ECE367 Cheatsheet

Hanhee Lee

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Contents

List of Figures

List of Tables

1 Vectors, Norms, Inner Products (Ch. 2.1-2.2)

1.1 Linear transformation

Definition: $T: X \to Y$ that satisfies

1. **Additivity:** $T(x_1 + x_2) = T(x_1) + T(x_2)$
2. **Homogeneity:** $T(\alpha x) = \alpha T(x)$

- **Note:** Linear algebra is the study of linear transformations over vector spaces.

1.1.1 Matrix representation of a linear transformation

Definition: Let $\mathcal{V}$ and $\mathcal{W}$ be vector spaces. Let $T : \mathcal{V} \to \mathcal{W}$ be a linear transformation. When $\mathcal{V} = \mathbb{R}^n$ (or $\mathbb{C}^n$) and $\mathcal{W} = \mathbb{R}^m$ (or $\mathbb{C}^m$), then T can be uniquely represented as a matrix $A \in \mathbb{R}^{m\times n}$ such that:

$$T(\mathbf{x}) = A\mathbf{x}$$

where

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

- **Key:** Any linear transformation is a matrix multiplication. Any matrix multiplication is a linear transformation.

1.2 Vectors

Definition: Ordered collection of numbers, where $x_i \in \mathbb{R}$ or $\mathbb{C}$

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}, \quad \mathbf{x}^T = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}.$$

- n: Dimension of $\mathbf{x}$
- $\mathbf{x}$: Column vector
- $\mathbf{x}^T$: Transpose of x (row vector)
- T: Transpose
- x_i: i-th element of x.

1.3 Vector spaces

Definition: A vector space over a field $\mathbb{F}$ (e.g. $\mathbb{R}/\mathbb{C}$) consists of:

1. A set of vectors $\mathcal{V}$
2. A vector addition operator $+$: $\mathcal{V} \times \mathcal{V} \to \mathcal{V}$ s.t. $\forall x, y \in \mathcal{V} \to x + y \in \mathcal{V}$ (i.e. closed under VA)
3. A scalar multiplication operator $\cdot$: $\mathbb{F} \times \mathcal{V} \to \mathcal{V}$ s.t. $\forall \alpha \in \mathbb{F}$, $\forall x \in \mathcal{V} \to \alpha x \in \mathcal{V}$ (i.e. closed under SM)

- $\times$ is not scalar multiplication.

For $\mathbf{x}, \mathbf{y}, \mathbf{z} \in \mathcal{V}$ and $\alpha, \beta \in \mathbb{F}$. The following properties are satisfied:

- **Vector addition** satisfies (i.e., Abelian group):
  1. **Commutativity:** $\mathbf{x} + \mathbf{y} = \mathbf{y} + \mathbf{x}$.
  2. **Associativity:** $\mathbf{x} + (\mathbf{y} + \mathbf{z}) = (\mathbf{x} + \mathbf{y}) + \mathbf{z}$.
  3. **Additive identity:** $\exists\, \mathbf{0} \in \mathcal{V}$ s.t. $\mathbf{x} + \mathbf{0} = \mathbf{0} + \mathbf{x} = \mathbf{x}$.
  4. **Additive inverse:** $\forall\, \mathbf{x}$, $\exists\, \mathbf{y}$ s.t. $\mathbf{x} + \mathbf{y} = \mathbf{0}$ (i.e. $\mathbf{y} = -\mathbf{x}$).
- **Scalar multiplication** satisfies:
  1. **Associativity:** $\alpha \cdot (\beta \cdot \mathbf{x}) = (\alpha \cdot \beta) \cdot \mathbf{x}$.
  2. **Multiplicative Identity:** $\exists\, 1 \in \mathbb{F}$ s.t. $1 \cdot \mathbf{x} = \mathbf{x}$.
  3. **Right Distributivity:** $\alpha \cdot (\mathbf{x} + \mathbf{y}) = \alpha \cdot \mathbf{x} + \alpha \cdot \mathbf{y}$.
  4. **Left Distributivity:** $(\alpha + \beta) \cdot \mathbf{x} = \alpha \cdot \mathbf{x} + \beta \cdot \mathbf{x}$.

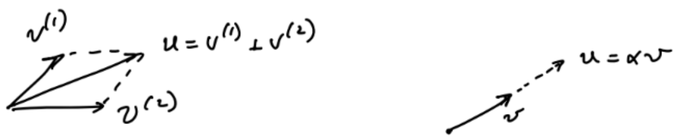

Figure 1: Vector addition and scalar multiplication.

1.3.1 How to prove or disprove a vector space?

Process:

Prove:

1. Prove that $\mathcal{V}$ is closed under VA and SM.
2. Prove all the properties under VA and SM.

Disprove:

1. Disprove one of the properties or that it isn't closed under VA and SM.

Warning: If standard addition and multiplication then, closed under VA and SM properties is enough to prove it's a vector space.

Example:

- Let $\mathcal{V} = \mathbb{R}^n$ and $\mathbb{F} = \mathbb{R}$: This represents vectors of dimension n where each element belongs to $\mathbb{R}$.

$$\mathcal{V} = \mathbb{R}^n = \left\{ \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} : x_i \in \mathbb{R} \right\}$$

For $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^n$ and $\mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \in \mathbb{R}^n$:

$$\mathbf{x} + \mathbf{y} = \begin{bmatrix} x_1 + y_1 \\ \vdots \\ x_n + y_n \end{bmatrix}$$

For $\alpha, \beta \in \mathbb{R}$:

$$\alpha \cdot \mathbf{x} = \begin{bmatrix} \alpha x_1 \\ \vdots \\ \alpha x_n \end{bmatrix}$$

- Let $\mathcal{V} = \mathbb{C}^n$ and $\mathbb{F} = \mathbb{C}$: This represents vectors of dimension n with complex components.

$$\mathcal{V} = \left\{ \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} : x_i \in \mathbb{C} \right\}$$

  $\mathcal{V}$ is a vector space over $\mathbb{C}$ under element-wise addition and scalar multiplication.
- Let $\mathcal{V} = \{\text{set of all continuous functions } f : \mathbb{R} \to \mathbb{R}^n\}$ and $\mathbb{F} = \mathbb{R}$:
  Let $f_1, f_2 \in \mathcal{V}$, and for $t \in \mathbb{R}$:

$$(f_1 + f_2)(t) = f_1(t) + f_2(t) \quad \Rightarrow \quad f_1 + f_2 \in \mathcal{V}$$

  For $\alpha \in \mathbb{R}$:

$$(\alpha f)(t) = \alpha f(t) \quad \Rightarrow \quad \alpha f \in \mathcal{V}$$

  - f is the vector, $\mathbb{R} \to \mathbb{R}^n$ is the input-output relationship. For 2D, $f(x) = [x_1, x_2]^T$, where x is the input, the vector is the output in 2D, and the vector is f.
- Let $\mathcal{V} = \mathcal{P}_n$, the set of all polynomials with real coefficients and degree $\leq n$:

$$\mathcal{V} = \mathcal{P}_n = \left\{ p(x) = a_0 + a_1 x + a_2 x^2 + \ldots + a_n x^n : a_0, a_1, \ldots, a_n \in \mathbb{R} \right\}$$

  $\mathcal{V}$ is a vector space over $\mathbb{R}$ under standard addition and scalar multiplication.

1.4 Subspace

Definition: A **subspace** is a subset of a vector space $\mathcal{V}$ that is a vector space by itself.
- **Test:** To check whether a subset is a subspace, check that it is closed under VA & SM.

