

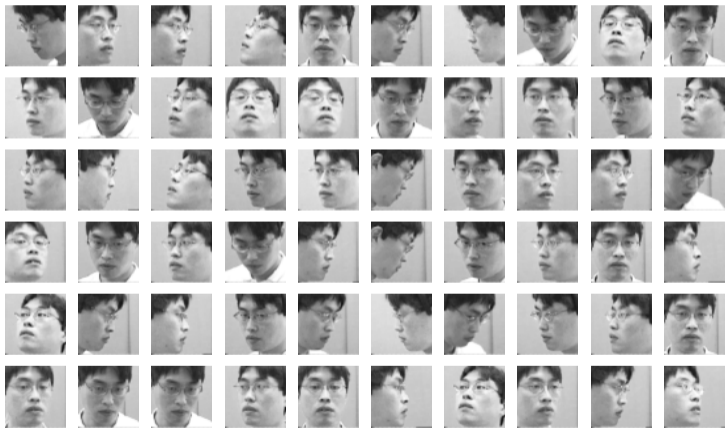
DSC 140B

Representation Learning

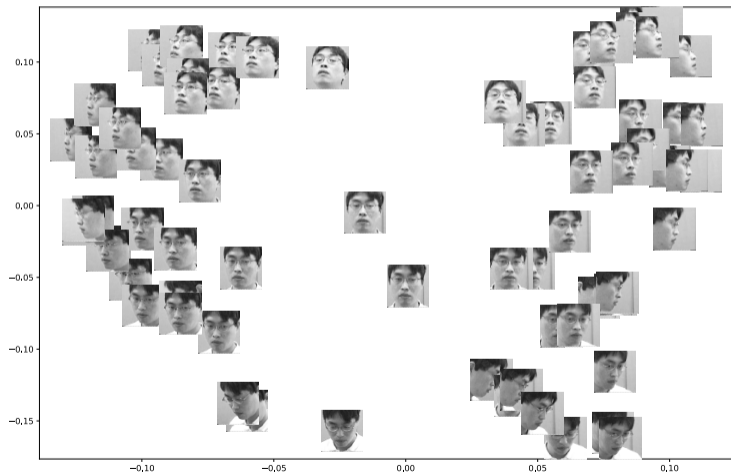
Lecture 02 | Part 1

Why Linear Algebra?

Last Time



Last Time



Dimensionality Reduction

- ▶ This is an example of **dimensionality reduction**:
 - ▶ Input: vectors in $\mathbb{R}^{10,000}$.
 - ▶ Output: vectors in \mathbb{R}^2 .
- ▶ The method which produced this result is called **Laplacian Eigenmaps**.
- ▶ How does it work?

A Preview of Laplacian Eigenmaps

To reduce dimensionality from d to d' :

1. Create an undirected **similarity graph** G
 - ▶ Each vector in \mathbb{R}^d becomes a node in the graph.
 - ▶ Make edge (u, v) if u and v are “close”
2. Form the **graph Laplacian matrix**, L :
 - ▶ Let A be the adjacency matrix, D be the degree matrix.
 - ▶ Define the graph Laplacian matrix, $L = D - A$.
3. Compute d' **eigenvectors** of L .
 - ▶ Each eigenvector gives one new feature.

Why eigenvectors?

- ▶ We will cover Laplacian Eigenmaps in much greater detail.
- ▶ For now: why do eigenvectors appear here?
 - ▶ What are eigenvectors?
 - ▶ How are they useful?
 - ▶ Why is linear algebra important in ML?

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Representation Learning

Lecture 02 | Part 2

Coordinate Vectors

Coordinate Vectors

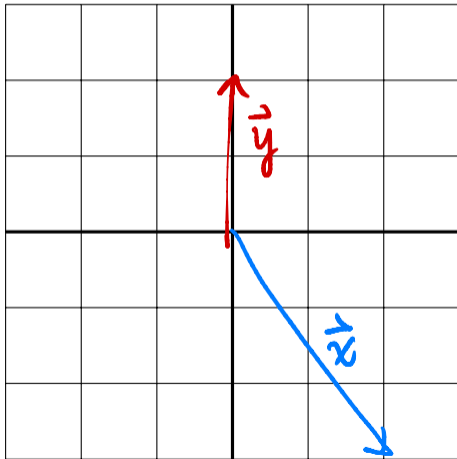
- ▶ We can write a vector $\vec{x} \in \mathbb{R}^d$ as a **coordinate vector**:

$$\vec{x} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix}$$

Example

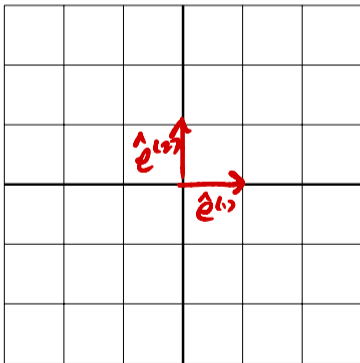
$$\vec{x} = \begin{pmatrix} 2 \\ -3 \end{pmatrix}$$

$$\vec{y} = \begin{pmatrix} 0 \\ 2 \end{pmatrix}$$



Standard Basis

- ▶ Writing a vector in coordinate form requires choosing a **basis**.
- ▶ The “default” is the **standard basis**: $\hat{e}^{(1)}, \dots, \hat{e}^{(d)}$.

