Math for ML Notes

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Chapter 2

2.6.2 Rank

Definition (Rank)

The number of **linearly independent** columns of a matrix $A \in \mathbb{R}^{m \times n}$ equals the number of **linearly independent** rows of A and is called the **rank** of A, and is denoted by $\operatorname{rk}(A)$

Remark (Matrix Rank Properties)

- Rank equality: For any matrix A, the column rank equals the row rank: $rk(A) = rk(A^{\top})$
- Column space (image/range): The columns of $A \in \mathbb{R}^{m \times n}$ span a subspace $U \subseteq \mathbb{R}^m$ with $\dim(U) = \operatorname{rk}(A)$. A basis for U can be found using Gaussian elimination to identify pivot columns.
- **Row space**: The rows of $A \in \mathbb{R}^{m \times n}$ span a subspace $W \subseteq \mathbb{R}^n$ with $\dim(W) = \operatorname{rk}(A)$. A basis for W can be found by applying Gaussian elimination to A^{\top} .
- **Invertibility condition**: For square matrices $A \in \mathbb{R}^{n \times n}$, A is regular (invertible) if and only if rk(A) = n.
- **Linear system solvability**: For $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$, the system Ax = b can be solved if and only if rk(A) = rk(A|b), where A|b is the augmented matrix.
- Null space (kernel): For $A \in \mathbb{R}^{m \times n}$, the solution space of Ax = 0 has dimension n rk(A). This subspace is called the kernel or null space.
- **Full rank**: A matrix $A \in \mathbb{R}^{m \times n}$ has full rank when $\text{rk}(A) = \min(m, n)$, meaning its rank equals the maximum possible rank for its dimensions.
- Rank deficient: A matrix that does not have full rank is called rank deficient.

2.7 Linear Mappings

Definition (Linear Mapping)

For vector spaces V and W, a mapping $\Phi: V \to W$ is called a **linear mapping (or linear transformation/vector space homomorphism)** if

$$\Phi(x + y) = \Phi(x) + \Phi(y)$$

 $\Phi(\lambda x) = \lambda \Phi(x)$

$\forall x, y \in V \text{ and } \lambda \in \mathbb{R}$

Remark

Consider a mapping $\Phi: \mathcal{V} \to \mathcal{W}$, where \mathcal{V} and \mathcal{W} can be arbitrary sets. Then Φ is called:

- **Injective (one-to-one)** if $\forall x, y \in \mathcal{V} : \Phi(x) = \Phi(y) \Longrightarrow x = y$ i.e. there is no two different elements in \mathcal{V} that map to the same element in \mathcal{W} .
- Surjective (onto) if $\Phi(\mathcal{V}) = \mathcal{W}$ i.e. every element in \mathcal{W} can be reached from \mathcal{V} using Φ .
- Bijective if Φ is both injective and surjective.

Remark

A bijective mapping $\Phi: \mathcal{V} \to \mathcal{W}$ is reversible: there exists a mapping $\Psi: \mathcal{W} \to \mathcal{V}$ such that $\Psi \circ \Phi(x) = x$ and $\Phi \circ \Psi(y) = y$. This mapping Ψ is the **inverse** of Φ , denoted Φ^{-1} .

Remark Special cases of linear mappings between vector spaces

- **Isomorphism**: $\Phi: V \to W$ linear and bijective (maps between different spaces, reversible)
- **Endomorphism**: $\Phi: V \to V$ linear (maps a space to itself)
- **Automorphism**: $\Phi: V \to V$ linear and bijective (maps a space to itself, reversible)
- **Identity mapping**: $id_V: V \to V, x \mapsto x$ (leaves every vector unchanged)

Remark

Finite dimensional vector spaces V and W are **isomorphic** if and only if $\dim(V) = \dim(W)$

Remark

Consider vector spaces V, W, X. Then:

- If $\Phi: V \to W$ and $\Psi: W \to X$ are **linear** then $\Psi \circ \Phi: V \to X$ is **linear**.
- If $\Phi: V \to W$ is an **isomorphism** then $\Phi^{-1}: W \to V$ is an **isomorphism**.
- If $\Phi: V \to W$ and $\Psi: V \to W$ are **linear** then $\Phi + \Psi: V \to W$ and $\lambda \Phi: V \to W, \lambda \in \mathbb{R}$ are **linear**.

