# Linear Transformations Geometric Algorithms Lecture 7

CAS CS 132

# **Recap Problem**

Find three vectors  $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3$  in  $\mathbb{R}^3$  such that » every pair of vectors (i.e.,  $\{v_1, v_2\}$ ,  $\{v_1, v_3\}$ , {v<sub>2</sub>, v<sub>3</sub>}) are linearly independent »  $\{v_1, v_2, v_3\}$  is linearly dependent



# **Demo: Geometry of Linear Dependence**





# **Objectives**

- 1. Introduce Matrix Transformations
- 2. Define Linear Transformations
- 3. Start looking at the Geometry of Linear Transformations
- 4. See an Non-Geometric Application

# Keywords

Transformations Domain, Codomain Image, Range Matrix Transformations Linear Transformations Additivity, Homogeneity Dilation, Contraction, Shearing, Rotation

# Introduction

# **Recall: Spans (with Matrices)**

set of all possible linear combinations of them.

# Definition. The span of a set of vectors is the

## $span\{a_1, a_2, ..., a_n\} = \{ [a_1 \ a_2 \ ... \ a_n] \mathbf{v} : \mathbf{v} \in \mathbb{R}^n \}$

# **Recall: Spans (with Matrices)**

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# Definition. The span of a set of vectors is the

- $span\{a_1, a_2, ..., a_n\} = \{ [a_1 \ a_2 \ ... \ a_n] \ v : v \in \mathbb{R}^n \}$ 
  - The span of the columns of a matrix A is the set of of vectors resulting from multiplying A by any vector.

# **Matrices as Transformations**

## Matrices allow us to transform vectors. The transformed vector lies in the span of its columns.



map a vector x to the vector Av

# **Example (Algebraic)**







# **Example (Algebraic)**



# Example (Geometric)









### !!Important!!

# The vector may be a different size after translation.

## **Recall: Matrix-Vector Multiplication and Dimension**

matrix-vector multiplication only works if the number of columns of the matrix matches the dimension of the vector



 $(m \times n)$ 



# **Motivating Questions**

What kind of functions can we define in this way?

How do we interpret what the transformation does to a set of vectors?

How does this relate back to matrix equations?

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# **A New Interpretation of the Matrix Equation**



### 

- is there a vector which A transforms into b?
- find a vector which A
  transforms into b



# Question (Conceptual)

### Suppose a matrix transforms a vector according to the following picture. What is the size of the matrix?



## Answer: $3 \times 1$





### Mapping between the same space can be viewed as a way of moving around points.



-10.0

# Transformations

vector  $T(\mathbf{v})$  in  $\mathbb{R}^m$ .

### **Definition.** A *transformation* T from $\mathbb{R}^n$ to $\mathbb{R}^m$ is a function which maps every vector v in $\mathbb{R}^n$ to a

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 $T: \mathbb{R}^n \to \mathbb{R}^m$ 

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 $R' \rightarrow R^3$ 



### **Definition.** A *transformation* T from $\mathbb{R}^n$ to $\mathbb{R}^m$ is a function which maps every vector v in $\mathbb{R}^n$ to a vector $T(\mathbf{v})$ in $\mathbb{R}^m$ . $A_X = b$



### It's just a function, like in calculus.

**Definition.** For a vector  $\mathbf{v}$ , the *image* of  $\mathbf{v}$  under the transformation T is the vector  $T(\mathbf{v})$ .

the transformation T is the vector  $T(\mathbf{v})$ .

Definition. The range of a transformation  $T: \mathbb{R}^n \to \mathbb{R}^m$  is the set of all possible images under T.

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- Definition. For a vector v, the *image* of v under

 $\operatorname{ran}(T) = \{T(\mathbf{v}) : v \in \mathbb{R}^n\}$ AMain

image of v under  $T \equiv \text{output of } T$  applied to v range of  $T \equiv all possible output of T$ 

# **Codomain and Range**

# The codomain and range of a transformation may or may not be the same.



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# Matrix Transformations

## **Transformation of a Matrix**
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#### The transformation of $a (m \times n)$ matrix A is the function $T: \mathbb{R}^n \to \mathbb{R}^m$ such that

#### $T(\mathbf{v}) = A\mathbf{v}$

#### **Transformation of a Matrix**

#### The transformation of a $(m \times n)$ matrix A is the function $T: \mathbb{R}^n \to \mathbb{R}^m$ such that

#### Tancformation is function



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#### **Transformation of a Matrix**

#### The transformation of $a (m \times n)$ matrix A is the function $T: \mathbb{R}^n \to \mathbb{R}^m$ such that

given v, return A multiplied by v  $\mathbf{e.g.} \quad T(\mathbf{v}) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \mathbf{v} \qquad ---\left( \begin{bmatrix} 1 & 1 \\ 1 \end{bmatrix} \right) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0$ ▲ \_

#### $T(\mathbf{v}) = A\mathbf{v}$

The span of the columns of a matrix A is the set of all possible *images* under A.

