

Calculus Intuition for Machine Learning 2025

Lecture 1: Linear Algebra

Tim van Erven

- ▶ This lecture covers **crucial foundations** for all machine learning techniques! (revisit these slides during the next weeks when needed)

Poll

This lecture will be about **matrices** and **vectors**.

Q. Who has seen matrices and vectors before?

(Except for [3Blue1Brown video](#).)

Outline

Intro: machine learning concepts for linear regression

Vectors: addition, scaling, length

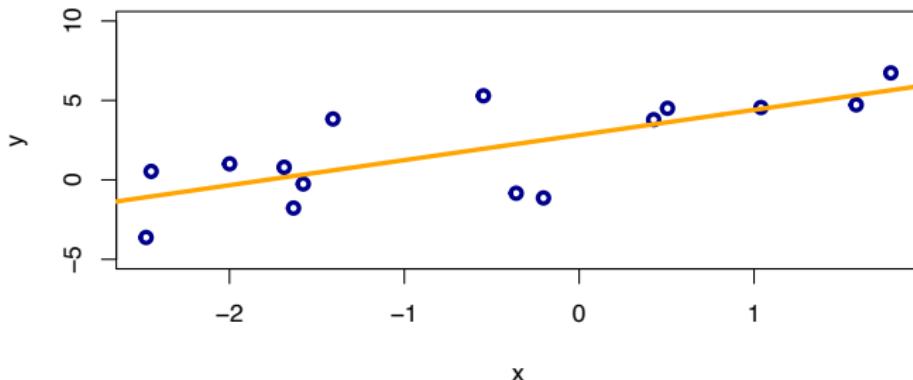
Matrices: addition, scaling, transpose

Vectors and matrices: multiplication

Identity matrix and matrix inverse

Reading the Least Squares Formula

Linear Regression with 1 Feature



$n = 15$ data points:

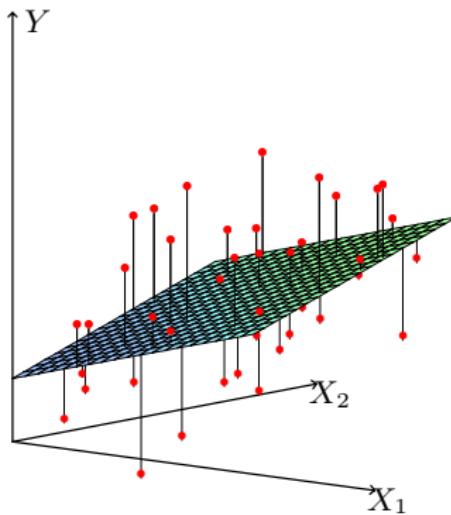
$$\begin{pmatrix} y_1 \\ x_1 \end{pmatrix}, \begin{pmatrix} y_2 \\ x_2 \end{pmatrix}, \dots, \begin{pmatrix} y_n \\ x_n \end{pmatrix}$$

Fit a line to the data: $f(x) = \theta_0 + x\theta_1$

- ▶ Can be used to predict y for a new unseen x
- ▶ Example: predict weight y from height x

Linear Regression with Multiple Features

Image from Hastie, Tibshirani,
and Friedman (2009)

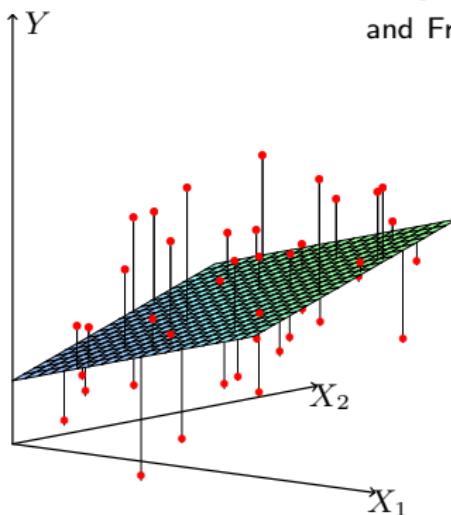


$$f(x_1, \dots, x_d) = \theta_0 + x_1\theta_1 + \dots + x_d\theta_d$$

- ▶ More information: d features instead of 1
- ▶ Example: predict weight y from $x = (\text{height}, \text{age})$