Example:
- Let $\mathcal{V} = \mathbb{R}^3$, and consider the set:

$$S = \left\{ \begin{bmatrix} x_1 \\ x_2 \\ 0 \end{bmatrix} : x_1, x_2 \in \mathbb{R} \right\}$$

  This set S is a subspace of $\mathbb{R}^3$.
- Let $\mathcal{V} = \mathbb{R}^3$, and consider the set:

$$S = \left\{ \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix} : x_1, x_2 \in \mathbb{R} \right\}$$

  This set S is **not** a subspace of $\mathbb{R}^3$ because adding two vectors will make the last component 2.
- Let $\mathcal{V} = \mathbb{R}^n$, and consider the set:

$$S = \{\mathbf{0}\}$$

  This set S is a subspace of $\mathbb{R}^n$.

1.5 Span

Definition: Given a finite set of vectors $S = \{\mathbf{v}_1, \ldots, \mathbf{v}_k\}$ in the same vector space $\mathcal{V}$ over some field $\mathbb{F}$ then,

$$\text{Span}(S) = \left\{ \sum_{i=1}^{m} \alpha_i \mathbf{v}_i \mid \alpha_i \in \mathbb{F} \right\}$$

- **Note:** Span(S) is always a subspace of V.

1.5.1 How to draw the span?

Process:

1. Identify the vectors.
2. Plot the vectors: Plot each vector on a coordinate plane starting at the origin.
3. Draw the span: Extend the vectors in both directions to show the line or plane formed by their span. If they span the entire plane, draw dashed lines extending their direction.

Example:

- Let $S = \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} \right\}$:
$$\text{span}(S) = \left\{ \begin{bmatrix} x_1 \\ x_2 \\ 0 \end{bmatrix} : x_1, x_2 \in \mathbb{R} \right\}$$
This set span(S) forms a plane in $\mathbb{R}^3$. The vectors span the xy-plane with the z-coordinate fixed at zero.
- Let $S = \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ -1 \\ 0 \end{bmatrix} \right\}$:
$$\text{span}(S) = \left\{ x \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} : x \in \mathbb{R} \right\}$$
In this case, span(S) is a line in $\mathbb{R}^3$ along the x-axis with y and z coordinates fixed at zero.

1.6 Linear independent (LI) set

Definition: A set of vectors $S = \{\mathbf{v}_1, \ldots, \mathbf{v}_k\}$ is LI if no vector in S can be written as a LC of other vectors in S. In other words, the only α_i's that makes $\sum_{i=1}^{m} \alpha_i \mathbf{v}_i = 0$ is $\alpha_i = 0$, $\forall i$.

- If $S = \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_k\}$ is LI, then $\forall$ $\mathbf{u} \in \text{span}(S)$, there is a **unique** set of α_i's s.t. $\mathbf{u} = \sum_{i=1}^{k} \alpha_i \mathbf{v}_i$ (i.e. there is no redundancies in representation)
  - **Coordinates:** $\{\alpha_1, \alpha_2, \ldots, \alpha_k\}$ of $\mathbf{u}$ w.r.t. S.
- If S is linearly dependent, then one of the vectors can be written as a LC of the other vectors. In this case, we can remove that vector and continue this process until the remaining set is LI.
  - **Note:** Such an irreducible linearly independent set is called a **basis** of span(S).

1.6.1 How to determine if a set is linearly independent

Process:

1. Write a linear combination with coefficients $\alpha_1, \ldots, \alpha_k$.
2. Set the linear combination equal to 0.
3. Solve for $\alpha_1, \ldots, \alpha_k$ by solving the set of equations (i.e. each component is one equation).
4. If $\alpha_1 = \ldots = \alpha_k = 0$, then it is linearly independent.
5. Else, linearly dependent by finding a counter example, where the linear combination is 0 for $\alpha_1, \ldots, \alpha_k$ not all equal to 0.

1.7 Basis

Definition: A set of vectors B is a basis of a vector space $\mathcal{V}$ if
- B is LI
- $Span(B) = \mathcal{V}$

Example: What is the standard basis for $\mathcal{V} = \mathbb{R}^n$?

$$\mathbf{e}^{(1)} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad \mathbf{e}^{(2)} = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \quad \dots \quad, \quad \mathbf{e}^{(n)} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \quad \text{for } \mathbb{R}^n$$

If $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^n$, then:

$$\mathbf{x} = x_1\mathbf{e}_1 + x_2\mathbf{e}_2 + \dots + x_n\mathbf{e}_n$$

1.7.1 Dimension

Definition: The dimension is the number of basis vectors.
- **Note:** Basis is not unique. But $dim(\mathcal{V})$ is well-defined.

Example:
- $\dim\left(\text{span}\left(\left\{\begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix}\right\}\right)\right) = 2$
- $\dim\left(\text{span}\left(\left\{\begin{bmatrix} 1 \\ 0 \end{bmatrix}\right\}\right)\right) = 1$
- $\dim(\{\mathbf{0}\}) = 0$
- The dimension for $\mathcal{V} = \mathbb{R}^n$ of the standard basis is n

1.8 Norms (Notion of distance)

Definition: Let $\mathcal{V}$ be a vector space over $\mathbb{R}$ or $\mathbb{C}$. A norm is a function $\|\cdot\|$: $\mathcal{V} \to \mathbb{R}$ that satisfies
1. **Non-negativity:** $\|\mathbf{x}\| \geq 0,\ \forall \mathbf{x} \in \mathcal{V},$ and $\|\mathbf{x}\| = 0$ iff $\mathbf{x} = \mathbf{0}$
2. **Homogeneity:** $\|\alpha\mathbf{x}\| = |\alpha|\|\mathbf{x}\|\ \forall \mathbf{x} \in \mathcal{V},\ \alpha \in \mathbb{F}$
3. **Triangle inequality:** $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$, $\forall \mathbf{x}, \mathbf{y} \in \mathcal{V}$ (triangular inequality)

Example: ℓ_p norms:

$$\|\mathbf{x}\|_p \equiv \left(\sum_{k=1}^{n} |x_k|^p\right)^{1/p}, \quad 1 \leq p < \infty.$$

- **Note:** For $p < 1$, triangular inequality doesn't hold.

1. **Sum-of-absolute-values length** $p = 1$: $\|\mathbf{x}\|_1 \equiv \sum_{k=1}^{n} |x_k|$
2. **Euclidean length** $p = 2$: $\|\mathbf{x}\|_2 \equiv \sqrt{\sum_{k=1}^{n} x_k^2}$
3. **Max absolute value norm** $p = \infty$: $\|\mathbf{x}\|_\infty \equiv \max_{k=1,\dots,n} |x_k|$
   - Largest term will dominate as if we common factor out the largest term, each of the other terms will go to 0 as noted in the lp norm.

4. **Cardinality** $p = 0$: The number of non-zero vectors in x is

$$\|\mathbf{x}\|_0 = \text{card}(\mathbf{x}) \equiv \sum_{k=1}^{n} \mathbb{I}(x_k \neq 0), \quad \text{where} \quad \mathbb{I}(x_k \neq 0) \equiv \begin{cases} 1 & \text{if } x_k \neq 0 \\ 0 & \text{otherwise.} \end{cases}$$

- **Key:** Not a norm since $\|\alpha \mathbf{x}\|_0 = \|\mathbf{x}\|_0 \neq |\alpha| \cdot \|\mathbf{x}\|_0$ (e.g. if $\alpha = 2$ then this would double the count of number of non-zero vectors for the RS)

1.8.1 Norm balls

Definition: The set of all vectors with ℓ_p norm less than or equal to one,

$$B_p = \{\mathbf{x} : \|\mathbf{x}\|_p \leq 1\} \tag{1}$$

Example: For 2D, the norm balls are as follows:
- $\ell_2 :\ B_2 = \left\{ \mathbf{x} \;\middle|\; \sqrt{x_1^2 + x_2^2} \leq 1 \right\}$
- $\ell_1 :\ B_1 = \{\mathbf{x} \mid |x_1| + |x_2| \leq 1\}$
- $\ell_\infty :\ B_\infty = \{\mathbf{x} \mid \max |x_i| \leq 1 \text{ or } |x_1| \leq 1, |x_2| \leq 1\}$
- $\ell_0 :\ B_0 = \{\mathbf{x} \mid \text{card}(\mathbf{x}) \leq 1\}$