2.7.1 Matrix Representation of Linear Mappings

Remark (Notaion)

- $B = \{b_1, ..., b_n\}$ is an **unordered** basis
- $B = (b_1, ..., b_n)$ is an **ordered** basis
- $B = \begin{bmatrix} b_1 & ... & b_n \end{bmatrix}$ is a **matrix** whose columns are the vectors $b_1, ..., b_n$

Definition (Coordinates)

Consider a vector space V and an **ordered** basis $B = (b_1, ..., b_n)$ of V. For any vector $x \in V$ we obtain a **unique** representation (linear combination)

$$\pmb{x} = \alpha_1 b_1 + \ldots + \alpha_n b_n$$

of x with respect to B. Then $\alpha_1, ..., \alpha_n$ are the coordinates of x with respect to B, and the vector

$$\alpha = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} \in \mathbb{R}^n$$

is the coordinate vector/coordinate representation of x with respect to the ordered basis B.

Remark

A basis effectively defines a coordinate system and any basis of the vector space defines a valid coordinate system. The coordinates of a vector may be different between different basis.

Remark

For an *n*-dimensional vector space V and an ordered basis B of V, the mapping $\Phi: \mathbb{R}^n \to V, \Phi(e_i) = b_i, \ i = 1, ..., n$, is **linear** and **bijective** (since V and \mathbb{R}^n are of the same dimension), where $(e_i, ..., e_n)$ is the **standard basis** of \mathbb{R}^n .

Definition (Transformation Matrix)

Consider vector spaces V and W with corresponding **ordered** bases $B = (\boldsymbol{b_1},...,\boldsymbol{b_n})$ and $C = (\boldsymbol{c_1},...,\boldsymbol{c_m})$. Also condier a **linear mapping** $\Phi: V \to W$. For $j \in \{i,...,n\}$

$$\Phi(\boldsymbol{b_j}) = \alpha_{1j}\boldsymbol{c_1} + \alpha_{2j}\boldsymbol{c_2} + ... + \alpha_{mj}\boldsymbol{c_j} = \sum_{i=1}^{m} \alpha_{ij}\boldsymbol{c_i}$$

is the unique representaion (linear combination) of $\Phi(b_j)$ with respect to the C. Then we call the $m \times n$ matrix A_{Φ} , whose elements are given by

$$A_{\Phi(i,j)} = \alpha_{ij},$$

The transformation matrix of Φ with respect to the ordered bases B of V and C of W.

Remark

From the definition of the transformation matrix we can see that the coordinates of $\Phi(b_j)$ with respect to the ordered basis C of W are the j-th column of A_{Φ}

Corollary

Consider finite dimensional vector spaces V, W with ordered basis B, C and a linear mapping $\Phi: V \to W$ with transformation matrix \mathbf{A}_{Φ} . If $\hat{\mathbf{x}}$ is the **coordinate vector** of $\mathbf{x} \in V$ with respect to B and $\hat{\mathbf{y}}$ is the **coordinate vector** of $\mathbf{y} = \Phi(\mathbf{x}) \in W$ with respect to C, then

$$\hat{y} = A_{\Phi} \hat{x}$$
.

This means that the transformation matrix can be used to map coordinates with respect to an ordered basis in V to coordinates with respect to an ordered basis in W.

2.7.2 Basis Change

Theorem (Basis Change)

Let $\Phi: V \to W$ be a linear mapping between vector spaces with ordered bases

$$B = (\boldsymbol{b}_1, ..., \boldsymbol{b}_n)$$
 and $\tilde{B} = (\tilde{\boldsymbol{b}}_1, ..., \tilde{\boldsymbol{b}}_n)$

of V, and

$$C = (\boldsymbol{c}_1, ..., \boldsymbol{c}_m) \quad \text{and} \quad \tilde{C} = (\tilde{\boldsymbol{c}}_1, ..., \tilde{\boldsymbol{c}}_m)$$

of W.