Linear Regression with Multiple Features

Image from Hastie, Tibshirani, and Friedman (2009)



$$f(x_1, \dots, x_d) = \theta_0 + x_1\theta_1 + \dots + x_d\theta_d$$

Each x_i with d features is a **vector**:

$$x_1 = \begin{pmatrix} x_{1,1} \\ \vdots \\ x_{1,d} \end{pmatrix}, \quad x_2 = \begin{pmatrix} x_{2,1} \\ \vdots \\ x_{2,d} \end{pmatrix}, \quad \dots, \quad x_n = \begin{pmatrix} x_{n,1} \\ \vdots \\ x_{n,d} \end{pmatrix}$$

How to represent this on a computer

Put all the responses together in one **vector** y :

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$

How to represent this on a computer

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- ▶ How can we collect the feature vectors x_1, \dots, x_n , which are already vectors?

How to represent this on a computer

Put all the responses together in one **vector** y :

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$

- ▶ How can we collect the feature vectors x_1, \dots, x_n , which are already vectors?

Put all the feature vectors together in one $n \times d$ **matrix**¹ X :

$$X = \begin{pmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,d} \\ x_{2,1} & x_{2,2} & \dots & x_{2,d} \\ \vdots & \vdots & & \vdots \\ x_{n,1} & x_{n,2} & \dots & x_{n,d} \end{pmatrix}$$

¹Programmers call this an 'array'

How to represent this on a computer

Put all the responses together in one **vector** y :

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$

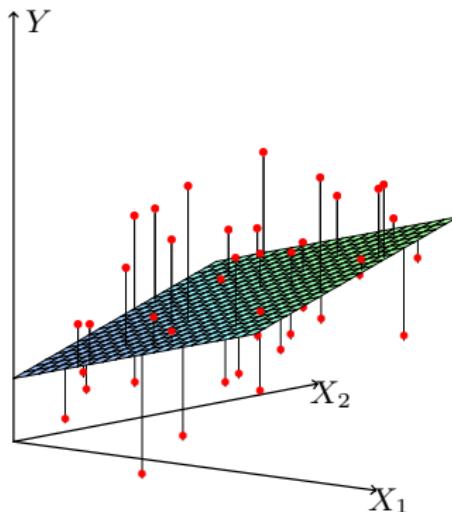
- ▶ How can we collect the feature vectors x_1, \dots, x_n , which are already vectors?

Put all the feature vectors together in one $n \times d$ **matrix**¹ X :

$$X = \begin{pmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,d} \\ x_{2,1} & x_{2,2} & \dots & x_{2,d} \\ \vdots & \vdots & & \vdots \\ x_{n,1} & x_{n,2} & \dots & x_{n,d} \end{pmatrix}$$


¹Programmers call this an 'array'

The Least Squares Method

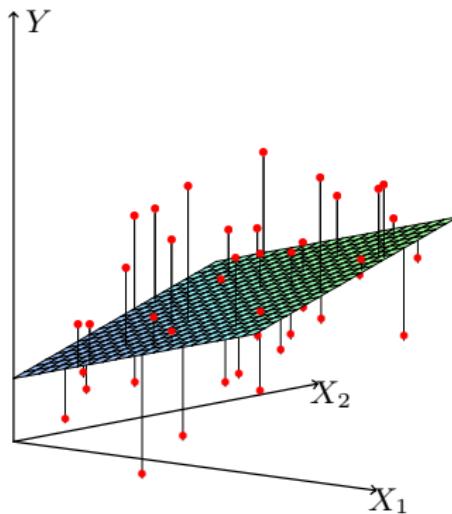


$$f(x_1, \dots, x_d) = \theta_0 + x_1\theta_1 + \dots + x_d\theta_d$$

Choose coefficients $\theta_0, \dots, \theta_d$ to minimize the **sum of squared errors** on the data:

$$\sum_{i=1}^n (y_i - f(x_i))^2$$

The Least Squares Method



$$f(x_1, \dots, x_d) = \theta_0 + x_1\theta_1 + \dots + x_d\theta_d$$

Choose coefficients $\theta_0, \dots, \theta_d$ to minimize the **sum of squared errors** on the data:

$$\sum_{i=1}^n (y_i - f(x_i))^2 = \sum_{i=1}^n (y_i - (\theta_0 + x_{i,1}\theta_1 + \dots + x_{i,d}\theta_d))^2$$

