle w, w \rangle} + \sqrt{\langle w, w \rangle} &\leq \langle v, v + w \rangle + \langle w, v + w \rangle \leq \langle v, v \rangle + 2\sqrt{\langle v, v \rangle \langle w, w \rangle} + \sqrt{\langle w, w \rangle} \end{aligned}$$

$$\begin{aligned}
&\Leftrightarrow \langle v, v \rangle - 2\sqrt{\langle v, v \rangle \langle w, w \rangle} + \langle w, w \rangle \leq \langle v, v \rangle + \langle v, w \rangle + \langle w, v \rangle + \langle w, w \rangle \leq \langle v, v \rangle + 2\sqrt{\langle v, v \rangle \langle w, w \rangle} + \langle w, w \rangle \\
&\Leftrightarrow -2\sqrt{\langle v, v \rangle \langle w, w \rangle} \leq \langle v, w \rangle + \langle w, v \rangle \leq 2\sqrt{\langle v, v \rangle \langle w, w \rangle}
\end{aligned}$$

According to Cauchy-Schwarz inequality, we have:

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

Therefore, we can the above inequality is true, and thus the Triangle Inequality.

P3.3

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

We have the left-hand side of the equation:

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

which is equal to the right-hand side. We thus prove the Parallelogram law.

P3.4

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

We have the right-hand side of the equation:

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

which is equal to the left-hand side. We thus prove the Polarization identity.

P3.5

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 .

The equation of the plane H_n is:

$$\begin{aligned} H_n &= a(x - x_0) \\ &= a(x - x_0) + b(y - y_0) + c(z - z_0) \\ &= ax + by + cz - (ax_0 + by_0 + cz_0) \end{aligned}$$

Distance from the point w to the plane H_n is:

$$D(w, H_n) = \frac{aw_x + bw_y + cw_z - (ax_0 + by_0 + cz_0)}{\sqrt{a^2 + b^2 + c^2}}$$

Assume for contradiction that there exists a point $w_{p1} \in H_n$ beside w_p (the orthogonal projection of w on H_n) whose length $ww_{p1} < ww_p$. According to the Pythagorean theorem, we have:

$$\begin{aligned} ww_{p1}^2 &= ww_p^2 + w_{p1}w_p^2 \\ &\Rightarrow ww_{p1} > ww_p \end{aligned}$$

which contradicts the previous statement. Thus, ww_p is the smallest distance to any point in H_n .

P3.6

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

1. **expand** $\|u - v\|^2 = \langle u - v, u - v \rangle$.
2. **using Pythagorean theorem**

In order to prove the above, we have to prove, for any $w_{p1} \in V$, $\|w - w_{p1}\| > \|w - w_p\|$.

1. expand $\|u - v\|^2 = \langle u - v, u - v \rangle$.

2. using Pythagorean theorem

Let $a = w - w_p$, $b = w_p - w_{p1} \Rightarrow b + a = w - w_{p1}$. Since $a \perp b \Leftrightarrow \langle a, b \rangle = \langle b, a \rangle = 0$, we have the following:

$$\begin{aligned} \|w - w_{p1}\|^2 &= \|b + a\|^2 = \langle b + a, b + a \rangle \\ &= \langle b, b \rangle + \langle b, a \rangle + \langle a, b \rangle + \langle a, a \rangle \\ &= \|b\|^2 + 0 + 0 + \|a\|^2 > \|a\|^2 = \|w - w_p\|^2 \\ &\Rightarrow \|w - w_{p1}\| > \|w - w_p\| \end{aligned}$$

We have thus proved the above using Pythagorean theorem.

P3.7

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: $P_{\text{Col}(A)} = A(A^\top A)^{-1}A^\top$.

Assume that $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$ are the columns of A , we have $(\mathbf{b} - A\hat{\mathbf{x}}) \perp \text{Col}(A)$ in matrix form is:

$$[\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} - [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n] \begin{bmatrix} \hat{x}_1 \\ \hat{x}_2 \\ \vdots \\ \hat{x}_n \end{bmatrix}$$

We have that $\mathbf{b} = \mathbf{b}_{\text{Col}(A)} + \mathbf{b}_{\text{Col}(A)^\perp}$, and $\mathbf{b}_{\text{Col}(A)} = A\hat{\mathbf{x}}$, so $\mathbf{b} - \mathbf{b}_{\text{Col}(A)} = \mathbf{b} - A\hat{\mathbf{x}}$, which also equals to zero, because $\mathbf{b} - \mathbf{b}_{\text{Col}(A)} = \mathbf{b}_{\text{Col}(A)^\perp} \in \text{Col}(A)^\perp = N(\text{Col}(A))$. We then have:

$$\begin{aligned} 0 &= A^\top(\mathbf{b} - A\hat{\mathbf{x}}) = A^\top \mathbf{b} - A^\top A\hat{\mathbf{x}} \\ &\Leftrightarrow A^\top \mathbf{b} = A^\top A\hat{\mathbf{x}} \\ &\Leftrightarrow \hat{\mathbf{x}} = (A^\top A)^{-1}A^\top \mathbf{b} \end{aligned}$$