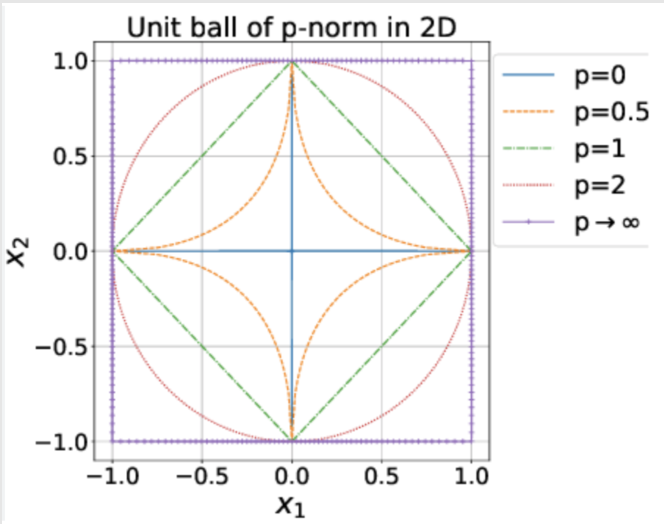

Figure 2: Norm balls of different p values.

1.8.2 Motivation for Norms

Example: In optimization problems, different norms are used to achieve various goals. Suppose we are trying to solve an optimal control problem, where $x = (x_1, \ldots, x_n)$ are some action variables.
- $\min \|\mathbf{x}\|_2^2 = x_1^2 + \ldots + x_n^2$ (i.e. minimizing the total energy (power) in $\mathbf{x}$)
- $\min \|\mathbf{x}\|_\infty$ (i.e. minimizing the peak energy in $\mathbf{x}$).
- $\min \|\mathbf{x}\|_1$ (i.e. minimizing the sum of action variables).
- $\min \|\mathbf{x}\|_0$ (i.e. find sparse solution)

1.8.3 Distance metric

Definition: A norm induces a distance metric between two vectors x and y in $\mathbb{V}$ as

$$d(x, y) = \|x - y\|$$

- **Note:** The ℓ_2-norm induces the Euclidean distance

$$\|x - y\|_2 = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

1.9 Inner product (Notion of angle)

Definition: An inner product on a vector space $\mathcal{V}$ is a function $\langle \cdot, \cdot \rangle : \mathcal{V} \times \mathcal{V} \to \mathcal{F}$ such that:

1. **Positive definiteness:** $\langle \mathbf{x}, \mathbf{x} \rangle \geq 0 \ \forall \mathbf{x} \in \mathcal{V}$ and $\langle \mathbf{x}, \mathbf{x} \rangle = 0$ iff $\mathbf{x} = 0$
2. **Conjugate Symmetry:** $\langle \mathbf{x}, \mathbf{y} \rangle = \overline{\langle \mathbf{y}, \mathbf{x} \rangle}$
   - $\langle \mathbf{x}, \mathbf{y} \rangle = \underline{\langle \mathbf{y}, \mathbf{x} \rangle}$ in $\mathbb{R}^n$
   - $\langle \mathbf{x}, \mathbf{y} \rangle = \overline{\langle \mathbf{y}, \mathbf{x} \rangle}$ in $\mathbb{C}^n$.
3. **Linearity in first argument:** $\langle \alpha \mathbf{x} + \mathbf{y}, \mathbf{z} \rangle = \alpha \langle \mathbf{x}, \mathbf{z} \rangle + \langle \mathbf{y}, \mathbf{z} \rangle \quad \forall \mathbf{x}, \mathbf{y}, \mathbf{z} \in \mathcal{V}, \ \alpha \in \mathbb{F}$

Example: How to use the properties of inner products?

$$\begin{aligned}
\langle x, \alpha y + z \rangle &\stackrel{(2)}{=} \overline{\langle \alpha y + z, x \rangle} \\
&\stackrel{(3)}{=} \overline{\alpha}\, \overline{\langle y, x \rangle} + \overline{\langle z, x \rangle} \qquad \text{also by conjugate prop.} \\
&\stackrel{(2)}{=} \overline{\alpha} \langle x, y \rangle + \langle x, z \rangle
\end{aligned}$$

1.9.1 Examples of inner products

Example:

- In $\mathbb{R}^n$ (Dot product): $\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^{n} x_i y_i = \mathbf{x}^\top \mathbf{y} = \mathbf{y}^\top \mathbf{x}$
  - **Key:** $\langle \mathbf{x}, \mathbf{x} \rangle = \sum_{i=1}^{n} x_i^2 = \mathbf{x}^\top \mathbf{x} = \|\mathbf{x}\|_2^2$
- In $\mathbb{C}^n$: $\langle \mathbf{x}, \mathbf{y} \rangle = \sum_{i=1}^{n} \overline{x_i} y_i = \mathbf{y}^H \mathbf{x} = \overline{\mathbf{x}^H \mathbf{y}}$
  - $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \quad \mathbf{x}^H = \begin{bmatrix} \overline{x_1} & \cdots & \overline{x_n} \end{bmatrix}$
- $\mathcal{V} = \left\{ f : \mathbb{R} \to \mathbb{R} \, ; \int_{-\infty}^{+\infty} f^2(t) \, dt < \infty \right\}$ (i.e. the set of square integrable functions)

$$\langle f, g \rangle = \int_{-\infty}^{+\infty} f(t) g(t) \, dt$$

1.9.2 Connection of inner product to angle

In $\mathbb{R}^n$, the notion of inner product has a geometric interpretation, and is closely related to the notion of angle between vectors.

Definition:

$$\cos\theta = \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\|_2 \|\mathbf{y}\|_2} = \left\langle \frac{\mathbf{x}}{\|\mathbf{x}\|_2}, \frac{\mathbf{y}}{\|\mathbf{y}\|_2} \right\rangle \tag{2}$$

- $\langle \mathbf{x}, \mathbf{y} \rangle = 0 \Rightarrow \cos\theta = 0 \Rightarrow \theta = \frac{\pi}{2}$ (i.e. perpendicular)
- $\langle \mathbf{x}, \mathbf{y} \rangle = \|\mathbf{x}\|_2 \|\mathbf{y}\|_2 \Rightarrow \cos\theta = 1 \Rightarrow \theta = 0$ (i.e. $\mathbf{x}$ and $\mathbf{y}$ are aligned)
- $\langle \mathbf{x}, \mathbf{y} \rangle = -\|\mathbf{x}\|_2 \|\mathbf{y}\|_2 \Rightarrow \cos\theta = -1 \Rightarrow \theta = \pi$ (i.e $\mathbf{x}$ and $\mathbf{y}$ are in opposite directions)
- $\langle \mathbf{x}, \mathbf{y} \rangle > 0 \Rightarrow \cos\theta > 0 \Rightarrow$ angle is acute
- $\langle \mathbf{x}, \mathbf{y} \rangle < 0 \Rightarrow \cos\theta < 0 \Rightarrow$ angle is obtuse

Derivation: L3: Inner products and orthogonality.