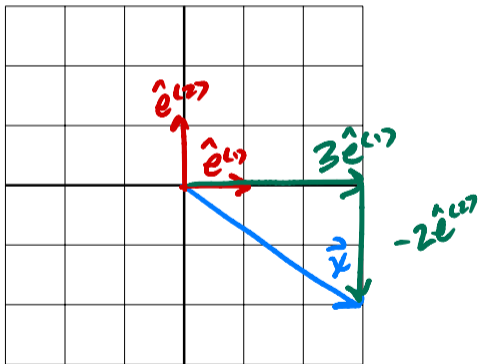


Standard Basis

- ▶ When we write $\vec{x} = (x_1, \dots, x_d)^T$, we mean that $\vec{x} = x_1 \hat{e}^{(1)} + x_2 \hat{e}^{(2)} + \dots + x_d \hat{e}^{(d)}$.

Example: $\vec{x} = (3, -2)^T$

$$\vec{x} = 3\hat{e}^{(1)} - 2\hat{e}^{(2)}$$



Standard Basis Coordinates

- ▶ In coordinate form:

$$\hat{e}^{(1)} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$\hat{e}^{(2)} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$\hat{e}^{(i)} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \\ 0 \end{pmatrix}$$

where the 1 appears in the i th place.

Exercise

Let $\vec{x} = (3, 7, 2, -5)^T$. What is $\vec{x} \cdot \hat{e}^{(4)}$?

-5

Recall: the Dot Product

- ▶ The **dot product** of \vec{u} and \vec{v} is defined as:

$$\vec{u} \cdot \vec{v} = \|\vec{u}\| \|\vec{v}\| \cos \theta$$

where θ is the angle between \vec{u} and \vec{v} .

- ▶ $\vec{u} \cdot \vec{v} = 0$ if and only if \vec{u} and \vec{v} are orthogonal

Dot Product (Coordinate Form)

- ▶ In terms of coordinate vectors:

$$\vec{u} \cdot \vec{v} = \vec{u}^T \vec{v}$$

$$= (u_1 \quad u_2 \quad \dots \quad u_d) \begin{pmatrix} v_1 \\ v_2 \\ \dots \\ v_d \end{pmatrix}$$

$$= u_1 v_1 + u_2 v_2 + \dots + u_d v_d$$

- ▶ This definition assumes the standard basis.

$$\vec{x} = 3\hat{e}^{(1)} + 7\hat{e}^{(2)} + 2\hat{e}^{(3)} - 5\hat{e}^{(4)}$$

Example

$$\begin{pmatrix} 3 \\ 7 \\ 2 \\ -5 \end{pmatrix} \cdot \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} = -5$$

$$\begin{aligned} \vec{x} \cdot \hat{e}^{(4)} &= (3\hat{e}^{(1)} + 7\hat{e}^{(2)} + 2\hat{e}^{(3)} - 5\hat{e}^{(4)}) \cdot \hat{e}^{(4)} \\ &= 3\hat{e}^{(1)} \cdot \hat{e}^{(4)} + 7\hat{e}^{(2)} \cdot \hat{e}^{(4)} + 2\hat{e}^{(3)} \cdot \hat{e}^{(4)} - 5\hat{e}^{(4)} \cdot \hat{e}^{(4)} \end{aligned}$$

What does ChatGPT say?



I will ask you a simple vector math question. Respond with the answer, and nothing else. Do not provide an explanation. Your answer should be a number.

Let $\vec{x} = (3, 7, 2, -5)^T$. What is $\vec{x} \cdot \hat{e}_4$?



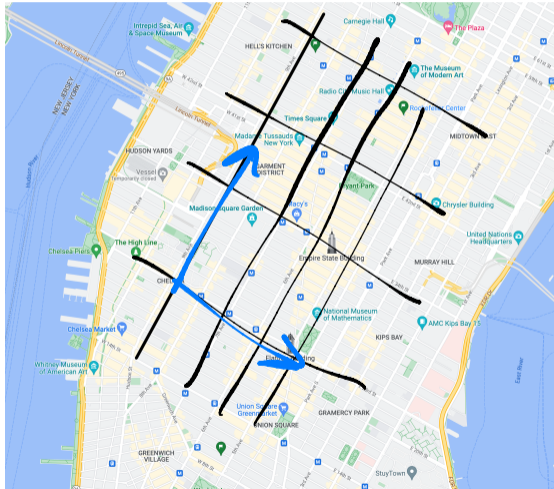
-5.



Other Bases

- ▶ The standard basis is not the **only** basis.
- ▶ Sometimes more convenient to use another.