If A_{Φ} is the transformation matrix of Φ with respect to bases B and C, then the transformation matrix \tilde{A}_{Φ} with respect to bases \tilde{B} and \tilde{C} is given by:

$$ilde{m{A}}_{\Phi} = m{T}^{-1} m{A}_{\Phi} m{S}$$

where:

- $S \in \mathbb{R}^{n \times n}$ is the transformation matrix of Id_V that maps coordinates with respect to B onto coordinates with respect to B in V
- $T \in \mathbb{R}^{m \times m}$ is the transformation matrix of Id_W that maps coordinates with respect to \tilde{C} onto coordinates with respect to C in W

Definition (Equivalence)

Two matrices A and $\tilde{A} \in \mathbb{R}^{m \times n}$ are **equivalent** if there exists **regular** matrices $S \in \mathbb{R}^{n \times n}$ and $T \in \mathbb{R}^{m \times m}$, such that $\tilde{A} = T^{-1}AS$

in other words, two matrices A and \tilde{A} are **equivalent** if they represent the **same linear** transformation $\Phi: V \to W$.

Definition (Similarity)

Two matrices A and $\tilde{A} \in \mathbb{R}^{n \times n}$ are **similar** if there exists a **regular** matrix $S \in \mathbb{R}^{n \times n}$, such that $\tilde{A} = S^{-1}AS$

in other words, two matrices A and \tilde{A} are **similar** if they represent the **same linear transformation** $\Phi: V \to V$.

Remark

Similar matrices are always **equivalent**. However, **equivalent** matrices are not necessary **similar**.

Remark

The composition of two linear transformations, $\Phi: V \to W$ and $\Psi: W \to X$, results in another linear transformation $\Psi \circ \Phi: V \to X$. The matrix representing this combined transformation, $A_{\Psi \circ \Phi}$, is the product of the individual transformation matrices: $A_{\Psi \circ \Phi} = A_{\Psi} A_{\Phi}$.

Definition (Kernel (Null Space))

For a linear transformation $\Phi: V \to W$, the **kernel** is the set of all vectors $v \in V$ that are mapped to the zero vector of W.

$$\ker(\Phi) \coloneqq \Phi^{-1}(\mathbf{0}_W) = \{ \boldsymbol{v} \in V \mid \Phi(\boldsymbol{v}) = \mathbf{0}_W \}$$

Definition (Image (Range))

For a linear transformation $\Phi: V \to W$, the **image** is the set of all vectors $\mathbf{w} \in W$ that can be "reached" by the transformation from some vector in V.

$$\operatorname{Im}(\Phi) \coloneqq \Phi(V) = \{ \boldsymbol{w} \in W \mid \exists \boldsymbol{v} \in V, \Phi(\boldsymbol{v}) = \boldsymbol{w} \}$$

Intuitively, the **kernel** is the set of vector $v \in V$ that Φ maps onto the zero vector $\mathbf{0}_W \in W$. The **image** is the set of all vectors $w \in W$ that can be *reached* by Φ from any vector in V.

Remark

For $\Phi: V \to W$, we call V the **domain** and W the **codomain**

The kernel is the set of vectors $v \in V$ that Φ maps onto the neutral element $\mathbf{0}_W \in W$

Remark

Consider a linear mapping $\Phi: V \to W$, where V and W are vector spaces:

- It always holds that $\Phi(\mathbf{0}_V) = \mathbf{0}_W$, therefore, $\mathbf{0}_V \in \ker(\Phi)$. In particular, the null spaces is never empty.
- $\operatorname{Im}(\Phi) \subseteq W$ is a **subspace** of W, and $\ker(\Phi) \subseteq V$ is a **subspace** of V.

Theorem (Rank-Nullity Theorem or Fundamental Theorem of Linear Mappings)

For vector spaces V and W and linear mapping $\Phi: V \to W$ it holds that

$$\dim(\ker(\Phi)) + \dim(\operatorname{Im}(\Phi)) = \dim(V)$$

Remark (Direct Consequences of the Rank-Nullity Theorem)

- If $\dim(\operatorname{im}(\Phi)) < \dim(V)$, then the $\ker(\Phi)$ is **non-trivial**, i.e., the kernel contains more than $\mathbf{0}_V$ and $\dim(\ker(\Phi)) \geq 1$
- If A_{Φ} is the transformation matrix of Φ with respect to an ordered basis and dim(Im(Φ)) < dim(V), the the system of linear equations $A_{\Phi}x = 0$ has **infinitely many solutions**.