1.9.3 Cauchy-Schwartz inequality and its generalization

Definition:

$$|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \|\mathbf{x}\|_2 \|\mathbf{y}\|_2 \tag{3}$$

Hölder's Inequality (generalization):

$$|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \|\mathbf{x}\|_p \|\mathbf{y}\|_q \quad \text{where } 1 \leq p, q < \infty \text{ and } \frac{1}{p} + \frac{1}{q} = 1 \tag{4}$$

Example: For $p = 1$ and $q = \infty$, we have:

$$|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \|\mathbf{x}\|_1 \cdot \|\mathbf{y}\|_\infty$$

$$|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \left(\sum_{i=1}^{n} |x_i| \right) \cdot \max_i |y_i|$$

1.9.4 Inner product induces a norm

Definition: Any inner product induces a norm, but not all norms are induced by an inner product.

- **Key:** If given an inner product, take the square root of the inner product to get the norm.
  - e.g. $\|\mathbf{x}\|_2 = \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle}$, which holds for $\mathbb{R}^n$ and $\mathbb{C}^n$

Figure 3: Ordering of the vector spaces.

Warning: A norm doesn't induce an inner product (e.g. l_1 or l_∞)

1.10 Orthogonal decomposition

1.10.1 Mutually orthogonal

Definition: A set of non-zero vectors $S = \left\{\mathbf{v}^{(1)}, \mathbf{v}^{(2)}, \ldots, \mathbf{v}^{(d)}\right\}$ is **mutually orthogonal** if $\langle \mathbf{v}^{(i)}, \mathbf{v}^{(j)} \rangle = 0 \; \forall \; i \neq j$.

- **Fact:** Orthogonal set of vectors $S = \left\{\mathbf{v}^{(1)}, \mathbf{v}^{(2)}, \ldots, \mathbf{v}^{(d)}\right\}$ is linearly independent.
  - **Proof:** In L3.

1.10.2 Orthonormal basis

Definition: Set of orthogonal basis vectors that have unit norm.

If $S = \left\{\mathbf{v}^{(1)}, \mathbf{v}^{(2)}, \ldots, \mathbf{v}^{(d)}\right\}$ is a set of mutually orthogonal vectors, then $\left\{\frac{\mathbf{v}_1}{\|\mathbf{v}_1\|}, \ldots, \frac{\mathbf{v}_d}{\|\mathbf{v}_d\|}\right\}$ is an orthonormal basis for $span(S)$

Example: Standard basis is an orthonormal basis for $\mathbb{R}^n$

1.10.3 Orthogonal

Definition: Consider $\mathbf{x} \in \mathcal{V}$, and let S be a subspace of $\mathcal{V}$. We say $\mathbf{x}$ is orthogonal to S if:

$$\langle \mathbf{x}, \mathbf{v} \rangle = 0 \quad \forall \, \mathbf{v} \in S.$$

We write: $\mathbf{x} \perp S$.

1.10.4 Orthogonal complement

Definition: The **orthogonal complement** of S, denoted $S^\perp$, is the set of all orthogonal vectors to S:

$$S^\perp = \{\mathbf{x} \in \mathcal{V} : \mathbf{x} \perp S\}$$

- $S^\perp$ is a subspace. (Closed under addition and scalar multiplication)
- $S \cap S^\perp = \{\mathbf{0}\}$
- **Orthogonal decomposition:** Any $\mathbf{x} \in \mathcal{V}$ can be uniquely written as: $\mathbf{x} = \mathbf{x}_S + \mathbf{x}_{S^\perp}$ where $\mathbf{x}_S \in S$ and $\mathbf{x}_{S^\perp} \in S^\perp$

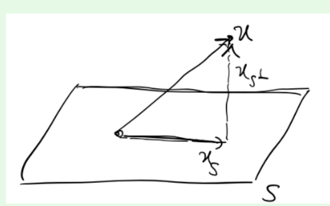

Figure 4: Drawing any x.

- $\mathcal{V} = S + S^\perp = \left\{\mathbf{u} + \mathbf{v} : \mathbf{u} \in S, \mathbf{v} \in S^\perp\right\}$

2 Orthogonal Decomposition, Projecting onto Subspaces, Gram-Schmidt, QR Decomposition, Hyperplanes and Half-Spaces (Ch. 2.2-2.3)

2.1 Projection onto subspaces

Definition:

$$x^* = \mathrm{Proj}_S(x) = \arg\min_{y \in S} \|x - y\|_2 \tag{5}$$

If $\{v^{(1)}, \dots, v^{(d)}\}$ is an orthonormal basis of S then

$$x^* = \sum_{i=1}^{d} \langle x, v^{(i)} \rangle v^{(i)} \tag{6}$$

- The error vector should be orthogonal to each vector in the subspace.

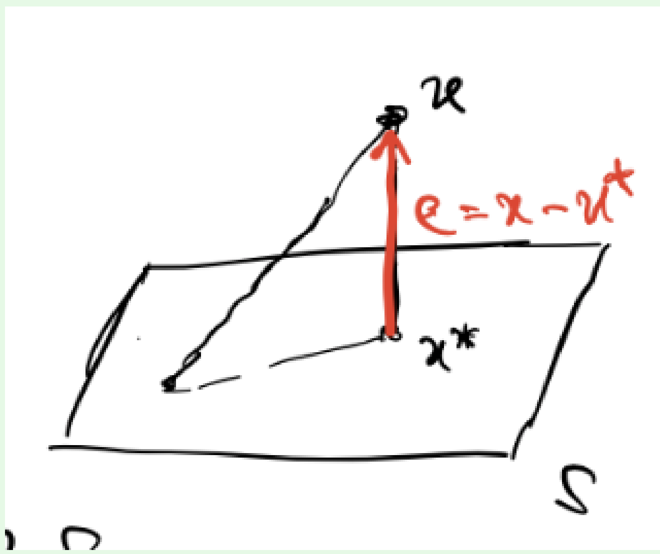

Figure 5: Error vector being perp. to S.

Example: For $v = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}$

The ith component can be extracted by doing the inner product with the ith standard basis:

$$\begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = v_1$$

$$\begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = v_2$$

$$\begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = v_3$$

Therefore, analogous to x*, we can write them as the sum of the inner product times the standard basis.

$$v = v_1 \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + v_2 \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + v_3 \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

2.1.1 Basic problem

Intuition: Given $x \in \mathcal{V}$ and a subspace S. Find the closest point (in norm) in S to x:

$$\text{Proj}_S(x) = \arg\min_{y \in S} \|y - x\| \tag{7}$$

- $\|y - x\|$: Some norm.
- **Subspace:** S doesn't have to be a subspace.
- $\arg\min$: Vector y that minimizes $\|x - y\|$

2.1.2 Projection onto a 1D subspace

Derivation: Projection onto a 1-dimensional subspace.
Let $S = \text{span}(\mathbf{v})$, and we denote the projection of $\mathbf{x}$ onto S as:

$$\text{Proj}_S(\mathbf{x}) = \mathbf{x}^*$$

Under the Euclidean norm (i.e. l2 norm), we have nice geometry: we should have

$$\langle \mathbf{x} - \mathbf{x}^*, \mathbf{v} \rangle = 0$$

Since $\mathbf{x}^* \in S$, $\mathbf{x}^* = \alpha \mathbf{v}$ for some scalar α.
We need to find α.
So,

$$\langle \mathbf{x} - \alpha \mathbf{v}, \mathbf{v} \rangle = 0$$

$$\Rightarrow \langle \mathbf{x}, \mathbf{v} \rangle - \alpha \langle \mathbf{v}, \mathbf{v} \rangle = 0$$

$$\Rightarrow \alpha = \frac{\langle \mathbf{x}, \mathbf{v} \rangle}{\langle \mathbf{v}, \mathbf{v} \rangle}$$

Thus,

$$\mathbf{x}^* = \alpha \mathbf{v} = \frac{\langle \mathbf{x}, \mathbf{v} \rangle}{\langle \mathbf{v}, \mathbf{v} \rangle} \mathbf{v}$$

which simplifies to:

$$\mathbf{x}^* = \frac{\mathbf{x}^\top \mathbf{v}}{\|\mathbf{v}\|_2^2} \mathbf{v} = \left\langle \mathbf{x}, \frac{\mathbf{v}}{\|\mathbf{v}\|_2} \right\rangle \frac{\mathbf{v}}{\|\mathbf{v}\|_2}$$

- **Orthonormal Basis for S:** $\left\{ \frac{\mathbf{v}}{\|\mathbf{v}\|_2} \right\}$ since $\left\| \frac{\mathbf{v}}{\|\mathbf{v}\|_2} \right\|_2 = 1$
- **Projection Coefficient:** $\left\langle \mathbf{x}, \frac{\mathbf{v}}{\|\mathbf{v}\|_2} \right\rangle$
- **Note:** x^* is the point we are looking for in the projection problem.