Example

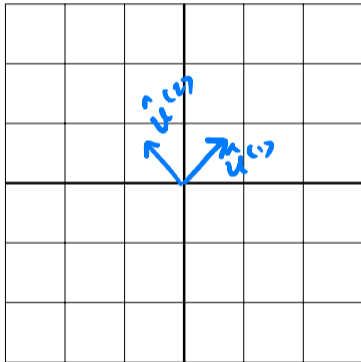


Orthonormal Bases

- ▶ **Orthonormal bases** are particularly nice.
- ▶ A set of vectors $\hat{u}^{(1)}, \dots, \hat{u}^{(d)}$ forms an **orthonormal basis** \mathcal{U} for R^d if:
 - ▶ They are mutually orthogonal: $\hat{u}^{(i)} \cdot \hat{u}^{(j)} = 0$.
 - ▶ They are all unit vectors: $\|\hat{u}^{(i)}\| = 1$.

Example

$$\hat{u}^{(1)} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \hat{u}^{(2)} = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix}$$



Coordinate Vectors

- ▶ A vector's coordinates depend on the basis used.
- ▶ If we are using the basis $\mathcal{U} = \{\hat{u}^{(1)}, \hat{u}^{(2)}\}$, then $[\vec{x}]_{\mathcal{U}} = (x_1, x_2)^T$ means $\vec{x} = x_1 \hat{u}^{(1)} + x_2 \hat{u}^{(2)}$.
- ▶ We will write $[\vec{x}]_{\mathcal{U}} = (x_1, \dots, x_d)^T$ to denote that the coordinates are with respect to the basis \mathcal{U} .

Exercise

Let $\hat{u}^{(1)} = \frac{1}{\sqrt{2}}(1, 1)^T$ and $\hat{u}^{(2)} = \frac{1}{\sqrt{2}}(-1, 1)^T$. Suppose $[\vec{x}]_{\mathcal{U}} = (3, -4)^T$. What is $\vec{x} \cdot \hat{u}^{(1)}$?

3

$$\vec{x} = 3\hat{u}^{(1)} - 4\hat{u}^{(2)}$$

$$\begin{aligned}\vec{x} \cdot \hat{u}^{(1)} &= (3\hat{u}^{(1)} - 4\hat{u}^{(2)}) \cdot \hat{u}^{(1)} \\ &= 3\hat{u}^{(1)} \cdot \hat{u}^{(1)} - 4\hat{u}^{(2)} \cdot \hat{u}^{(1)}\end{aligned}$$

What did ChatGPT say?



Let $\vec{u}_1 = \frac{1}{\sqrt{2}}(1,1)^T$ and $\vec{u}_2 = \frac{1}{\sqrt{2}}(-1,1)^T$. Suppose $\vec{x} \in \mathcal{U} = \text{span}\{\vec{u}_1, \vec{u}_2\}$. What is $\vec{x} \cdot \vec{u}_1$?



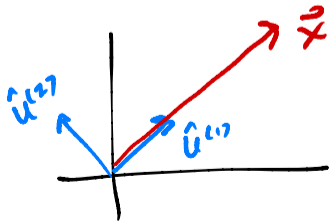
-0.5. (Note: This answer assumes that $\vec{x} \in \mathcal{U}$ represents the coordinate vector of \vec{x} with respect to the basis \mathcal{U} , and that \vec{u}_1 and \vec{u}_2 are orthonormal basis vectors.) The dot product between \vec{x} and \vec{u}_1 represents the projection of \vec{x} onto the direction of \vec{u}_1 . In this case, \vec{u}_1 is a unit vector, so the dot product gives the signed length of the projection of \vec{x} onto the direction of \vec{u}_1 . The result of -0.5 indicates that the projection of \vec{x} onto the direction of \vec{u}_1 is in the opposite direction of \vec{u}_1 , and the magnitude of the projection is 0.5 times the length of \vec{u}_1 . Note that the negative sign indicates that the projection is in the opposite direction of \vec{u}_1 . The dot product can be used to determine the alignment or misalignment of vectors, and is a useful tool in various applications, such as in physics, engineering, and computer graphics. It is important to understand how to compute and interpret dot products in the context of vector projections and geometric relationships between vectors. Therefore, the result of -0.5 indicates that \vec{x} is projected onto the opposite direction of \vec{u}_1 with a magnitude of 0.5 times the length of \vec{u}_1 . Keep practicing vector math problems to further strengthen your understanding of dot products and their applications!



$$\begin{aligned}
 2\sqrt{2} \cdot \frac{1}{\sqrt{2}}(1,1) &= \frac{2\sqrt{2}}{\sqrt{2}}(1,1) \\
 &= 2(1,1) \\
 &= (2,2)
 \end{aligned}$$

Exercise

Consider $\vec{x} = (2, 2)^T$ and let $\hat{u}^{(1)} = \frac{1}{\sqrt{2}}(1, 1)^T$ and $\hat{u}^{(2)} = \frac{1}{\sqrt{2}}(-1, 1)^T$. What is $[\vec{x}]_U$?



