CSE 840: Computational Found	: Computational Foundations of Artificial Intelligence	
Linear Mapping		
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1 Linear Mapping

Definition 1 Let U, V be vector spaces over the same field \mathbb{F} . A mapping $T : U \to V$ is called a linear map if $\forall \mathbf{u}_1, \mathbf{u}_2 \in U, \lambda \in \mathbb{F}$.

$$t(\mathbf{u}_1 + \mathbf{u}_2) = t(\mathbf{u}_1) + t(\mathbf{u}_2)$$
$$t(\lambda \mathbf{u}_1) = \lambda t(\mathbf{u}_1)$$

The set of all linear mappings from $U \to V$ is denoted $\mathcal{L}(U, V)$. If U = V, then we denote $\mathcal{L}(U)$.

Definition 2 $T \in \mathcal{L}(U, V)$. Then <u>kernel</u> of T (null-space of T) is defined as

 $ker(T) := null(T) := \{ \mathbf{u} \in U | T\mathbf{u} = \mathbf{0} \}$

Proposition 3

- ker(T) is a subspace of U
- T injective iff $ker(T) = \{\mathbf{0}\}$

Definition 4 The range of T (image of T) is defined as,

 $range(T) := image(T) := \{T\mathbf{u} | \mathbf{u} \in U\}$

Proposition 5

- The range is always a subspace of V
- T is a subjective iff range(T) = V

Definition 6 Let V' be any subset of V, i.e. $V' \subset V$. The pre-image of V' is defined as

$$T^{-1}(V') = \{\mathbf{u} \in U | T\mathbf{u} \in V'\}$$

Proposition 7 If $V' \subset V$ is a subspace of V, then $T^{-1}(V')$ is a subspace of V

Theorem 8 Let V be finite-dim, W is any vector space, $T \in \mathcal{L}(V, W)$. Let $(\mathbf{u}_1, \ldots, \mathbf{u}_n)$ be a basis of $ker(T) \subset V$. Let $(\mathbf{w}_1, \ldots, \mathbf{w}_m)$ be a basis of $range(T) \subset W$. Then $\mathbf{u}_1, \ldots, \mathbf{u}_n, T^{-1}(\mathbf{w}_1), \ldots, T^{-1}(\mathbf{w}_m) \subset V$ form a basis of V. In particular, dim(V) = dim(ker(T)) + dim(range(T)).

Proof: Denote $T^{-1}(\mathbf{w}_1) = \mathbf{z}_1, ..., T^{-1}(\mathbf{w}_m) = \mathbf{z}_m$

Step 1: $V \subset span\{\mathbf{u}_1, \ldots, \mathbf{u}_n, \mathbf{z}_1, \ldots, \mathbf{z}_m\}$

Let $\mathbf{v} \in V$ consider $T\mathbf{v} \in range(T)$.

$$\implies \exists \lambda_1, \dots, \lambda_m \in \mathbb{F}, s.t.$$
$$T\mathbf{v} = \lambda_1 \mathbf{w}_1 + \lambda_2 \mathbf{w}_2 + \dots + \lambda_m \mathbf{w}_m$$
$$= \lambda_1 T(\mathbf{z}_1) + \lambda_1 T(\mathbf{z}_2) \dots + \lambda_1 T(\mathbf{z}_3)$$
$$= T(\lambda_1 \mathbf{z}_1 + \lambda_1 \mathbf{z}_2 \dots + \lambda_1 \mathbf{z}_3)$$

$$\implies T\mathbf{v} - T(\lambda_1\mathbf{z}_1 + \lambda_1\mathbf{z}_2... + \lambda_1\mathbf{z}_3) = 0$$
$$\implies T(\underbrace{\mathbf{v} - (\lambda_1\mathbf{z}_1 + \lambda_1\mathbf{z}_2... + \lambda_1\mathbf{z}_3)}_{\in ker(T)}) = 0$$