P3.8

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

Let $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$, $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$ and $M = \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \vdots \\ \mathbf{m}_n \end{bmatrix}$ with \mathbf{m}_i , $i = 1, 2, \dots, n$, having n

elements. For any \mathbf{x}, \mathbf{x}' in the same inner product space, $c \in R$, we have the following 3 requirements of an inner product:

1. $\langle \mathbf{x} + \mathbf{x}', \mathbf{y} \rangle = \langle \mathbf{x}, \mathbf{y} \rangle + \langle \mathbf{x}', \mathbf{y} \rangle$ and $\langle c\mathbf{x}, \mathbf{y} \rangle = c\langle \mathbf{x}, \mathbf{y} \rangle$

We have the following:

$$\begin{aligned} \langle \mathbf{x} + \mathbf{x}', \mathbf{y} \rangle &= \begin{bmatrix} x_1 + x'_1 & x_2 + x'_2 & \dots & x_n + x'_n \end{bmatrix} M \mathbf{y} \\ &= \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} M \mathbf{y} + \begin{bmatrix} x'_1 \\ x'_2 \\ \vdots \\ x'_n \end{bmatrix} M \mathbf{y} \\ &= \langle \mathbf{x}, \mathbf{y} \rangle + \langle \mathbf{x}', \mathbf{y} \rangle \end{aligned}$$

and

$$\begin{aligned} \langle c\mathbf{x}, \mathbf{y} \rangle &= \begin{bmatrix} cx_1 \\ cx_2 \\ \vdots \\ cx_n \end{bmatrix} M \mathbf{y} \\ &= c \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} M \mathbf{y} \\ &= c\langle \mathbf{x}, \mathbf{y} \rangle \end{aligned}$$

2. $\langle \mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{y}, \mathbf{x} \rangle$

$$\begin{aligned}
\langle \mathbf{x}, \mathbf{y} \rangle &= \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \vdots \\ \mathbf{m}_n \end{bmatrix} \mathbf{y} \\
&= x_1 \mathbf{m}_1 \mathbf{y} + x_2 \mathbf{m}_2 \mathbf{y} + \dots + x_n \mathbf{m}_n \mathbf{y} \\
&= y_1 \mathbf{m}_1 \mathbf{x} + y_2 \mathbf{m}_2 \mathbf{x} + \dots + y_n \mathbf{m}_n \mathbf{x} \\
&= \begin{bmatrix} y_1 & y_2 & \dots & y_n \end{bmatrix} \begin{bmatrix} \mathbf{m}_1 \\ \mathbf{m}_2 \\ \vdots \\ \mathbf{m}_n \end{bmatrix} \mathbf{x} \\
&= \langle \mathbf{y}, \mathbf{x} \rangle
\end{aligned}$$

3. $\langle \mathbf{x}, \mathbf{x} \rangle > 0$

Since M is a positive definite matrix, it is obvious that:

$$\langle \mathbf{x}, \mathbf{x} \rangle = \mathbf{x}^T M \mathbf{x} > 0$$

With the 3 requirements proved, we have the above.

P3.9

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).

Assume we have a matrix $A = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$, its null space $N(A)$ which contains

vectors x satisfying $Ax = 0$, and its row space $R = \text{span}(v_1, \dots, v_n)$. We have $Ax = 0 \Leftrightarrow v_1 x = 0, \dots, v_n x = 0$. Therefore, for $r \in R$, we have the following:

$$rx = \text{span}(v_1, \dots, v_n)x = a_1 v_1 x + \dots + a_n v_n x = 0$$

From here we have proven that $rx = 0 \forall r \in R$, which means every r is orthogonal with x , which proves what we have to prove.

Assume we have a matrix $A = \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$, its null space $N(A)$ which contains vectors x satisfying $Ax = 0$, and its row space $R = \text{span}(v_1, \dots, v_n)$. We have $Ax = 0 \Leftrightarrow v_1x = 0, \dots, v_nx = 0$. Therefore, for $r \in R$, we have the following:

$$rx = \text{span}(v_1, \dots, v_n)x = a_1v_1x + \dots + a_nv_nx = 0$$

From here we have proven that $rx = 0$, $\forall r \in R$, which means every r is orthogonal with x , which proves what we have to prove.