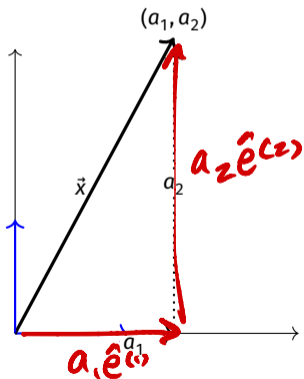
$$[\vec{x}]_U = (2\sqrt{2}, 0)^T$$

$$\vec{x} = 2\sqrt{2}\hat{u}^{(1)}$$

Change of Basis

- ▶ How do we compute the coordinates of a vector in a new basis, \mathcal{U} ?
- ▶ Some trigonometry is involved.
- ▶ **Key Fact:** $\vec{a} \cdot \vec{b} = \|\vec{a}\| \|\vec{b}\| \cos \theta$

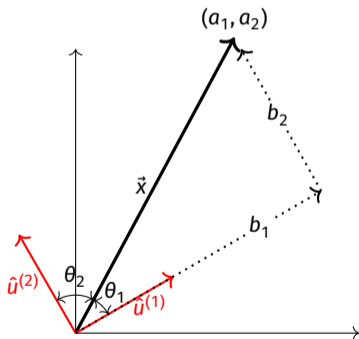
Change of Basis



^ What \rightarrow Vec

- ▶ Suppose we know $\vec{x} = (a_1, a_2)^T$ w.r.t. standard basis.
- ▶ Then $\vec{x} = a_1 \hat{e}^{(1)} + a_2 \hat{e}^{(2)}$

Change of Basis

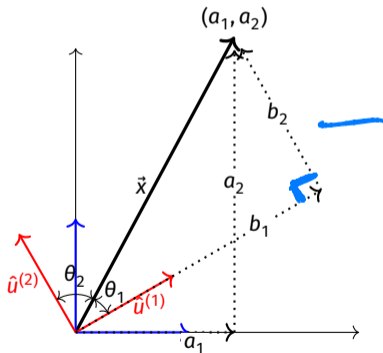
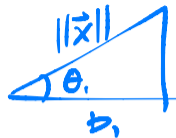


$$[\vec{x}]_{\mathcal{U}} = (b_1, b_2)^T$$

- ▶ Want to write:
 $\vec{x} = b_1 \hat{u}^{(1)} + b_2 \hat{u}^{(2)}$
- ▶ Need to find b_1 and b_2 .

Change of Basis

$$b_1 = \|\vec{x}\| \cos \theta_1$$



► **Exercise:** Solve for b_1 , writing the answer as a dot product.

► Hint: $\cos \theta =$ adjacent/hypotenuse

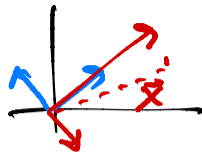
$$\vec{x} \cdot \hat{u}^{(1)} = \|\vec{x}\| \|\hat{u}^{(1)}\| \cos \theta_1$$
$$b_1 = \vec{x} \cdot \hat{u}^{(1)}$$

Change of Basis

- ▶ Let $\mathcal{U} = \{\hat{u}^{(1)}, \dots, \hat{u}^{(d)}\}$ be an orthonormal basis.
- ▶ The coordinates of \vec{x} w.r.t. \mathcal{U} are:

$$[\vec{x}]_{\mathcal{U}} = \begin{pmatrix} \vec{x} \cdot \hat{u}^{(1)} \\ \vec{x} \cdot \hat{u}^{(2)} \\ \vdots \\ \vec{x} \cdot \hat{u}^{(d)} \end{pmatrix}$$

$$[\vec{x}]_u = \begin{pmatrix} \vec{x} \cdot \hat{u}^{(1)} \\ \vec{x} \cdot \hat{u}^{(2)} \end{pmatrix} = \begin{pmatrix} 3/\sqrt{2} \\ -1/\sqrt{2} \end{pmatrix}$$



Exercise

Suppose $\vec{x} = (2, 1)^T$ and let $\hat{u}^{(1)} = \frac{1}{\sqrt{2}}(1, 1)^T$ and $\hat{u}^{(2)} = \frac{1}{\sqrt{2}}(-1, 1)^T$. What is $[\vec{x}]_u$?

$$\begin{aligned} \vec{x} \cdot \hat{u}^{(1)} &= \begin{pmatrix} 2 \\ 1 \end{pmatrix} \cdot \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \\ &= \frac{1}{\sqrt{2}} \begin{pmatrix} 2 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}} \times 3 = \frac{3}{\sqrt{2}} \end{aligned}$$

$$\begin{aligned} \vec{x} \cdot \hat{u}^{(2)} &= \begin{pmatrix} 2 \\ 1 \end{pmatrix} \cdot \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix} \\ &= \frac{1}{\sqrt{2}} \times -1 = \frac{-1}{\sqrt{2}} \end{aligned}$$

$$\hat{u}^{(1)} = 3\hat{e}^{(1)} - 2\hat{e}^{(2)} = \begin{pmatrix} 3 \\ -2 \end{pmatrix}$$

$$\hat{u}^{(2)} = \begin{pmatrix} -1 \\ 5 \end{pmatrix}$$

Exercise

Let $\vec{x} = (-1, 4)^T$ and suppose:

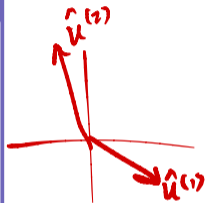
$$\vec{u}^{(1)} \cdot \hat{e}^{(1)} = 3$$

$$\vec{u}^{(2)} \cdot \hat{e}^{(1)} = -1$$

$$\vec{u}^{(1)} \cdot \hat{e}^{(2)} = -2$$

$$\vec{u}^{(2)} \cdot \hat{e}^{(2)} = 5$$

What is $[\vec{x}]_{\mathcal{U}}$?