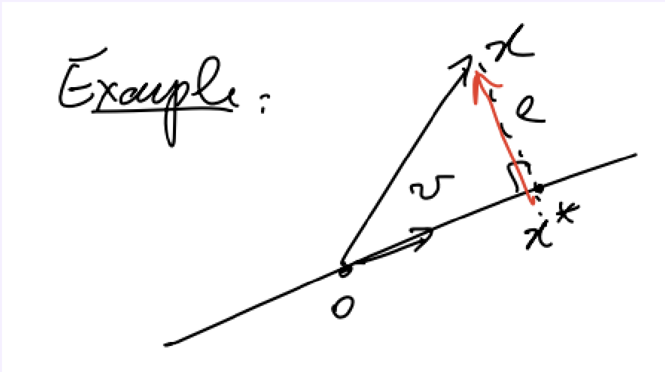

Figure 6: Visual representation of the projection problem.

2.1.3 Projection onto an n dimensional space

Derivation: Let S be a subspace of $\mathcal{V}$, and let $\{\mathbf{v}_1, \dots, \mathbf{v}_d\}$ be an orthonormal basis of S.

1. **Problem setup**

$$\mathbf{x}^* = \sum_{i=1}^{d} \alpha_i \mathbf{v}_i$$

   Goal: Find $\alpha_1, \dots, \alpha_d$ so as to minimize the norm $\|\mathbf{x} - \mathbf{x}^*\|_2$.

2. **Derivation:** By geometry, we require that

$$\langle \mathbf{e}, \mathbf{v}_j \rangle = 0 \quad \forall\, j = 1, \dots, d$$

   which implies:

$$\langle \mathbf{x} - \mathbf{x}^*, \mathbf{v}_j \rangle = 0 \quad \forall\, j$$

$$\Rightarrow \langle \mathbf{x} - \sum_{i=1}^{d} \alpha_i \mathbf{v}_i, \mathbf{v}_j \rangle = 0 \quad \forall\, j$$

   Using linearity of the inner product:

$$\Rightarrow \langle \mathbf{x}, \mathbf{v}_j \rangle = \sum_{i=1}^{d} \alpha_i \langle \mathbf{v}_i, \mathbf{v}_j \rangle$$

   Since $\langle \mathbf{v}_i, \mathbf{v}_j \rangle = 0$ if $i \neq j$ and 1 if $i = j$, this simplifies to:

$$\alpha_j = \langle \mathbf{x}, \mathbf{v}_j \rangle \quad \text{b/c only the i=j term survives}$$

   Thus,

$$\mathbf{x}^* = \sum_{i=1}^{d} \alpha_i \mathbf{v}_i = \sum_{i=1}^{d} \langle \mathbf{x}, \mathbf{v}_i \rangle \mathbf{v}_i$$

3. **Solution:**

$$= \sum_{i=1}^{d} (\mathbf{x}^\top \mathbf{v}_i) \mathbf{v}_i$$

   - $\mathbf{v}_i \in \mathbb{R}^n$.
   - **Projection Coefficients:** $\mathbf{x}^\top \mathbf{v}_i$

4. **Example of Orthogonal Decomposition:**

$$\mathbf{e} = \mathbf{x} - \mathbf{x}^* \in S^\perp, \quad \mathbf{x}^* \in S$$

   So,

$$\mathbf{x} = \mathbf{x}^* + \mathbf{e}, \quad \text{where} \quad \mathbf{x}^* \in S, \quad \mathbf{e} \in S^\perp$$

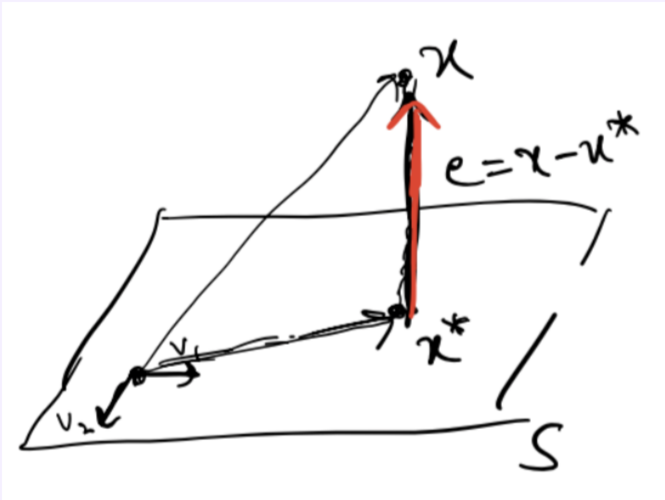

Figure 7: Generalization of projection.

2.1.4 Application of projections: Fourier series

Example: Fourier series:

1. Suppose we have a periodic function $x(t)$ with period T_0.

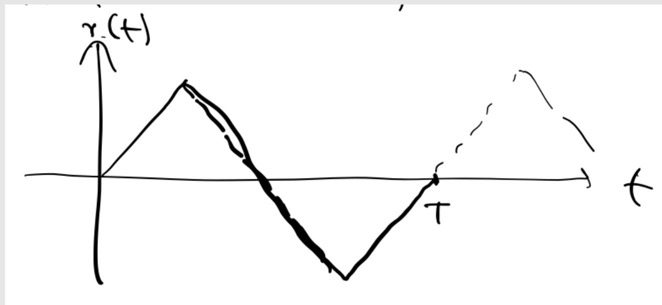

Figure 8: Periodic triangle function.

2. **Inner product for time domain (complex version):** $a_k = \langle x(t), y(t) \rangle = \frac{1}{T}\int_T x(t)\overline{y(t)}\,dt$
   - **Note:** Real version is without the conjugate.
3. **Projection (i.e. one component of the sum):** $\text{Proj}_{\underline{v}_i}(\underline{x}) = \langle \underline{x}, \underline{v}_i \rangle \underline{v}_i$
4. **Goal:** Express $x(t)$ (i.e. any periodic function) as a sum of complex exponentials:

$$x^*(t) = \sum_{k=-\infty}^{\infty} a_k e^{jk\omega_0 t}$$

   - **Projection:** $\text{Proj}_{e^{jk\omega_0 t}}(x(t)) = \langle x(t), \exp(jk\omega_0 t) \rangle e^{jk\omega_0 t} = a_k e^{jk\omega_0 t}$ for a certain value of k.
   - **Projection coefficient:** $a_k = \left\langle x(t), e^{jk\omega_0 t} \right\rangle = \frac{1}{T_0}\int_0^T x(t)e^{-jk\omega_0 t}dt$
   - **Fundamental frequency:** $\omega_0 = \frac{2\pi}{T_0}$.
5. **Prove orthonormal basis for the complex exponentials:** To prove it's a orthnormal basis, must prove it has unit norm 1 and each pair of vectors are orthogonal (i.e. inner product is 0).
   (a) **Magnitude of exp:** $\left|e^{j\theta}\right| = 1$. Therefore, it has unit norm.
   (b) **Orthogonality:**

$$\left\langle e^{ji\omega_0 t}, e^{jl\omega_0 t} \right\rangle = \begin{cases} 1, & i = l \\ 0, & i \neq l \end{cases}$$

   Therefore, for each pair of basis vectors, they are orthogonal.
   - **Conjugate of exp:** $\overline{(e^{j\theta})} = e^{-j\theta}$
6. **Conclusion:** Fourier series is a projection of a function onto the set of othonormal basis functions $\exp(jk\omega_0 t)$, where k is an integer.
   - **Optimal:** This projection is optimal as it minimizes the approximation error $\|x(t) - x^*(t)\|$, i.e.

$$\frac{1}{T}\int_0^T (x(t) - x^*(t))^2\,dt$$

   As the number of terms in the summation increases to infinity, the error goes to 0.