 $\begin{aligned} & Reminder: \ \mathbf{u}_1, \dots, \mathbf{u}_n \ are \ basis \ of \ ker(T) \\ & \Longrightarrow \exists \mu_1, \dots, \mu_n \in \mathbb{F}, s.t. \\ & \mathbf{v} - (\lambda_1 \mathbf{z}_1 + \lambda_1 \mathbf{z}_2 \dots + \lambda_1 \mathbf{z}_3) = \mu_1 \mathbf{u}_1 + \mu_2 \mathbf{u}_2 + \dots + \mu_n \mathbf{u}_n \\ & \Longrightarrow \mathbf{v} = \lambda_1 \mathbf{z}_1 + \lambda_1 \mathbf{z}_2 \dots + \lambda_1 \mathbf{z}_3 + \mu_1 \mathbf{u}_1 + \mu_2 \mathbf{u}_2 + \dots + \mu_n \mathbf{u}_n \end{aligned}$

Step 2: $\mathbf{u}_1 \dots \mathbf{u}_n, \mathbf{z}_1 \dots \mathbf{z}_m$ are linearly independent.

Assume that

$$\mu_1 \mathbf{u}_1 + \ldots + \mu_n \mathbf{u}_n + \lambda_1 \mathbf{z}_1 + \ldots + \lambda_m \mathbf{z}_m = \mathbf{0}$$
(1)

Now consider:

$$\lambda_{1}\mathbf{w}_{1} + \dots + \lambda_{m}\mathbf{w}_{m}$$

$$=\lambda_{1}T(\mathbf{z}_{1}) + \dots + \lambda_{m}T(\mathbf{z}_{m})$$

$$=\lambda_{1}T(\mathbf{z}_{1}) + \dots + \lambda_{m}T(\mathbf{z}_{m}) + \underbrace{\mu_{1}T(\mathbf{u}_{1}) + \dots + \mu_{n}T(\mathbf{u}_{n})}_{0}$$

$$=T(\underbrace{\lambda_{1}\mathbf{z}_{1} + \lambda_{1}\mathbf{z}_{2} \dots + \lambda_{1}\mathbf{z}_{3} + \mu_{1}\mathbf{u}_{1} + \mu_{2}\mathbf{u}_{2} + \dots + \mu_{n}\mathbf{u}_{n})}_{=0 \ by \ (1)}$$

$$=\mathbf{0}$$

$$\Rightarrow \lambda_1 \mathbf{w}_1 + \ldots + \lambda_m \mathbf{w}_m = 0.$$

$$\Rightarrow \lambda_1 = \lambda_2 = \ldots = \lambda_m = 0, \text{ since } \mathbf{w}_1, \ldots, \mathbf{w}_m \text{ are basis.}$$

$$\Rightarrow \mu_1 \mathbf{u}_1 + \ldots + \mu_n \mathbf{u}_n = 0$$

$$\Rightarrow \mu_1 = \mu_2 = \ldots = \mu_n = 0, \text{ since } \mathbf{u}_1, \ldots, \mathbf{u}_m \text{ are basis.}$$

Proposition 9 $T \in \mathcal{L}(V, V), V$ is finite-dim. Then the following statements are equivalent.

- 1. T is injective.
- 2. T is surjective.
- 3. T is bijective.

Proof: Direct consequence of theorem.

Does not hold in ∞ -dim spaces.

Additional material 10 T is said to be injective or a monomorphism if any of the following equivalent conditions are true:

- T is one-to-one as a map of sets.
- $kerT = 0_V$
- dim(kerT) = 0
- T is left-invertible, which is to say there exists a linear map S : W → V such that ST is the identity map on V.

For further readings, please refer to Wikipedia: https://en.wikipedia.org/wiki/Linear_map.

2 Matrices and Linear Mapping

Notation:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix} = (a_{ij})_{i=1,\dots,m,j=1,\dots,n}$$

Proposition 11 Consider $T \in \mathcal{L}(v, w), v, w$ finite-dim. Let $\mathbf{v}_1 \dots \mathbf{v}_n$ be a basis of $V, \mathbf{w}_1 \dots \mathbf{w}_m$ be a basis of w.