$\hat{u}^{(1)}$ & $\hat{u}^{(2)}$ are not orthonormal

$$\vec{x} = \alpha \vec{u}^{(1)} + \beta \vec{u}^{(2)} \quad \begin{pmatrix} -1 \\ 4 \end{pmatrix} = \alpha \begin{pmatrix} 3 \\ -2 \end{pmatrix} + \beta \begin{pmatrix} -1 \\ 5 \end{pmatrix} \quad \begin{aligned} -1 &= 3\alpha - \beta \\ 4 &= -2\alpha + 5\beta \end{aligned}$$

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Representation Learning

Lecture 02 | Part 3

Functions of a Vector

Functions of a Vector

- ▶ In ML, we often work with functions of a vector:
 $\vec{f} : \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$.
- ▶ Example: a prediction function, $H(\vec{x})$.
- ▶ Functions of a vector can return:
 - ▶ a number: $f : \mathbb{R}^d \rightarrow \mathbb{R}^1$
 - ▶ a vector $\vec{f} : \mathbb{R}^d \rightarrow \mathbb{R}^{d'}$
 - ▶ something else?

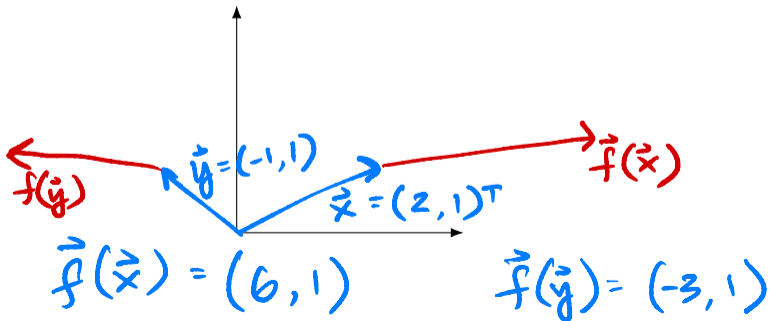
Transformations

- ▶ A **transformation** \vec{f} is a function that takes in a vector, and returns a vector *of the same dimensionality*.
- ▶ That is, $\vec{f} : \mathbb{R}^d \rightarrow \mathbb{R}^d$.

Visualizing Transformations

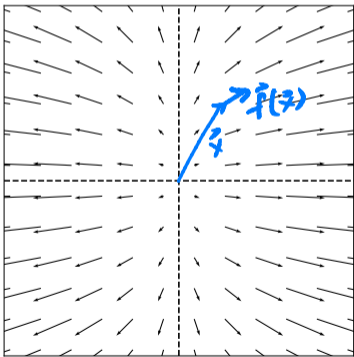
- ▶ A transformation is a **vector field**.
 - ▶ Assigns a vector to each point in space.
 - ▶ Example: $\vec{f}(\vec{x}) = (3x_1, x_2)^T$

$$\vec{f}(\vec{x})$$



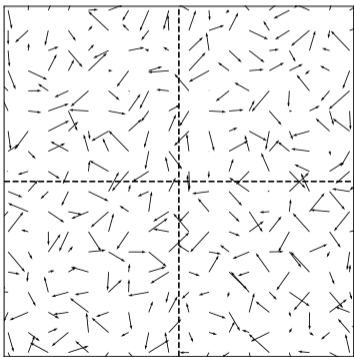
Example

► $\vec{f}(\vec{x}) = (3x_1, x_2)^T$



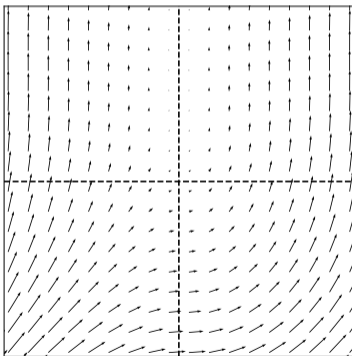
Arbitrary Transformations

- ▶ Arbitrary transformations can be quite complex.



Arbitrary Transformations

- ▶ Arbitrary transformations can be quite complex.



Linear Transformations

- ▶ Luckily, we often¹ work with simpler, **linear transformations**.
- ▶ A transformation f is linear if:

$$\vec{f}(\alpha\vec{x} + \beta\vec{y}) = \alpha\vec{f}(\vec{x}) + \beta\vec{f}(\vec{y})$$

¹Sometimes, just to make the math tractable!

