Homework Week #2

Ho Chi Vuong AI Math Foundations: Abstract Vector Spaces CENTER OF TALENT IN AI

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Section P

P2.1

The last (seems redundant) line allows us to combine any number of affine transformations (e.g., a series of rotation, translation, then rotation) into one by multiplying the respective matrices. Verify this for yourself!

 \mathbf{tl} ; \mathbf{dr} : The last line in the augmented matrix $0, \dots, 1$ is used to aid in the multiplication of matrices. Without it, we have undefined results in our matrix multiplication

Let's say we have a series of two affine transformation, wrapped in two augmented matrice

$$T_{t_1} = \begin{bmatrix} 1, 0, 0, p_1 \\ 0, 1, 0, p_2 \\ 0, 0, 1, p_2 \\ 0, 0, 0, 1 \end{bmatrix}, T_{t_2} = \begin{bmatrix} 1, 0, 0, p_3 \\ 0, 1, 0, p_4 \\ 0, 0, 1, p_5 \\ 0, 0, 0, 1 \end{bmatrix}$$

When combining in series of affine transformations, we have the following matrix multiplication:

$$T_{t_1}T_{t_2} = \begin{bmatrix} 1 & 0 & 0 & p_1 \\ 0 & 1 & 0 & p_2 \\ 0 & 0 & 1 & p_3 \\ 0 & 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 & 0 & p_3 \\ 0 & 1 & 0 & p_4 \\ 0 & 0 & 1 & p_5 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & p_1 + p_3 \\ 0 & 1 & 0 & p_2 + p_4 \\ 0 & 0 & 1 & p_3 + p_5 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

allowing us combine any number of affine transformation. If the line $0, \ldots, 1$ is not there, we have the following matrix multiplication:

$$T_{t_1}T_{t_2} = \begin{bmatrix} 1 & 0 & 0 & p_1 \\ 0 & 1 & 0 & p_2 \\ 0 & 0 & 1 & p_3 \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 & 0 & p_3 \\ 0 & 1 & 0 & p_4 \\ 0 & 0 & 1 & p_5 \end{bmatrix} = undefined$$

P2.2

P2.3

Prove that Matrix multiplication $T: \mathbb{R}^{n \times p} \to \mathbb{R}^{m \times p}$ with $TC = D, T = B_{m \times n}$ is a linear map. Find matrix representation of this linear transformation in the standard bases.

To prove $T: \mathbb{R}^{n \times p} \to \mathbb{R}^{m \times p}$ with TC = D, $T = B_{m \times n}$ is a linear transformation, we have to prove:

1. For
$$x, x' \in \mathbb{R}^{n \times p}$$
, $T(x + x') = Tx + Tx'$

2. For
$$x \in \mathbb{R}^{n \times p}$$
 and $c \in \mathbb{R}$, $T(cx) = cTx$

1. We have

$$T(x+x') = B_{m \times n}(x+x') = B_{m \times n} \cdot \begin{bmatrix} x_{11} + x'_{11} & \dots & x_{n1} + x'_{n1} \\ \dots & \ddots & \dots \\ x_{1p} + x'_{1p} & \dots & x_{np} + x'_{np} \end{bmatrix}$$

and

$$Tx + Tx' = B_{m \times n} \cdot \begin{bmatrix} x_{11} & \dots & x_{n1} \\ \dots & \ddots & \dots \\ x_{1p} & \dots & x_{np} \end{bmatrix} + B_{m \times n} \cdot \begin{bmatrix} x'_{11} & \dots & x'_{n1} \\ \dots & \ddots & \dots \\ x'_{1p} & \dots & x'_{np} \end{bmatrix}$$

making T(x + x') = Tx + Tx' true.