- $\mathbf{v} = \lambda_1 \mathbf{v}_1 \dots + \lambda_n \mathbf{v}_n$ $T(\mathbf{v}) = T(\lambda_1 \mathbf{v}_1 \dots + \lambda_n \mathbf{v}_n)$ $= \lambda_1 T(\mathbf{v}_1) \dots + \lambda_n T(\mathbf{v}_n)$
- Each image vector $T(\mathbf{v}_j)$ can be expressed in basis $\mathbf{w}_1 \dots \mathbf{w}_m$. There exists co-efficient $a_{1j} \dots a_{mj}$, s.t.

$$T(\mathbf{v}_j) = a_{1j}\mathbf{w}_1 + \ldots + a_{mj}\mathbf{w}_m.$$

• We can stack these coefficients in a matrix that $\begin{pmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{m1} & \cdots & a_{mj} & \cdots & a_{mn} \end{pmatrix}$

Notation: Let $T: V \to W$ be linear, let \mathcal{B} a basis of V, \mathcal{C} basis of W, We denote by $M(T, \mathcal{B}, \mathcal{C})$ the matrix corresponding to T w.r.t. bases \mathcal{B} and \mathcal{C} .

Proposition 12 Convenient properties of matrices: Let V, W be vector spaces, and consider the bases fixed. Let $S, \overline{T \in \mathcal{L}(V, W)}$.

- M(S+T) = M(S) + M(T)
- $M(\lambda S) = \lambda M(S)$

• For
$$\mathbf{v} = \lambda_1 \mathbf{v}_1 + \ldots + \lambda_n \mathbf{v}_n$$
 we have that $T(V) = M(T0) \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \end{pmatrix}$ where $(\mathbf{v}_1 \ldots \mathbf{v}_n)$ is basis of V

• $T: U \to V, S: V \to W$ linear, then $M(S \circ T) = M(S) \cdot M(T)$

Additional material 13 Matrix Row Operation

Matrix row operations are operations that can be applied to the rows of a matrix to transform it. There are three primary types of matrix row operations:

- 1. Scalar Multiplication: Multiply a row by a nonzero scalar.
- 2. Row Addition: Add a multiple of one row to another row.
- 3. Row Interchange: Swap the positions of two rows.

Example

Consider the following matrix:

$$A = \begin{bmatrix} 2 & 1 & 3 \\ 0 & 4 & -1 \\ 5 & 2 & 0 \end{bmatrix}$$

We will perform the following row operations on matrix A:

- 1. Multiply the first row by 2.
- 2. Subtract 5 times the first row from the third row.
- 3. Swap the second and third rows.

After applying these operations, we obtain the transformed matrix B:

$$B = \begin{bmatrix} 4 & 2 & 6\\ 5 & 2 & 0\\ 0 & 14 & -31 \end{bmatrix}$$

Matrix row operations are commonly used in Gaussian elimination and matrix row reduction to solve linear systems and manipulate matrices in various applications.

For further readings, please refer to Wikipedia: https://en.wikipedia.org/wiki/Matrix_(mathematics)

3 Invertible maps and Matrices

Definition 14 $T \in \mathcal{L}(V, W)$ is called invertible if there exists a linear map $S \in \mathcal{L}(W, V)$ such that

 $S \circ T = Id_V$ and $T \circ S = Id_W$.

The map S is called the inverse of T, denoted by T^{-1} .

Remark 15 Inverse maps exist and are unique.

Proposition 16 A linear map is invertible iff it is injective an subjective i.e. bijective.

Proof: " \Rightarrow ": invertible \implies injective: Suppose $T(\mathbf{u}) = T(\mathbf{v})$. Then $\mathbf{u} = T^{-1}(T(\mathbf{u})) = T^{-1}(T(\mathbf{v})) = \mathbf{v} \implies \mathbf{u} = \mathbf{v} \implies$ injective. injective \implies invertible: $\mathbf{w} \in W$. Then $\mathbf{w} = T(T^{-1}(\mathbf{w})) \implies w \in$ range of $T \implies$ subjective.