Checking Linearity

- ▶ To check if a transformation is linear, use the definition.

$$f(\vec{z}) = (z_2, -z_1)^T \quad \vec{f}(\alpha \vec{x} + \beta \vec{y}) = \alpha f(\vec{x}) + \beta f(\vec{y})$$

- ▶ **Example:** $f(\vec{x}) = (x_2, -x_1)^T$

$$\text{Let } \vec{x} = (x_1, x_2)^T \quad \vec{y} = (y_1, y_2)^T.$$

Then:

$$\begin{aligned} f(\alpha \vec{x} + \beta \vec{y}) &= f\left(\alpha \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \beta \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}\right) \\ &= f\left(\begin{pmatrix} \alpha x_1 \\ \alpha x_2 \end{pmatrix} + \begin{pmatrix} \beta y_1 \\ \beta y_2 \end{pmatrix}\right) \end{aligned}$$

$$\begin{aligned} &= f\left(\begin{pmatrix} \alpha x_1 + \beta y_1 \\ \alpha x_2 + \beta y_2 \end{pmatrix}\right) \\ &= \begin{pmatrix} \alpha x_2 + \beta y_2 \\ -(\alpha x_1 + \beta y_1) \end{pmatrix} \\ &= \underbrace{\alpha \begin{pmatrix} x_2 \\ -x_1 \end{pmatrix}}_{f(\vec{x})} + \beta \underbrace{\begin{pmatrix} y_2 \\ -y_1 \end{pmatrix}}_{f(\vec{y})} \end{aligned}$$

z_1

z_2

z_2

$-z_1$

$$(x_1^2 + x_2, x_2 - x_1^3)$$

Exercise

Let $\vec{f}(\vec{x}) = (x_1 + 3, x_2)$. Is \vec{f} a linear transformation?

$$f\left(3\begin{pmatrix} 1 \\ 0 \end{pmatrix} + 4\begin{pmatrix} 1 \\ 1 \end{pmatrix}\right) \neq 3f\left(\begin{pmatrix} 1 \\ 0 \end{pmatrix}\right) + 4f\left(\begin{pmatrix} 1 \\ 1 \end{pmatrix}\right)$$

Implications of Linearity

- ▶ Suppose \vec{f} is a linear transformation. Then:

$$\begin{aligned}\vec{f}(\vec{x}) &= \vec{f}(x_1\hat{e}^{(1)} + x_2\hat{e}^{(2)}) \\ &= x_1\vec{f}(\hat{e}^{(1)}) + x_2\vec{f}(\hat{e}^{(2)})\end{aligned}$$

- ▶ I.e., \vec{f} is **totally determined** by what it does to the basis vectors.

The **Complexity** of Arbitrary Transformations

- ▶ Suppose f is an **arbitrary** transformation.
- ▶ I tell you $\vec{f}(\hat{e}^{(1)}) = (2, 1)^T$ and $\vec{f}(\hat{e}^{(2)}) = (-3, 0)^T$.
- ▶ I tell you $\vec{x} = (x_1, x_2)^T$.
- ▶ What is $\vec{f}(\vec{x})$?

The **Simplicity** of Linear Transformations

- ▶ Suppose f is a **linear** transformation.
- ▶ I tell you $\vec{f}(\hat{e}^{(1)}) = (2, 1)^T$ and $\vec{f}(\hat{e}^{(2)}) = (-3, 0)^T$.
- ▶ I tell you $\vec{x} = (x_1, x_2)^T$.
- ▶ What is $\vec{f}(\vec{x})$?

Exercise

- ▶ Suppose f is a **linear** transformation.
- ▶ I tell you $\vec{f}(\hat{e}^{(1)}) = (2, 1)^T$ and $\vec{f}(\hat{e}^{(2)}) = (-3, 0)^T$.
- ▶ I tell you $\vec{x} = (3, -4)^T$.
- ▶ What is $\vec{f}(\vec{x})$?

Key Fact

- ▶ Linear functions are determined **entirely** by what they do on the basis vectors.
- ▶ I.e., to tell you what f does, I only need to tell you $\vec{f}(\hat{e}^{(1)})$ and $\vec{f}(\hat{e}^{(2)})$.
- ▶ This makes the math easy!