2. We have

$$T(cx) = B_{m \times n} \cdot \begin{bmatrix} cx_{11} & \dots & cx_{n1} \\ \dots & \ddots & \dots \\ cx_{1p} & \dots & cx_{np} \end{bmatrix}$$

and

$$cTx = cB_{m \times n} \cdot \begin{bmatrix} x_{11} & \dots & x_{n1} \\ \dots & \ddots & \dots \\ x_{1p} & \dots & x_{np} \end{bmatrix} = B_{m \times n} \cdot \begin{bmatrix} cx_{11} & \dots & cx_{n1} \\ \dots & \ddots & \dots \\ cx_{1p} & \dots & cx_{np} \end{bmatrix}$$

making $c \in R$, T(cx) = cTx true.

With 1 and 2 we can prove the above.

P2.4

Prove that for linear map f,the $\ker(f)$ is a subspace of \mathbb{R}^5 with $f: \mathbb{R}^5 \mapsto \mathbb{R}^5$. If $f(x_1,...,x_5) = (x_1,....,x_4,0)$ then is f a linear function? Find the matrix of f, $\ker(f)$ and $\dim(\ker)$. Note that f is a projection.

f is of course a linear function because it is itself a map between two vector spaces that preserves addition and scalar multiplication. We have the following:

- 1. For $x, x' \in \mathbb{R}^5$, $T(x+x') = T((x_1+x'_1, \dots, x_5+x'_5) = (x_1+x'_1, \dots, 0) = (x_1, \dots, 0) + (x'_1, \dots, 0) = Tx + Tx'$
- 2. For $x \in \mathbb{R}^5$ and $c \in \mathbb{R}$, $T(cx) = T((cx_1, ..., cx_5)) = (cx_1, ..., 0) = c(x_1, ..., 0) = cTx$

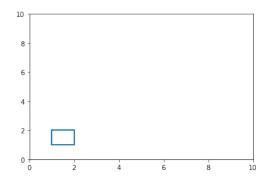
The matrix of f is $\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$

 $ker(f) = \{(0, ..., x_5) \in \mathbb{R}^5 : x_5 \in \mathbb{R}\}, \text{ and as the basis of } ker(f) \text{ is } (0, 0, 0, 0, 1), dim(ker) = 1.$

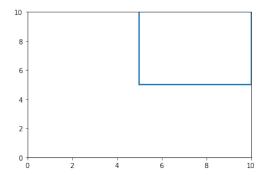
P2.5

Verify for yourself the effect of coordinate scaling Sx with scaling or diagonal matrix $S = \text{diag}(\lambda_1, \dots, \lambda_n) \in \mathbb{R}^{n \times n}$.

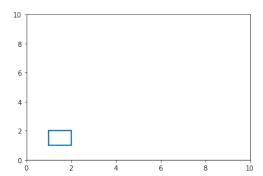
I have visualized it down here for the sake of comprehension. Sx with $S=\mathsf{diag}(5,5)$ Before:



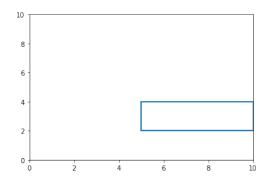
After:



 $Sx \text{ with } S = \mathsf{diag}(5,2)$



After:



P2.8

In PCA: input image $X \stackrel{T}{\rightleftharpoons}$ Coordinate vector $\bar{z} = (1, w_1, \dots, w_n)^{\top}$ (no reduction). Then with dimensionality reduction: $\bar{z} \stackrel{A}{\to} z = (1, w_1, \dots, w_k)^{\top}$, i.e., keeping only first k+1 coordinates. Find matrix A of the coordinate transformation.

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & 0 & \dots & 0 \\ 0 & 0 & 0 & 1 & \dots & 0 \end{bmatrix}$$

or in other words, A is a $(k+1) \times n$ matrix with $a_{ii} = 1, i = 1, 2, \dots, k+1$, and the rest equals 0

P2.9

Prove that for any A: $\operatorname{rank}(A^{\top}A) = \operatorname{rank}(AA^{\top}) = \operatorname{rank}(A)$. Let's first prove $\operatorname{rank}(AA^{\top}) = \operatorname{rank}(A)$.