The Least Squares Formula

The data can be pre-processed such that $\theta_0 = 0$. Put the other coefficients together in a vector:

$$\theta = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_d \end{pmatrix}$$

The Least Squares Formula

The data can be pre-processed such that $\theta_0 = 0$. Put the other coefficients together in a vector:

$$\theta = \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_d \end{pmatrix}$$

Then the **least squares solution** can be computed from the data by:

$$\theta = (X^T X)^{-1} X^T y$$

- ▶ Rest of the lecture: explain how to read this formula

Outline

Intro: machine learning concepts for linear regression

Vectors: addition, scaling, length

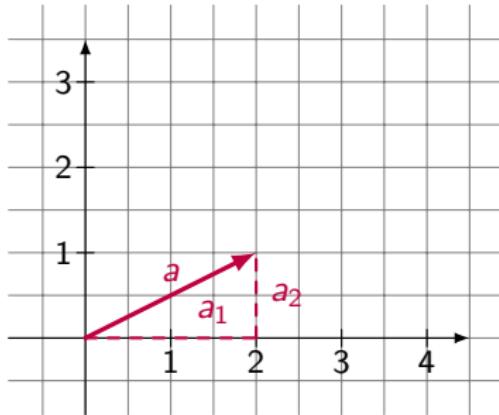
Matrices: addition, scaling, transpose

Vectors and matrices: multiplication

Identity matrix and matrix inverse

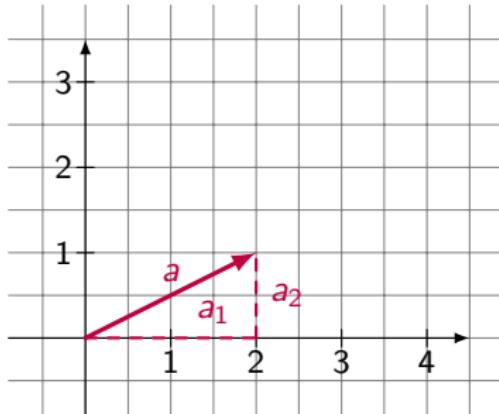
Reading the Least Squares Formula

Pictures of 2D Vectors



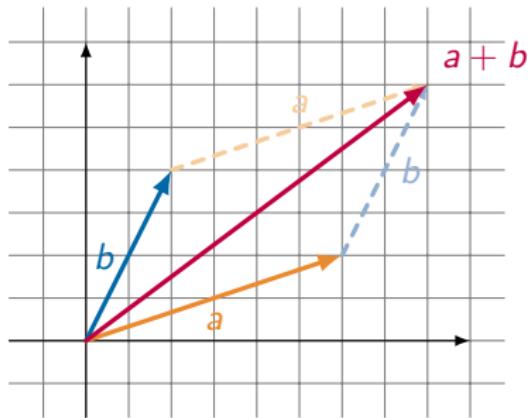
$$a = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix}$$

Pictures of 2D Vectors

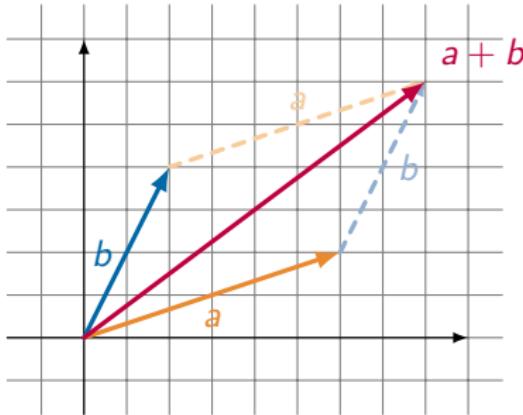


$$a = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$$

Vectors: addition



Vectors: addition

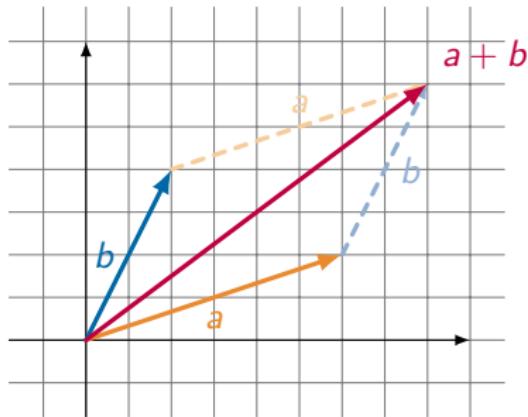


Addition: $a + b$

$$\begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_d \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_d \end{pmatrix} = \begin{pmatrix} a_1 + b_1 \\ a_2 + b_2 \\ \vdots \\ a_d + b_d \end{pmatrix}$$