2.2 Gram-Schmidt and QR decomposition

2.2.1 What if the set of basis vectors is not orthonormal?

Derivation: Let $\{u^{(1)}, \ldots, u^{(d)}\}$ be a set of basis vectors for a subspace $S($ not necessarily orthonormal)

We can still use the orthogonality principle, i.e.,

$$e = x - x^* \perp S$$

Therefore,

$$\langle x - x^*, u^{(j)} \rangle = 0 \quad \forall j = 1, \dots, d$$

Also, $x^* \in S$ so x^*can be written as a linear combination of basis vectors, so $x^* = \sum_{i=1}^{d} \alpha_i u^{(i)}$

Need to find $\alpha_1, \dots, \alpha_d$ s.t.

$$\langle x - \sum_{i=1}^{d} \alpha_i u^{(i)}, u^{(j)} \rangle = 0 \quad \forall j = 1, \dots, d$$

$$\Rightarrow \langle x, u^{(j)} \rangle = \sum_{i=1}^{d} \alpha_i \langle u^{(i)}, u^{(j)} \rangle \quad \forall j = 1, \dots, d$$

$$\begin{bmatrix} \langle u^{(1)}, u^{(1)} \rangle & \langle u^{(2)}, u^{(1)} \rangle & \dots & \langle u^{(d)}, u^{(1)} \rangle \\ \langle u^{(1)}, u^{(2)} \rangle & \langle u^{(2)}, u^{(2)} \rangle & \dots & \langle u^{(d)}, u^{(2)} \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle u^{(1)}, u^{(d)} \rangle & \langle u^{(2)}, u^{(d)} \rangle & \dots & \langle u^{(d)}, u^{(d)} \rangle \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_d \end{bmatrix} = \begin{bmatrix} \langle x, u^{(1)} \rangle \\ \langle x, u^{(2)} \rangle \\ \vdots \\ \langle x, u^{(d)} \rangle \end{bmatrix}$$

Solve for $\alpha_1, \dots, \alpha_d$, Then, we get $x^* = \sum_{i=1}^{d} \alpha_i u^{(i)}$

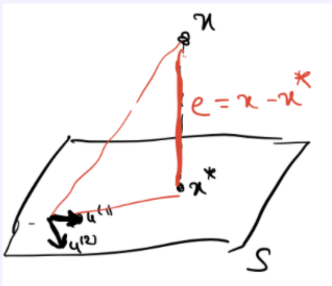

Figure 9: Not orthogonal, but similar to projection with orthonormal basis.

- **Note:** If $\{u^{(1)}, \dots, u^{(d)}\}$ is an orthonormal basis, then the matrix is the identity matrix, and we get $\alpha_j = \langle x, u^{(j)} \rangle$ as before.

Example: **Function approximation.** Let B be the set of basis functions that is not orthonormal:

$$\mathcal{B} = \{1, t, \dots, t^d\}$$

Let $x(t)$ be a function over $[0, 1]$.

- **1st Goal** Approximate $x(t)$ by $x^*(t) = \sum_{n=0}^{d} \alpha_n t^n$
- To find $\alpha_0, \alpha_1, \dots, \alpha_d$, need to solve the $Ax = b$.
- **2nd Goal:** Minimize the approximation error $\|x(t) - x^*(t)\|_2 = \left(\int_0^1 (x(t) - x^*(t))^2 dt \right)^{1/2}$

Recall: Taylor series expansion

$$x(t) \approx x(0) + x'(0)t + \frac{x''(0)}{2} t^2 + \dots$$

- Taylor series expansion is completely different from the projection method, and the reason is that Taylor series expansion is a local approximation.

2.2.2 Gram-Schmidt Procedure

Motivation: This is to get an orthonormal basis, so we can use the easier projection method.

Intuition: Another way to find the projection of x onto $S = \text{span}\{u^{(1)}, \dots, u^{(d)}\}$ is to first find an orthonormal basis of S, and then the projection problem becomes easier.

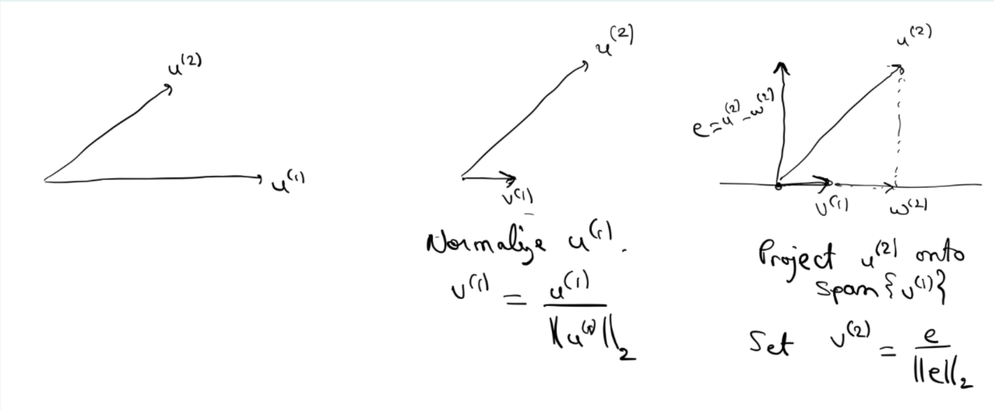

Figure 10: Gram-Schmidt Process for 2D.

1. Normalize $u^{(1)}$
2. Find the error vector by projecting $u^{(2)}$ onto the subspace $v^{(1)}$.
3. Normalize the error vector.
4. Now you have two vectors that form an orthonormal basis in 2D.

Definition: Turns any set of basis vectors of a subspace into an **orthonormal** set of basis vectors.

Process:

1. Normalize $u^{(1)}$ to get $v^{(1)}$:
$$v^{(1)} = \frac{u^{(1)}}{\|u^{(1)}\|_2}$$
2. (a) Project $u^{(2)}$ onto $S = \text{span}\{v^{(1)}\}$ to get:
$$w^{(2)} = \langle u^{(2)}, v^{(1)} \rangle v^{(1)}$$
   (b) Set:
$$v^{(2)} = \frac{u^{(2)} - w^{(2)}}{\|u^{(2)} - w^{(2)}\|_2}$$
3. Continue similarly:
   (a) Project $u^{(3)}$ onto $S = \text{span}\{v^{(1)}, v^{(2)}\}$ to get:
$$w^{(3)} = \langle u^{(3)}, v^{(1)} \rangle v^{(1)} + \langle u^{(3)}, v^{(2)} \rangle v^{(2)}$$
   (b) Set:
$$v^{(3)} = \frac{u^{(3)} - w^{(3)}}{\|u^{(3)} - w^{(3)}\|_2}$$
4. Continue this process for higher dimensions. Therefore, $\{v^{(1)}, \dots, v^{(d)}\}$ is an orthonormal basis for $\text{span}\{u^{(1)}, \dots, u^{(d)}\}$.