For $x \in N(A)$, we have:

$$Ax = 0$$

$$\Rightarrow A^{\top}Ax = 0$$

$$\Rightarrow x \in N(A^{\top}A)$$

therefore,

$$N(A) \subseteq N(A^{\top}A)$$

Again, for $x \in N(A^{\top}A)$, we have:

$$A^{\top}Ax = 0$$

$$\Rightarrow x^{\top}A^{\top}Ax = 0$$

$$\Rightarrow (Ax)^{\top}(Ax) = 0$$

$$\Rightarrow Ax = 0$$

therefore,

$$N(A^{\top}A) \subseteq N(A)$$

Thus,

$$\begin{split} N(A^\top A) &= N(A) \\ \Rightarrow \mathsf{nullity}(A^\top A) &= \mathsf{nullity}(A) \\ \Rightarrow \mathsf{rank}(A^\top A) &= \mathsf{rank}(A) \end{split}$$

Then we prove $\operatorname{\mathsf{rank}}(A^{\top}A) = \operatorname{\mathsf{rank}}(AA^{\top}).$ If n < m, we have:

$$\begin{split} \operatorname{rank}(AA^\top) &= \operatorname{rank} \left(\begin{bmatrix} AA^\top & \mathbf{0}_{n \times (m-n)} \\ \mathbf{0}_{(m-n) \times n} & \mathbf{0}_{(m-n) \times (m-n)} \end{bmatrix} \right) \\ &= \operatorname{rank} \left(\begin{bmatrix} A \\ \mathbf{0}_{(m-n) \times m} \end{bmatrix} \begin{bmatrix} A \\ \mathbf{0}_{(m-n) \times m} \end{bmatrix}^\top \right) \\ &= \operatorname{rank} \left(\begin{bmatrix} A \\ \mathbf{0}_{(m-n) \times m} \end{bmatrix} \right) \\ &= \operatorname{rank}(A) \end{split}$$

Otherwise, if m < n, we have:

$$\begin{aligned} \operatorname{rank}(AA^t) &= \operatorname{rank}\left(\begin{bmatrix} A & \mathbf{0}_{n\times(n-m)}\end{bmatrix}\begin{bmatrix} A & \mathbf{0}_{n\times(n-m)}\end{bmatrix}^\top\right) \\ &= \operatorname{rank}\left(\begin{bmatrix} A & \mathbf{0}_{n\times(n-m)}\end{bmatrix}\right) \\ &= \operatorname{rank}(A) \end{aligned}$$

P2.11

Show that for square & full rank matrices:

$$(ABC)^{-1} = C^{-1}B^{-1}A^{-1}$$

 $(A^{-1})^T = (A^T)^{-1} =: A^{-\top}$

To prove $(ABC)^{-1} = C^{-1}B^{-1}A^{-1}$, we have the following:

$$(ABC)C^{-1}B^{-1}A^{-1} = AB(CC^{-1})B^{-1}A^{-1} = ABB^{-1}A^{-1} = AA^{-1} = I$$

From this we can conclude that the inverse of ABC is $C^{-1}B^{-1}A^{-1}$, which also means $(ABC)^{-1} = C^{-1}B^{-1}A^{-1}$.

To prove $(A^{-1})^T = (A^T)^{-1} =: A^{-\top}$, we have the following:

$$A^{\top} (A^{-1})^{\top} = (A^{-1}A)^{\top} = I = A^{\top} (A^{\top})^{-1}$$
$$\Rightarrow (A^{-1})^{\top} = (A^{\top})^{-1}$$

P2.11

Prove again for yourself $rank(A_{m \times n}) = rank(A^{\top}) \le min(m, n)$

Since $\operatorname{rank}(A_{m\times n}) = \operatorname{the}$ number of linearly independent rows/columns, which is also $\leq \min(m,n)$, transposing the matrix which results in $A_{n\times m}$ will change nothing to this definition. That is, $\operatorname{rank}(A^{\top}) = \operatorname{rank}(A_{m\times n}) = \operatorname{the}$ number of linearly independent rows/columns, which is also $\leq \min(m,n)$, is also equals to $\operatorname{rank}(A_{m\times n})$, since the linear dependence property does not change when transposing matrix.