"⇐":

injective & subjective \implies invertible: Let $\mathbf{w} \in W$. There exists unique $\mathbf{v} \in V$. s.t. $T(\mathbf{u}) = \mathbf{w}$ Define the mapping: $S(\mathbf{w}) = \mathbf{v}$. Clearly have $T \circ S = Id$. Let $\mathbf{v} \in V$, Then $T((S \circ T)\mathbf{v}) = (T \circ S)(T\mathbf{v}) = Id \circ T\mathbf{v} = T\mathbf{v}$ $\implies (S \circ T)\mathbf{v} = \mathbf{v} \implies S \circ T = Id \implies S$ is inverse of T Linear mapping:

Let
$$\mathbf{w}_1, \mathbf{w}_2 \in W, \alpha \in \mathbb{F} : S(\mathbf{w}_1 + \mathbf{w}_2) = S(\mathbf{w}_1) + S(\mathbf{w}_2), S(\alpha \mathbf{w}_1) = \alpha S(\mathbf{w}_1)$$

Let $\mathbf{v}_1, \mathbf{v}_2 \in V$. s.t. $T(\mathbf{v}_i) = \mathbf{w}_i$. Then $S(\mathbf{w}_i) = \mathbf{v}_i$
 $S(\mathbf{w}_1 + \mathbf{w}_2) = S(T(\mathbf{v}_1) + T(\mathbf{v}_2))$
 $= S(T(\mathbf{v}_1 + \mathbf{v}_2))$
 $= \mathbf{v}_1 + \mathbf{v}_2$
 $= S(\mathbf{w}_1) + S(\mathbf{w}_2)$
 $S(\alpha \mathbf{w}_1) = S(\alpha T(\mathbf{v}_1))$
 $= S(T(\alpha \mathbf{v}_1))$

Additional material 17 Matrix Inversion with Gaussian Elimination

Consider a 2×2 matrix A:

$$A = \begin{bmatrix} 2 & 1 \\ 1 & 3 \end{bmatrix}$$

To find its inverse, A^{-1} , we can use Gaussian elimination. Here are the steps:

1. Form the augmented matrix $[A \mid I]$:

$$\begin{bmatrix} 2 & 1 & | & 1 & 0 \\ 1 & 3 & | & 0 & 1 \end{bmatrix}$$

2. Apply row operations to transform the left side into the identity matrix:

$$\begin{bmatrix} 1 & \frac{1}{2} & | & \frac{1}{2} & 0 \\ 0 & \frac{5}{2} & | & -\frac{1}{2} & 1 \end{bmatrix}$$

3. Divide the first row by 1 and the second row by $\frac{5}{2}$:

$$\begin{bmatrix} 1 & \frac{1}{2} & | & \frac{1}{2} & 0 \\ 0 & 1 & | & -\frac{1}{5} & \frac{2}{5} \end{bmatrix}$$

4. Subtract $\frac{1}{2}$ times the second row from the first row:

$$\begin{bmatrix} 1 & 0 & | & \frac{3}{5} & -\frac{1}{5} \\ 0 & 1 & | & -\frac{1}{5} & \frac{2}{5} \end{bmatrix}$$

After performing these row operations, the left side of the augmented matrix is the identity matrix and the right side is the inverse of matrix A:

$$A^{-1} = \begin{bmatrix} \frac{3}{5} & -\frac{1}{5} \\ -\frac{1}{5} & \frac{2}{5} \end{bmatrix}$$

So, the inverse of matrix A is the matrix displayed above.

For further readings, please refer to Wikipedia: https://en.wikipedia.org/wiki/Invertible_matrix

4 Inverse Matrix

Definition 18 A square matrix $A \in \mathbb{F}^{n \times n}$ is invertible if there exists a square matrix $B \in \mathbb{F}^{n \times n}$ such that: $A \cdot B = B \cdot A = Id = \begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{pmatrix}$

The matrix B is called the inverse matrix and is denoted by A^{-1} .

Proposition 19 The inverse matrix represents the inverse of the corresponding linear map, that is $T: V \to V$

$$M(T^{-1}) = (M(T))^{-1}$$

In particular, a matrix is invertible iff the corresponding map is invertible.

Remark 20

- The inverse matrix does not always exist.
- $(A^{-1})^{-1} = A, (A \cdot B)^{-1} = B^{-1} \cdot A^{-1}$
- A^T invertible $\Leftrightarrow A$ invertible $(A^T)^{-1} = (A^{-1})^T$
- $A \in \mathbb{F}^{n \times n}$ invertible \Leftrightarrow rank(A) = n
- The set of all invertible matrices is called a general linear group: $GL(n,F) = \{A \in \mathbb{F}^{n \times n} | A \text{ invertible} \}$