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 $\left[ \begin{array}{c} \left( \overrightarrow{v} \right) = \left[ \overrightarrow{q} \right] & \overrightarrow{q} \\ \overrightarrow{q} & \overrightarrow{q} \\ \end{array} \right] \xrightarrow{\gamma}$ 



#### The span of the columns of a matrix A is the set of all possible *images* under A.

$$span\{a_1, a_2, ..., a_n\}$$

The transformation of a vector v under the matrix A always lies in the span of its columns.

 $= ran([a_1 \ a_2 \ \dots \ a_n])$ 

## Example $f(x) = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \\ 1 & 3 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix} = \begin{bmatrix} 2 \\$





# $2\begin{bmatrix}1\\0\\1\end{bmatrix} + (-1)\begin{bmatrix}1\\1\\3\end{bmatrix} + 0\begin{bmatrix}1\\2\\0\end{bmatrix} =$

exercise

### **Motivating Questions**

What kind of functions can we define in this way?

How do we interpret what the transformation does to a set of vectors?



#### How does this relate back to matrix equations?

## Geometry of Matrix Transformations



## Matrix transformations change the "shape" of a set of set of vectors (points).

#### **Example: Dilation**





#### **Example: Dilation**







#### **Example: Contraction**





#### **Example: Contraction**



#### if $0 \le r \le 1$ , then the transformation pulls points towards the origin.



#### **Example: Shearing**





#### **Example: Shearing**



## $\begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{vmatrix} x_1 \\ x_2 \end{vmatrix} = \begin{bmatrix} x_1 + x_2 \\ x_2 \end{bmatrix}$



#### Imagine shearing like with rocks or metal.



#### Question



Draw how this matrix transforms points. What kind of transformation does it represent?





#### **Answer: Reflection**





### **Motivating Questions**

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## Linear Transformations

## **Recall: Algebraic Properties**

Matrix-vector multiplication satisfies the following two properties:

 $2 \quad A(c\mathbf{v}) = c(A\mathbf{v})$ 

## 1. $A(\mathbf{u} + \mathbf{v}) = A\mathbf{u} + A\mathbf{v}$ (additivity) (homogeneity)

#### Question

#### Verify the following.

# $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} 2 \\ 3 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} \end{pmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} 2 \begin{bmatrix} 2 \\ 3 \end{bmatrix} \end{pmatrix} = 2 \begin{pmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \end{bmatrix} \end{pmatrix}$

# Answer $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} 2 \\ 3 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} \end{pmatrix} =$

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

 $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} =$ 



# $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 5 \\ 3 \end{bmatrix}$ $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} 2 & 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \end{bmatrix} = \begin{bmatrix}$

#### **Linear Transformations**

**Definition.** A transformation  $T: \mathbb{R}^m \to \mathbb{R}^n$  is *linear* if it satisfies the following two properties.

1. T(u + v) = T(u) + T(v)2.  $T(c\mathbf{v}) = cT(\mathbf{v})$ 

(additivity) (homogeneity)

#### **Linear Transformations**

**Definition.** A transformation  $T: \mathbb{R}^m \to \mathbb{R}^n$  is linear if it satisfies the following two properties.

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Matrix transformations are linear transformations.

(additivity) (homogeneity)







#### **Example: Zero**





# Example: Rotation We'll see this on Thursday, but we can reason about it geometrically for now.





#### **Example: Indefinite I**

## T(f) =

 $T(f+g) = \int (f+g)(x)dx = \int f(x) + g(x)dx$  $T(cf) = \int (cf)(x)dx = \int dx$ the same goes

**ntegrals**  
= 
$$\int f(x) dx$$
 Disclaimers  
Advanced  
Material  
 $f(x) dx = \int f(x) dx + \int g(x) dx = T(f) + T(g)$   
 $cf(x) dx = c \int f(x) dx = cT(f)$   
for derivatives

(how are functions vectors???)



## **Example: Expectation**



#### This is exactly <u>linearity</u> of expectation.

## $T(X) = \mathbb{E}[X]$

#### Disclaimer: Advanced Material

#### (how are random variables vectors???)

## Non-Example: Squares



 $T(x) = x^2$ Note that  $T: \mathbb{R}^1 \to \mathbb{R}^1$ 

## Non-Example: Translation

**X** +





#### Question

# Show that $T(\mathbf{v}) = 5\mathbf{v}$ is a linear transformation.

Show that  $T(x) = e^x$  is not a linear transformation.