Section E

E2.1

Let $\beta = \{v_1, \dots, v_n\}$ be a basis of a vector space V, and $T: V \to W$ be a linear transformation from V to W. Is the following proposition true? Why? If the formula is wrong, correct it.

$$T(\sum_{i=1}^{n} a_i v_i) = T(v) \Leftrightarrow \sum_{i=1}^{n} a_i v_i = v$$

The proposition is correct. With T as a linear function, we have the following:

$$T(\sum_{i=1}^{n} a_i v_i) = \sum_{i=1}^{n} a_i T v_i = v = \sum_{i=1}^{n} a_i w_i = w = T(v)$$

with

$$\sum_{i=1}^{n} a_i v_i = v$$

E2.2

Let V be a finite-dimensional vector space and $\alpha = \{v_1, \ldots, v_n\}$ be a basis of V. Let W be another vector space with some vectors $\beta = \{w_1, \ldots, w_n\}$. Prove that there exists exactly one linear transformation $T: V \to W$ such that $T(v_j) = w_j, \forall j$.

We have to prove two things, that

- 1. there exists such linear transformation T, and
- 2. there is at most one such transformation.
- 1. Assume for contradiction that we have $T: V \to W, U: V \to W, T(v_j) = w_j$ and $U(v_j) = w_j$ for j = 1, ..., n. We have any $v \in V$ with the following:

$$v = a_1 v_1 + \ldots + a_n v_n$$

Since T is linear, we have:

$$Tv = a_1 T v_1 + \ldots + a_n T v_n$$

equals to

$$Tv = a_1w_1 + \ldots + a_nw_n$$

The same applies to Uv, as in the following:

$$Uv = a_1w_1 + \ldots + a_nw_n$$

As above, we have:

$$Tv = Uv \Leftrightarrow T = U$$

contradicting the original assumptions, proving (1) 2. We have the above in (1):

$$Tv = a_1w_1 + \ldots + a_nw_n$$

and

$$v_j = 0v_1 + \ldots + 1v_j + \ldots + 0v_n$$

giving us

$$Tv_j = 0w_1 + \ldots + 1w_j + \ldots + 0w_n = w_j$$

We also have to prove that T is linear, which is true because for any $v, v' \in V$ and $c \in \mathbb{R}$, we have the following:

$$cTv + cTv' = c(a_1w_1 + \dots + a_nw_n) + c(b_1w_1 + \dots + b_nw_n)$$

= $c(a_1 + b_1)w_1 + \dots + c(a_n + b_n)w_n = T(cv + cv')$

Thus we can prove (2). With (1),(2), we can prove the above.

E2.3

What I intuitively think of matrix multiplication is that the result of the calculation is the matrix containing the linear combination of, say AB, a row of A and column of B. We can also think of matrix multiplication as the composition of *linear functions*, as matrix can represent T in, for example, $T: V \to W$.

E2.4

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 $R = span(v_1, \ldots, v_n)$. We have $Ax = 0 \Leftrightarrow v_1x = 0, \ldots, v_nx = 0$. Therfore, for $r \in R$, we have the following:

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

From here we have proven that $rx = 0 \forall r \in R$, which means every r is ortogonal 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 $A_{n-1} = 0$

vectors x satisfying Ax = 0, and its row space $R = span(v_1, \ldots, v_n)$. We have $Ax = 0 \Leftrightarrow v_1x = 0, \dots, v_nx = 0$. Therfore, for $r \in R$, we have the following:

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

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

E2.5

How can we find the null space and the column space of a matrix ? Write a pseudocode for your algorithm.

Pseudocode for finding null space (incomplete): function ReducedEchelonForm(A):for i in size of A:multiply all elements of all A[k] (with k not equal i) with GCD(A[i][i], A[k][i]......minus all elements of all A[k] (with k not equal i) with (all elements of A[i]*GCD(A[i][i], A[k][i])......divide all elements of A[i] with A[i][i]