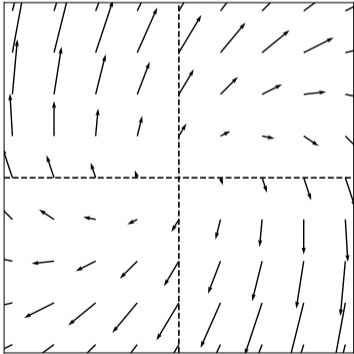
Arbitrary
Transformations

Linear
Transformations



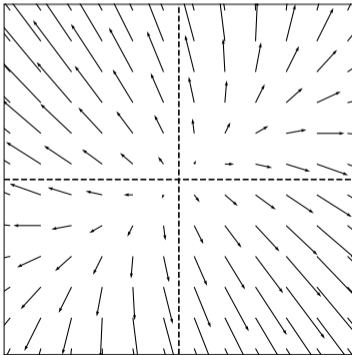
Example Linear Transformation

► $\vec{f}(\vec{x}) = (x_1 + 3x_2, -3x_1 + 5x_2)^T$



Another Example Linear Transformation

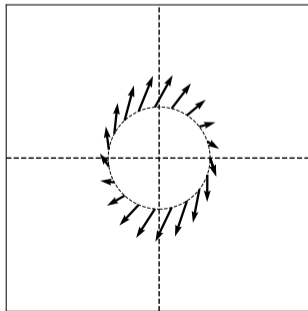
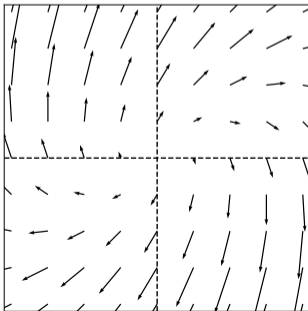
► $\vec{f}(\vec{x}) = (2x_1 - x_2, -x_1 + 3x_2)^T$

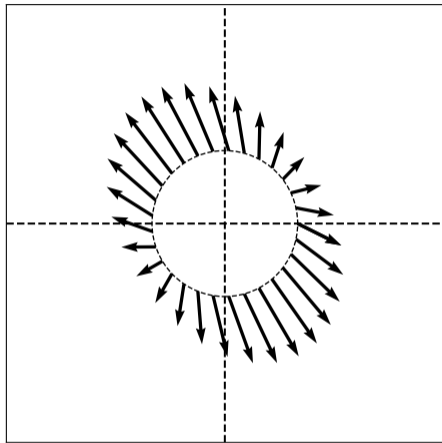
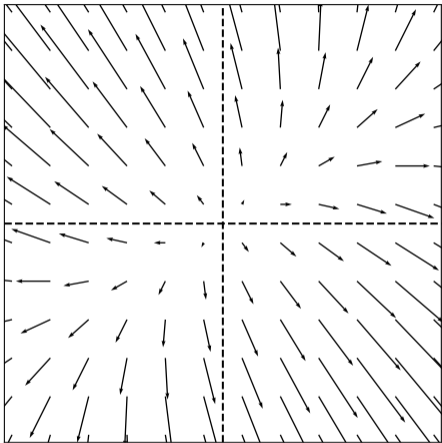


Note

- ▶ Because of linearity, along any given direction \vec{f} changes only in scale.

$$\vec{f}(\lambda \hat{x}) = \lambda \vec{f}(\hat{x})$$





Linear Transformations and Bases

- ▶ We have been writing transformations in coordinate form. For example:

$$\vec{f}(\vec{x}) = (x_1 + x_2, x_1 - x_2)^T$$

- ▶ To do so, we assumed the **standard basis**.
- ▶ If we use a different basis, the formula for \vec{f} changes.

Example

- ▶ Suppose that in the standard basis, $\vec{f}(\vec{x}) = (x_1 + x_2, x_1 - x_2)^T$.
- ▶ Let $\hat{u}^{(1)} = \frac{1}{\sqrt{2}}(1, 1)^T$ and $\hat{u}^{(2)} = \frac{1}{\sqrt{2}}(-1, 1)^T$.
- ▶ Write $[\vec{x}]_{\mathcal{U}} = (z_1, z_2)^T$.
- ▶ What is $[\vec{f}(\vec{x})]_{\mathcal{U}}$ in terms of z_1 and z_2 ?

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Representation Learning

Lecture 02 | Part 4

Matrices

Matrices?

- ▶ I thought this was supposed to be about linear algebra... Where are the matrices?

Matrices?

- ▶ I thought this was supposed to be about linear algebra... Where are the matrices?
- ▶ What is a matrix, anyways?

What is a matrix?

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$$

Recall: Linear Transformations

- ▶ A **transformation** $\vec{f}(\vec{x})$ is a function which takes a vector as input and returns a vector of the same dimensionality.
- ▶ A transformation f is **linear** if

$$\vec{f}(\alpha\vec{u} + \beta\vec{v}) = \alpha\vec{f}(\vec{u}) + \beta\vec{f}(\vec{v})$$

Recall: Linear Transformations

- ▶ A **key** property: to compute $\vec{f}(\vec{x})$, we only need to know what f does to basis vectors.
- ▶ Example:

$$\vec{x} = 3\hat{e}^{(1)} - 4\hat{e}^{(2)} = \begin{pmatrix} 3 \\ -4 \end{pmatrix}$$

$$\vec{f}(\hat{e}^{(1)}) = -\hat{e}^{(1)} + 3\hat{e}^{(2)}$$

$$\vec{f}(\hat{e}^{(2)}) = 2\hat{e}^{(1)}$$

$$\vec{f}(\vec{x}) =$$

Matrices

- ▶ f defined by what it does to basis vectors
- ▶ Place $\vec{f}(\hat{e}^{(1)})$, $\vec{f}(\hat{e}^{(2)})$, ... into a table as columns
- ▶ This is the **matrix** representing² f

$$\begin{aligned}\vec{f}(\hat{e}^{(1)}) &= -\hat{e}^{(1)} + 3\hat{e}^{(2)} = \begin{pmatrix} -1 \\ 3 \end{pmatrix} \\ \vec{f}(\hat{e}^{(2)}) &= 2\hat{e}^{(1)} = \begin{pmatrix} 2 \\ 0 \end{pmatrix}\end{aligned}\qquad \begin{pmatrix} -1 & 2 \\ 3 & 0 \end{pmatrix}$$