2.2.3 QR decomposition

Another way to see Gram-Schmidt procedure is through matrix multiplication.

Definition: Stack all $u^{(i)}$ vectors as columns of a matrix

$$\begin{bmatrix} u^{(1)} & \cdots & u^{(d)} \end{bmatrix} = QR$$

$$\begin{bmatrix} u^{(1)} & \cdots & u^{(d)} \end{bmatrix} = \begin{bmatrix} v^{(1)} & \cdots & v^{(d)} \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1d} \\ 0 & r_{22} & \cdots & r_{2d} \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & 0 & r_{dd} \end{bmatrix}$$

$$= \begin{bmatrix} r_{11}v^{(1)} & r_{12}v^{(1)} + r_{22}v^{(2)} & \cdots \end{bmatrix}$$

- Q: Orthonomral matrix (i.e., its columns are orthogonal to each other and have unit norm)
- R: Upper triangular.

Example:

$$\{1, t, t^2, \cdots, t^d\}$$

is *not an orthonormal basis*, which as an example is defined from $[0, 1]$

The L^2-norm for this example is given by

$$\|f\|_2 = \left(\int_0^1 f^2(t)\, dt \right)^{\frac{1}{2}}.$$

The inner product between two functions $f(t)$ and $g(t)$ is defined as:

$$\langle f, g \rangle = \int_0^1 f(t)g(t)\, dt.$$

1. Start with $u^{(1)} = 1$, which is equivalent to $v^{(1)}$ because it's unit norm.
2. For $u^{(2)}$, calculate the projection:

$$\omega^{(2)} = \text{Proj}_{\text{span}\{v^{(1)}\}} u^{(2)} = \langle u^{(2)}, v^{(1)} \rangle = \int_0^1 t \cdot 1\, dt = \frac{1}{2}..$$

   So, the projection of $u^{(2)}$ onto $u^{(1)}$ is:

$$\frac{1}{2} v^{(1)}.$$

3. Now subtract the projection from $u^{(2)}$ and normalize:

$$v^{(2)} = \frac{u^{(2)} - \omega^{(2)}}{\|u^{(2)} - \omega^{(2)}\|_2} = \frac{t - \frac{1}{2}}{\left(\int_0^1 \left(t - \frac{1}{2}\right)^2 dt \right)^{\frac{1}{2}}}.$$

2.3 Projection of a subspace defined by its orthogonal vectors

2.3.1 Subspace defined by its orthogonal vectors

Intuition:

1. So far, we have defined a subspace by its basis vectors:

$$S = \text{span}\{v^{(1)}, \ldots, v^{(d)}\}.$$

2. But, in many cases, we can define S in terms of the set of vectors that are orthogonal to it.

Definition: If $S = \left\{x \mid \left(a^{(i)}\right)^T x = 0,\ i = 1, \dots, m\right\}$, then the vectors $a^{(1)}, \dots, a^{(m)}$ are orthogonal to all vectors in S (i.e. the inner products are 0 for all vectors x with $a^{(i)}$). Therefore,

$$S^{\perp} = \text{span}\{a^{(1)}, \dots, a^{(m)}\} \tag{8}$$

2.3.2 Projection

Derivation:

1. Projecting a vector x onto a subspace S spanned by the vectors $\{a^{(1)}, \dots, a^{(m)}\}$. The projection x^* is given by:

$$x^* = \text{Proj}_S(x) = \arg\min_{y \in S} \|x - y\|_2$$

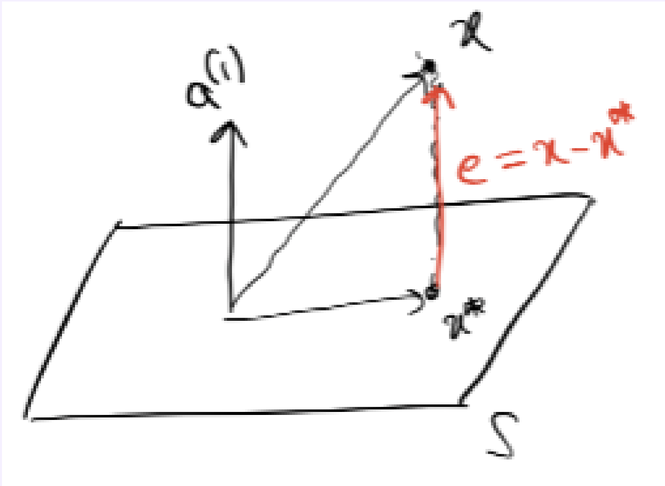

Figure 11: Projection onto a subspace defined by its orthogonal vectors

2. Using the orthogonality principle, the error $e = x - x^*$ must be orthogonal to the subspace S, i.e.,

$$e \perp S$$

   This implies that:

$$e \in \text{span}\{a^{(1)}, \dots, a^{(m)}\}$$

3. The error can be written as a linear combination of the basis vectors:

$$e = x - x^* = \sum_{i=1}^{m} \beta_i a^{(i)}$$

   We need to find the coefficients $\beta_1, \dots, \beta_m$.
4. Since $x^* \in S$, we have the condition:

$$\langle x^*, a^{(j)} \rangle = 0 \quad \forall j = 1, \dots, m$$

   which leads to the following equation:

$$(a^{(j)})^T x^* = 0 \quad \forall j = 1, \dots, m$$

5. Substituting $x^* = x - \sum_{i=1}^{m} \beta_i a^{(i)}$ into the above equation, we get:

$$(a^{(j)})^T \left(x - \sum_{i=1}^{m} \beta_i a^{(i)} \right) = 0 \quad \forall j$$

6. Expanding the terms using linearity in the first argument for inner products:

$$(a^{(j)})^T x = \sum_{i=1}^{m} \beta_i (a^{(j)})^T a^{(i)}$$

   This system of equations can be written in matrix form as:

$$\begin{bmatrix} (a^{(1)})^T a^{(1)} & \cdots & (a^{(1)})^T a^{(m)} \\ \vdots & \ddots & \vdots \\ (a^{(m)})^T a^{(1)} & \cdots & (a^{(m)})^T a^{(m)} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_m \end{bmatrix} = \begin{bmatrix} (a^{(1)})^T x \\ \vdots \\ (a^{(m)})^T x \end{bmatrix}$$

   We can solve this system of linear equations to obtain the values of $\beta_1, \ldots, \beta_m$.
7. Once we have the values of β_i, we can compute the projection as:

$$x^* = x - \sum_{i=1}^{m} \beta_i a^{(i)}$$

8. **Note:** If the set $\{a^{(i)}\}$ is orthonormal, the matrix on the left-hand side becomes the identity matrix I, and the coefficients simplify to:

$$\beta_j = (a^{(j)})^T x = \langle x, a^{(j)} \rangle$$

2.4 Projection onto Affine Spaces

2.4.1 Affine spaces

Definition: An affine space (or affine set) is a translation (or shift) of a subspace S.

Example: Consider a vector $x^{(0)}$ (not necessarily in S). The affine space $\mathcal{A}$ is defined as:

$$\mathcal{A} = \{u + x^{(0)} \mid u \in S\}$$

where $x^{(0)}$ is the shifting vector and S is the original subspace. This represents a shifted version of the subspace S.