- ▶ Add coordinates separately

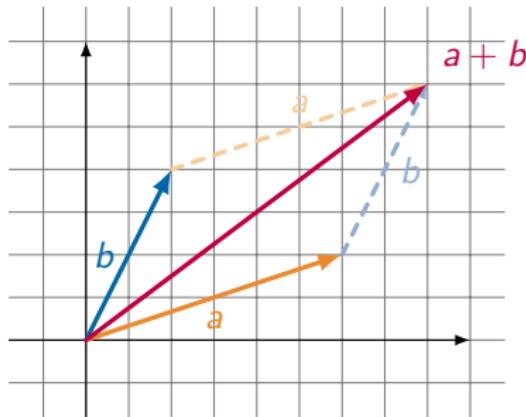
Vectors: addition



Example:

$$\begin{pmatrix} 1 \\ -2 \\ 3 \end{pmatrix} + \begin{pmatrix} 4 \\ 5 \\ -6 \end{pmatrix} = \begin{pmatrix} ? \\ ? \\ ? \end{pmatrix}$$

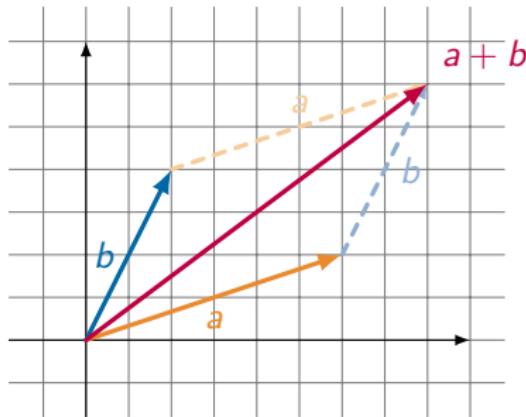
Vectors: addition



Example:

$$\begin{pmatrix} 1 \\ -2 \\ 3 \end{pmatrix} + \begin{pmatrix} 4 \\ 5 \\ -6 \end{pmatrix} = \begin{pmatrix} 5 \\ ? \\ ? \end{pmatrix}$$

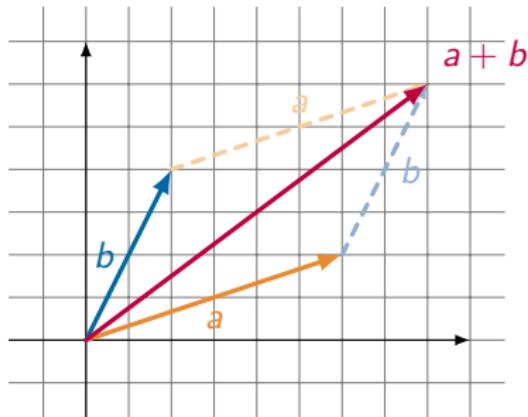
Vectors: addition



Example:

$$\begin{pmatrix} 1 \\ -2 \\ 3 \end{pmatrix} + \begin{pmatrix} 4 \\ 5 \\ -6 \end{pmatrix} = \begin{pmatrix} 5 \\ 3 \\ ? \end{pmatrix}$$

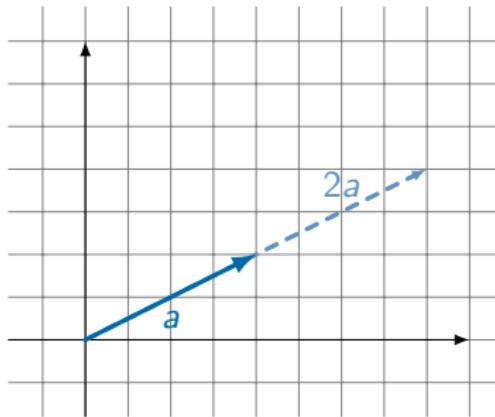
Vectors: addition



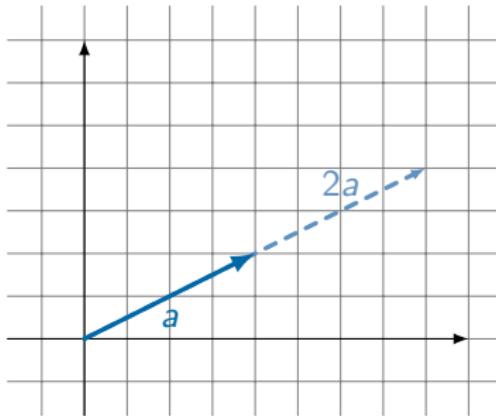
Example:

