DSC 140B Representation Learning

Lecture 04 | Part 1

**Matrices** 

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# **Matrices?**

- I thought this week 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  $\vec{f}$  is **linear** if

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

# **Recall: Linear Transformations**

• Key consequence of linearity: to compute  $\vec{f}(\vec{x})$ , only need to know what  $\vec{f}$  does to basis vectors.  $(\alpha \hat{e}^{(1)} + \beta \hat{e}^{(2)}) = 2 \hat{f}$ Example  $\vec{x} = 3\hat{e}^{(1)} - 4\hat{e}^{(2)} =$  $\vec{e}(\hat{e}^{(1)}) = -\hat{e}^{(1)} + 3\hat{e}^{(2)}$  $\vec{e}(\hat{e}^{(2)}) = 2\hat{e}^{(1)}$  $f = 0 - 4 + 0 = -11 e^{-0} + 9 e^{-0}$ 

# Matrices

- ▶ **Idea**: Since  $\vec{f}$  is defined by what it does to basis, place  $\vec{f}(\hat{e}^{(1)}), \vec{f}(\hat{e}^{(2)}), \dots$  into a table as columns
- This is the **matrix** representing<sup>1</sup>  $\vec{f}$

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





#### Exercise

Write the matrix representing  $\vec{f}$  with respect to the standard basis, given:

$$\vec{f}(\hat{e}^{(1)}) = (1, 4, 7)^T$$
  
 $\vec{f}(\hat{e}^{(2)}) = (2, 5, 7)^T$   
 $\vec{f}(\hat{e}^{(3)}) = (3, 6, 9)^T$ 



#### Main Idea

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

#### What is matrix multiplication?



#### A low-level definition





#### In general...

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

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

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

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

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

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

# **Matrix Multiplication**

Matrix A represents a linear transformation *f* With respect to the standard basis
 If we use a different basis, the matrix changes!

• Matrix multiplication  $A\vec{x}$  evaluates  $\vec{f}(\vec{x})$ 

AX = f(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  $\vec{f} : \mathbb{R}^n \to \mathbb{R}^n$ .

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  $\vec{f}$ .

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

Example  

$$A = \begin{pmatrix} -1 & 2 \\ 3 & 0 \end{pmatrix}$$

$$A\vec{x} = \begin{pmatrix} -1 & 2 \\ 3 & 0 \end{pmatrix} \begin{pmatrix} 3 \\ -4 \end{pmatrix}$$

$$= \begin{pmatrix} -1 & 2 \\ 3 & 0 \end{pmatrix} \begin{pmatrix} 3 \\ -4 \end{pmatrix}$$

#### 

#### 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!

## **Matrices in Other Bases**

The matrix of a linear transformation wrt the standard basis:

$$\begin{pmatrix} \uparrow & \uparrow & \uparrow \\ \vec{f}(\hat{e}^{(1)}) & \vec{f}(\hat{e}^{(2)}) & \cdots & \vec{f}(\hat{e}^{(d)}) \\ \downarrow & \downarrow & \downarrow & \downarrow \end{pmatrix}$$

• With respect to basis  $\mathcal{U}$ :

$$\begin{pmatrix} \uparrow & \uparrow & \uparrow \\ [\vec{f}(\hat{u}^{(1)})]_{\mathcal{U}} & [\vec{f}(\hat{u}^{(2)})]_{\mathcal{U}} & \cdots & [\vec{f}(\hat{u}^{(d)})]_{\mathcal{U}} \\ \downarrow & \downarrow & \downarrow & \downarrow \end{pmatrix}$$

# **Matrices in Other Bases**

• Consider the transformation  $\vec{f}$  which "mirrors" a vector over the line of 45°.







DSC 140B Representation Learning

Lecture 04 | Part 2

**The Spectral Theorem** 

# Eigenvectors

Let A be an n × n matrix. An eigenvector of A with eigenvalue λ is a nonzero vector v such that Av = λv.

# Eigenvectors (of Linear Transformations)

Let  $\vec{f}$  be a linear transformation. An **eigenvector** of  $\vec{f}$  with **eigenvalue**  $\lambda$  is a nonzero vector  $\vec{v}$  such that  $f(\vec{v}) = \lambda \vec{v}$ .

# **Geometric Interpretation**

• When  $\vec{f}$  is applied to one of its eigenvectors,  $\vec{f}$  simply scales it.

Possibly by a negative amount.



## **Symmetric Matrices**

► Recall: a matrix A is **symmetric** if  $A^T = A$ .

# The Spectral Theorem<sup>2</sup>

Theorem: Let A be an n × n symmetric matrix. Then there exist n eigenvectors of A which are all mutually orthogonal.

<sup>2</sup>for symmetric matrices

# What?

- What does the spectral theorem mean?
- ► What is an eigenvector, really?
- Why are they useful?

#### **Example Linear Transformation**



$$A = \begin{pmatrix} 5 & 5 \\ -10 & 12 \end{pmatrix}$$

#### **Example Linear Transformation**



$$A = \begin{pmatrix} -2 & -1 \\ -5 & 3 \end{pmatrix}$$

#### Example Symmetric Linear Transformation



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

#### Example Symmetric Linear Transformation



$$A = \begin{pmatrix} 5 & 0 \\ 0 & 2 \end{pmatrix}$$



 Symmetric linear transformations have axes of symmetry.



The axes of symmetry are **orthogonal** to one another.



The action of *f* along an axis of symmetry is simply to scale its input.



The size of this scaling can be different for each axis.

#### Main Idea

The **eigenvectors** of a symmetric linear transformation (matrix) are its axes of symmetry. The **eigenvalues** describe how much each axis of symmetry is scaled.

#### Exercise

Consider the linear transformation which mirrors its input over the line of 45°. Give two orthogonal eigenvector of the transformation.





 $A = \begin{pmatrix} 5 & -0.1 \\ -0.1 & 2 \end{pmatrix}$ 



 $A = \begin{pmatrix} 5 & -0.2 \\ -0.2 & 2 \end{pmatrix}$ 



$$A = \begin{pmatrix} 5 & -0.3 \\ -0.3 & 2 \end{pmatrix}$$



$$A = \begin{pmatrix} 5 & -0.4 \\ -0.4 & 2 \end{pmatrix}$$



$$A = \begin{pmatrix} 5 & -0.5 \\ -0.5 & 2 \end{pmatrix}$$



$$A = \begin{pmatrix} 5 & -0.6 \\ -0.6 & 2 \end{pmatrix}$$



 $A = \begin{pmatrix} 5 & -0.7 \\ -0.7 & 2 \end{pmatrix}$ 



$$A = \begin{pmatrix} 5 & -0.8 \\ -0.8 & 2 \end{pmatrix}$$



$$A = \begin{pmatrix} 5 & -0.9 \\ -0.9 & 2 \end{pmatrix}$$

# **The Spectral Theorem<sup>3</sup>**

Theorem: Let A be an n × n symmetric matrix. Then there exist n eigenvectors of A which are all mutually orthogonal.



<sup>3</sup>for symmetric matrices

#### What about total symmetry?



Every vector is an eigenvector.

$$A = \begin{pmatrix} 3 & 0 \\ 0 & 3 \end{pmatrix}$$

# **Computing Eigenvectors**