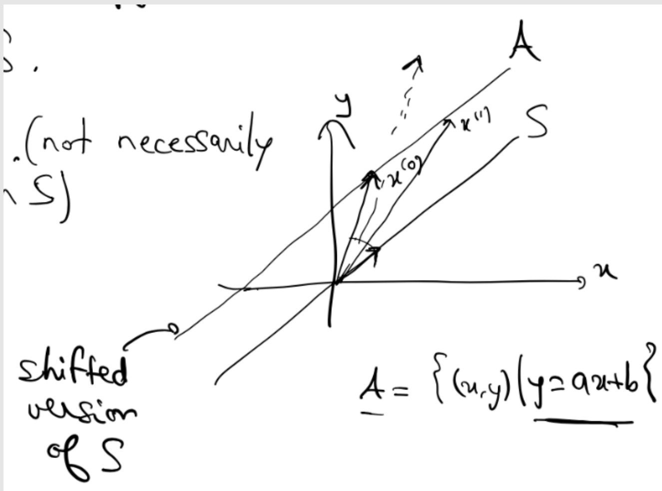

Figure 12: Affine space of a 2D space.

2.4.2 Projection of Affine space defined in terms of basis vectors of corresponding subspace

Derivation:

1. The affine space is described by:
$$\mathcal{A} = \left\{ x \mid x = \sum_{i=1}^{d} \alpha_i v^{(i)} + c \right\}$$
   - $\{v^{(1)}, \ldots, v^{(d)}\}$: Basis vectors of the subspace S
   - c: Vector (i.e. shift).
2. Using the orthogonality principle, we must have:
$$\langle x - x^*, v^{(j)} \rangle = 0 \quad \forall j = 1, \ldots, d$$
   where $x^* \in \mathcal{A}$. Therefore:
$$x^* = \sum_{i=1}^{d} \alpha_i v^{(i)} + c$$
3. This leads to the condition:
$$\left\langle x - \sum_{i=1}^{d} \alpha_i v^{(i)} - c, v^{(j)} \right\rangle = 0 \quad \forall j = 1, \ldots, d$$
4. Simplifying this expression using the linearity in first argument for inner product, we obtain:
$$\langle x - c, v^{(j)} \rangle = \sum_{i=1}^{d} \alpha_i \langle v^{(i)}, v^{(j)} \rangle \quad \forall j = 1, \ldots, d$$
5. To solve for $\alpha_1, \ldots, \alpha_d$, we set up the following system of linear equations in matrix form:
$$\begin{bmatrix} \langle v^{(1)}, v^{(1)} \rangle & \cdots & \langle v^{(1)}, v^{(d)} \rangle \\ \vdots & \ddots & \vdots \\ \langle v^{(d)}, v^{(1)} \rangle & \cdots & \langle v^{(d)}, v^{(d)} \rangle \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_d \end{bmatrix} = \begin{bmatrix} \langle x - c, v^{(1)} \rangle \\ \vdots \\ \langle x - c, v^{(d)} \rangle \end{bmatrix}$$
6. Solving this system gives us the values for $\alpha_1, \ldots, \alpha_d$. Finally, the projection x^* onto the affine space $\mathcal{A}$ is:
$$x^* = \sum_{i=1}^{d} \alpha_i v^{(i)} + c$$

2.4.3 Projection of Affine space defined in terms of orthogonal vectors to corresponding subspace

Derivation:

1. The affine set $\mathcal{A}$ is defined as:
$$\mathcal{A} = \left\{ x \mid \langle x, a^{(i)} \rangle = d_i, \ i = 1, \ldots, m \right\}$$
   - d_i: Scalars
   - $\{a^{(1)}, \ldots, a^{(m)}\}$: A set of vectors spanning the affine space. (Check why this is equivalent to the previous definition of an affine set.)
2. Since $x - x^*$ lies in the span of $\{a^{(1)}, \ldots, a^{(m)}\}$:
$$x - x^* = \sum_{i=1}^{m} \beta_i a^{(i)}$$
   where $\beta_1, \ldots, \beta_m$ are the coefficients to be determined.
3. Since $x^* \in \mathcal{A}$, we also have:
$$\langle x^*, a^{(j)} \rangle = d_j \quad \forall j = 1, \ldots, m$$

This implies the orthogonality condition for the projection:

$$\langle x - \sum_{i=1}^{m} \beta_i a^{(i)}, a^{(j)} \rangle = d_j \quad \forall j = 1, \ldots, m$$

4. Expanding the above expression using the linearity in first argument for inner product, we get:

$$\langle x, a^{(j)} \rangle - \sum_{i=1}^{m} \beta_i \langle a^{(i)}, a^{(j)} \rangle = d_j \quad \forall j = 1, \ldots, m$$

5. This leads to the system of linear equations:

$$\langle x, a^{(j)} \rangle - d_j = \sum_{i=1}^{m} \beta_i \langle a^{(i)}, a^{(j)} \rangle \quad \forall j$$

6. We now solve this system of linear equations for the coefficients $\beta_1, \ldots, \beta_m$. The system can be written in matrix form as:

$$\begin{bmatrix} \langle a^{(1)}, a^{(1)} \rangle & \cdots & \langle a^{(1)}, a^{(m)} \rangle \\ \vdots & \ddots & \vdots \\ \langle a^{(m)}, a^{(1)} \rangle & \cdots & \langle a^{(m)}, a^{(m)} \rangle \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_m \end{bmatrix} = \begin{bmatrix} \langle x, a^{(1)} \rangle - d_1 \\ \vdots \\ \langle x, a^{(m)} \rangle - d_m \end{bmatrix}$$

7. Solving this system gives the values for $\beta_1, \ldots, \beta_m$. Once the β_i values are known, the projection x^* is given by:

$$x^* = x - \sum_{i=1}^{m} \beta_i a^{(i)}$$

- WHAT WOULD BE THE FINAL PROJECTION

Example:

1. Consider the case where $m = 1$. The affine set $\mathcal{A}$ is defined as:

$$\mathcal{A} = \{x \mid a^T x = d\}$$

where a is a vector and d is a scalar.

2. To project x onto the affine subspace, we start by using the orthogonality condition:

$$\langle x, a \rangle - d = \beta \langle a, a \rangle$$

This ensures that the difference between x and its projection x^* lies in the direction of a.

3. Solving for β, we get:

$$\beta = \frac{\langle x, a \rangle - d}{\langle a, a \rangle} = \frac{a^T x - d}{\|a\|_2^2}$$

This provides the scalar β, which tells us how much of the vector a needs to be subtracted from x.

4. The projection x^* onto the affine subspace is then:

$$x^* = x - \beta a = x - \left(\frac{a^T x - d}{\|a\|_2^2} \right) a$$

This gives the final expression for the projection of x onto the affine set $\mathcal{A}$.

2.4.4 Eigen-composition

2.4.5 Singular value decomposition

2.5 Hyperplanes and half-spaces

2.6 Non-euclidean projection

3 Non-Euclidean Projection, Projection onto Affine Sets, Functions, Gradients and Hessians (Ch. 2.3-2.4)

3.1 Projection onto affine sets

3.2 Functions

3.3 Gradients

3.4 Hessians

4 Matrices, Range, Null Space, Eigenvalues, Eigenvectors, Matrix Diagonalization (Ch. 3.1-3.5)

4.1 Matrices

4.2 Range

4.3 Null Space

4.4 Eigenvalues and eigenvectors

4.5 Matrices diagonalization

5 Symmetric Matrices, Orthogonal Matrices, Spectral Decomposition, Positive Semidefinite Matrices, Ellipsoids (Ch. 4.1-4.4)

5.1 Symmetric matrices

5.2 Orthogonal matrices

5.3 Spectral decomposition

5.4 Positive semidefinite matrices

5.5 Ellipsoids

6 Singular Value Decomposition, Principal Component Analysis (Ch. 5.1, 5.3.2)

6.1 Singular value decomposition

6.2 Principle component analysis

7 Interpretations of SVD, Low-Rank Approximation (Ch. 5.2-5.3.1)

7.1 Interpretation of SVD

7.2 Low-rank approximation

8 Least Squares, Overdetermined and Underdetermined Linear Equations (Ch. 6.1-6.4)

8.1 Least squares

8.2 Overdetermined linear equation