²with respect to the standard basis $\hat{e}^{(1)}, \hat{e}^{(2)}$

Example

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix}$$

$$\vec{f}(\hat{e}^{(1)}) = (1, 4, 7)^T$$

$$\vec{f}(\hat{e}^{(2)}) = (2, 5, 7)^T$$

$$\vec{f}(\hat{e}^{(3)}) = (3, 6, 9)^T$$

Main Idea

A square ($n \times n$) matrix can be interpreted as a compact representation of a linear transformation $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$.

What is matrix multiplication?

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} \begin{pmatrix} -2 \\ 1 \\ 3 \end{pmatrix} = \begin{pmatrix} \\ \\ \end{pmatrix}$$

A low-level definition

$$(A\vec{x})_i = \sum_{j=1}^n A_{ij}x_j$$

A low-level interpretation

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} \begin{pmatrix} -2 \\ 1 \\ 3 \end{pmatrix} = -2 \begin{pmatrix} 1 \\ 4 \\ 7 \end{pmatrix} + 1 \begin{pmatrix} 2 \\ 5 \\ 8 \end{pmatrix} + 3 \begin{pmatrix} 3 \\ 6 \\ 9 \end{pmatrix}$$

In general...

$$\begin{pmatrix} \uparrow & \uparrow & \uparrow \\ \vec{a}^{(1)} & \vec{a}^{(2)} & \vec{a}^{(3)} \\ \downarrow & \downarrow & \downarrow \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = x_1 \vec{a}^{(1)} + x_2 \vec{a}^{(2)} + x_3 \vec{a}^{(3)}$$

Matrix Multiplication

$$\vec{x} = x_1 \hat{e}^{(1)} + x_2 \hat{e}^{(2)} + x_3 \hat{e}^{(3)} = (x_1, x_2, x_3)^T$$
$$\vec{f}(\vec{x}) = x_1 \vec{f}(\hat{e}^{(1)}) + x_2 \vec{f}(\hat{e}^{(2)}) + x_3 \vec{f}(\hat{e}^{(3)})$$

$$A = \begin{pmatrix} \uparrow & \uparrow & \uparrow \\ \vec{f}(\hat{e}^{(1)}) & \vec{f}(\hat{e}^{(2)}) & \vec{f}(\hat{e}^{(3)}) \\ \downarrow & \downarrow & \downarrow \end{pmatrix}$$
$$A\vec{x} = \begin{pmatrix} \uparrow & \uparrow & \uparrow \\ \vec{f}(\hat{e}^{(1)}) & \vec{f}(\hat{e}^{(2)}) & \vec{f}(\hat{e}^{(3)}) \\ \downarrow & \downarrow & \downarrow \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$
$$= x_1 \vec{f}(\hat{e}^{(1)}) + x_2 \vec{f}(\hat{e}^{(2)}) + x_3 \vec{f}(\hat{e}^{(3)})$$

Matrix Multiplication

- ▶ Matrix A represents a linear transformation \vec{f}
 - ▶ With respect to the standard basis
 - ▶ If we use a different basis, the matrix changes!

- ▶ Matrix multiplication $A\vec{x}$ **evaluates** $\vec{f}(\vec{x})$

What are they, *really*?

- ▶ Matrices are sometimes just tables of numbers.
- ▶ But they often have a deeper meaning.

Main Idea

A square ($n \times n$) matrix can be interpreted as a compact representation of a linear transformation $\vec{f} : \mathbb{R}^n \rightarrow \mathbb{R}^n$.

What's more, if A represents \vec{f} , then $A\vec{x} = \vec{f}(\vec{x})$; that is, multiplying by A is the same as evaluating \vec{f} .

Example

$$\vec{x} = 3\hat{e}^{(1)} - 4\hat{e}^{(2)} = \begin{pmatrix} 3 \\ -4 \end{pmatrix}$$

$$A =$$

$$\vec{f}(\hat{e}^{(1)}) = -\hat{e}^{(1)} + 3\hat{e}^{(2)}$$

$$\vec{f}(\hat{e}^{(2)}) = 2\hat{e}^{(1)}$$

$$\vec{f}(\vec{x}) =$$

$$A\vec{x} =$$

Note

- ▶ All of this works because we assumed \vec{f} is **linear**.
- ▶ If it isn't, evaluating \vec{f} isn't so simple.

Note

- ▶ All of this works because we assumed \vec{f} is **linear**.
- ▶ If it isn't, evaluating \vec{f} isn't so simple.
- ▶ Linear algebra = simple!