P3.10

Section E

E3.1

Let V be an n -dimensional inner product space with pairwise orthogonal subspaces

$$W_1, \dots, W_m,$$

where $\sum_{i=1}^m \dim(W_i) = n$. **Prove that every vector $v \in V$ can be represented uniquely as**

$$v = w_1 + \dots + w_m,$$

where $w_i \in W_i$ for $i = 1, \dots, m$, i.e.,

$$V = W_1 \oplus \dots \oplus W_m.$$

Assume that V has basis vectors $\{v_1, v_2, \dots, v_n\}$, and W_1 has bases $\{v_1, v_2, \dots, v_i\}$, W_2 has bases $\{v_{i+1}, v_{i+2}, \dots, v_j\}$, \dots , W_m has bases $\{v_{k+1}, v_{k+2}, \dots, v_n\}$. We

have any $v \in V$, $w_1 \in W_1$, $w_2 \in W_2, \dots, w_m \in W_m$, for any $a_1, a_2, \dots, a_i, a_{i+1}, a_{i+2}, \dots, a_j, \dots, a_{k+1}, a_{k+2}, \dots, a_n$ can be expressed as follow:

$$\begin{aligned}
v &= a_1 v_1 + a_2 v_2 + \dots + a_n v_n \\
w_1 &= a_1 v_1 + a_2 v_2 + \dots + a_i v_i \\
w_2 &= a_{i+1} v_{i+1} + a_{i+2} v_{i+2} + \dots + a_j v_j \\
&\vdots \\
w_m &= a_{k+1} v_{k+1} + a_{k+2} v_{k+2} + \dots + a_n v_n
\end{aligned}$$

We then have:

$$\begin{aligned}
w_1 + w_2 + \dots + w_m &= a_1 v_1 + a_2 v_2 + \dots + a_i v_i \\
&\quad + a_{i+1} v_{i+1} + a_{i+2} v_{i+2} + \dots + a_j v_j \\
&\quad \dots \\
&\quad + a_{k+1} v_{k+1} + a_{k+2} v_{k+2} + \dots + a_n v_n \\
&= v
\end{aligned}$$

since $\sum_{i=1}^m \dim(W_i) = n$. Therefore $v = w_1 + w_2 + \dots + w_m$ uniquely, for an unique set of a_1, a_2, \dots, a_n .

E3.2

Prove again for 2D geometry that $\cos \theta = \frac{\mathbf{a}^\top \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$ using only cosine (and sine) laws.

$$\begin{aligned}
\cos(\theta) &= \cos(\beta - \alpha) = \cos(\beta)\cos(\alpha) + \sin(\beta)\sin(\alpha) \\
&= \frac{b_1}{\|\mathbf{b}\|} \frac{a_1}{\|\mathbf{a}\|} + \frac{b_2}{\|\mathbf{b}\|} \frac{a_2}{\|\mathbf{a}\|} \\
&= \frac{b_1 a_1}{\|\mathbf{b}\| \|\mathbf{a}\|} + \frac{b_2 a_2}{\|\mathbf{b}\| \|\mathbf{a}\|} \\
&= \frac{b_1 a_1 + b_2 a_2}{\|\mathbf{b}\| \|\mathbf{a}\|} \\
&= \frac{\begin{bmatrix} a_1 & a_2 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}}{\|\mathbf{b}\| \|\mathbf{a}\|} \\
&= \frac{\mathbf{a}^\top \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}
\end{aligned}$$

E3.3

Given an orthonormal basis $\mathcal{U} = (u_1, \dots, u_n)$ of \mathbb{R}^n . Let U be the matrix whose distinct columns are the basis vectors in \mathcal{U} . Prove again U is a transformation that does not change distance, angle, size of the objects being transformed: geometrically it is a rotation or reflection!

Let A be the object being transformed, and $A = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n]$. Since U is a matrix consisting of orthonormal vector $\Leftrightarrow U^\top U = U U^\top = I_n$, then we have the following:

$$\langle U\mathbf{a}_i, U\mathbf{a}_j \rangle = U\langle \mathbf{a}_i, U\mathbf{a}_j \rangle = \langle \mathbf{a}_i; U^\top U\mathbf{a}_j \rangle = \langle \mathbf{a}_i, \mathbf{a}_j \rangle$$

for any $i, j = 1, 2, \dots, n$. We can conclude that the distance does not change after transforming.

We can prove that the angle and the size does not change by the following:

$$\begin{aligned} \|U\mathbf{a}_i\|^2 &= \langle U\mathbf{a}_i, U\mathbf{a}_i \rangle = \langle \mathbf{a}_i, \mathbf{a}_i \rangle = \|\mathbf{a}_i\|^2 \\ \cos(U\mathbf{a}_i, U\mathbf{a}_j) &= \frac{\langle U\mathbf{a}_i, U\mathbf{a}_j \rangle}{\|U\mathbf{a}_i\| \|U\mathbf{a}_j\|} = \frac{\langle \mathbf{a}_i, \mathbf{a}_j \rangle}{\|\mathbf{a}_i\| \|\mathbf{a}_j\|} = \cos(\mathbf{a}_i, \mathbf{a}_j) \end{aligned}$$