## $T(\mathbf{v}) = 5\mathbf{v}$




### $T(x) = e^x$

## Properties of Linear Transformations

## T(0) = ???

## T(0) = 0

#### The zero vector is *tixed* It can't move anywhere.

## T(0) = 0

#### The zero vector is *fixed* by linear transformations.

# T(0) = 0Note: These may be different dimensions!

It can't move anywhere.

#### The zero vector is *fixed* by linear transformations.

#### Verification

#### any matrix transformation:

rotation:

translation (non-example):

We can combine our linearity conditions:

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We can combine our linearity conditions:  $T(a\mathbf{v} + b\mathbf{u})$ (additivity)  $= T(a\mathbf{v}) + T(b\mathbf{u})$ 

We can combine our linearity conditions:  $T(a\mathbf{v} + b\mathbf{u})$ (additivity)  $= T(a\mathbf{v}) + T(b\mathbf{u})$ (homogeneity for each term)  $= aT(\mathbf{v}) + bT(\mathbf{u})$ 

if and only if for any vectors  $\mathbf{u}$  and  $\mathbf{v}$  in  $\mathbb{R}^m$ and any real numbers a and b,

# **Theorem.** A transformation $T: \mathbb{R}^m \to \mathbb{R}^n$ is linear

**Theorem.** A transformation  $T: \mathbb{R}^m \to \mathbb{R}^n$  is linear if and only if for any vectors  $\mathbf{u}$  and  $\mathbf{v}$  in  $\mathbb{R}^m$ and any real numbers a and b,

It's often easiest to show this single condition.

#### **Linear Combinations**

combination.

#### $T(a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \dots + a_n\mathbf{v}_n) = a_1T(\mathbf{v}_1) + a_2T(\mathbf{v}_2) + \dots + a_nT(\mathbf{v}_n)$

#### We can generalize this condition to any linear



#### Linear Combinations

$$T\left(\sum_{i=1}^{n} a_i \mathbf{v}_i\right)$$

## We can generalize this combination.



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#### Linear Combinations

$$T\left(\sum_{i=1}^{n} a_i \mathbf{v}_i\right)$$

## We can generalize this combination.

#### This is the most useful form.



#### We can generalize this condition to any linear

## **Application: Unit Cost Matrices**

Suppose you have a company that produces two products B and C.

(0).

#### For each product you know how much you spend per dollar on material (M), labor (L) and overhead

B C [.45 .40] M [.25 .30] L **.15** .15 **0** 



 B
 C

 .45
 .40
 M

 .25
 .30
 L

 .15
 .15
 0

How much are you spending, in total, on each cost, given that you made  $s_1$  dollars worth of B and  $s_2$  dollars worth of C?

 B
 C

 .45
 .40
 M

 .25
 .30
 L

 .15
 .15
 0

How much are you spending, in total, on each cost, given that you made  $s_1$  dollars worth of B and  $s_2$  dollars worth of C?

Solution. Use matrix transformations.

#### As a Matrix Transformation

# $T(\mathbf{x}) = \begin{bmatrix} 0.45 & 0.40 \\ 0.25 & 0.30 \\ 0.15 & 0.25 \end{bmatrix} \mathbf{x}$



 $T(\mathbf{x}) = \begin{bmatrix} 0.45 & 0.40 \\ 0.25 & 0.30 \\ 0.15 & 0.25 \end{bmatrix} \mathbf{x}$ 

# $T\left(\begin{bmatrix}s_1\\s_2\end{bmatrix}\right) = s_1\begin{bmatrix}0.45\\0.25\\0.15\end{bmatrix} + s_2\begin{bmatrix}0.40\\0.30\\0.15\end{bmatrix} = \begin{bmatrix}\text{total material cost}\\\text{total labor cost}\\\text{total overhead cost}\end{bmatrix}$



products and a complex collection of costs.

- $T(\mathbf{x}) = \begin{bmatrix} 0.45 & 0.40 \\ 0.25 & 0.30 \\ 0.15 & 0.25 \end{bmatrix} \mathbf{x}$
- $T\left(\begin{bmatrix}s_1\\s_2\end{bmatrix}\right) = s_1\begin{bmatrix}0.45\\0.25\\0.15\end{bmatrix} + s_2\begin{bmatrix}0.40\\0.30\\0.15\end{bmatrix} = \begin{bmatrix}\text{total material cost}\\\text{total labor cost}\\\text{total overhead cost}\end{bmatrix}$
- This is much more valuable if we had a lot of

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## transformations (which we will see, means via

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multiply every time.

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#### We can write down a *single* matrix which we can

We can manipulate data (linearly) via linear matrix multiplication).

multiply every time.

This is a very powerful algorithmic idea.

# transformations (which we will see, means via

#### We can write down a *single* matrix which we can

#### Summary

#### Matrices can be viewed as linear transformations.

Matrix transformations change the "shape" of points sets.

to linear combinations.

#### Linear transformations behave well with respect