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

Vectors: scaling



Vectors: scaling

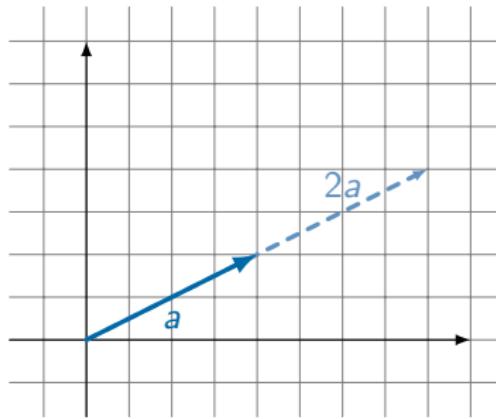


Scaling: $c \times a$ for some number c

$$c \times \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_d \end{pmatrix} = \begin{pmatrix} ca_1 \\ ca_2 \\ \vdots \\ ca_d \end{pmatrix}$$

- ▶ Scale coordinates separately

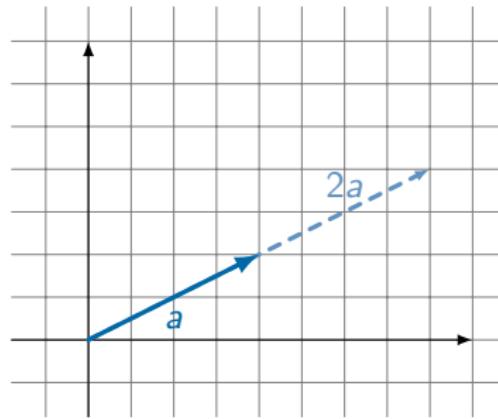
Vectors: scaling



Example:

$$-10 \times \begin{pmatrix} -1 \\ 6 \\ 3.14 \end{pmatrix} = \begin{pmatrix} ? \\ ? \\ ? \end{pmatrix}$$

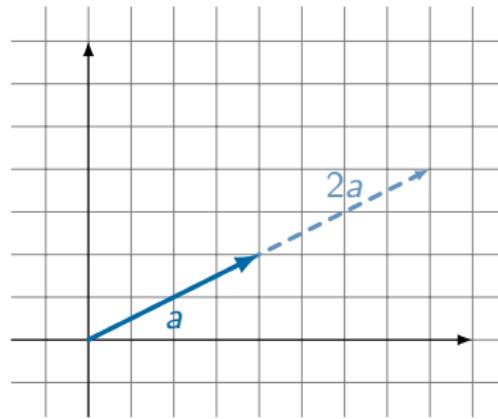
Vectors: scaling



Example:

$$-10 \times \begin{pmatrix} -1 \\ 6 \\ 3.14 \end{pmatrix} = \begin{pmatrix} 10 \\ ? \\ ? \end{pmatrix}$$

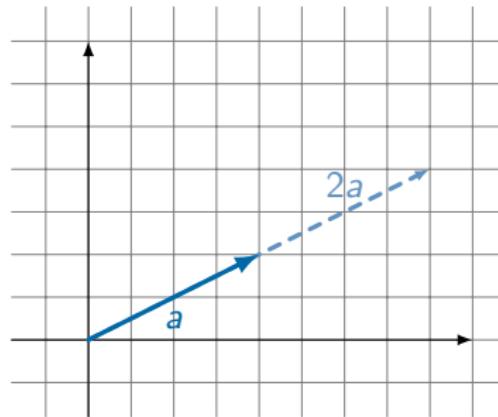
Vectors: scaling



Example:

$$-10 \times \begin{pmatrix} -1 \\ 6 \\ 3.14 \end{pmatrix} = \begin{pmatrix} 10 \\ -60 \\ ? \end{pmatrix}$$

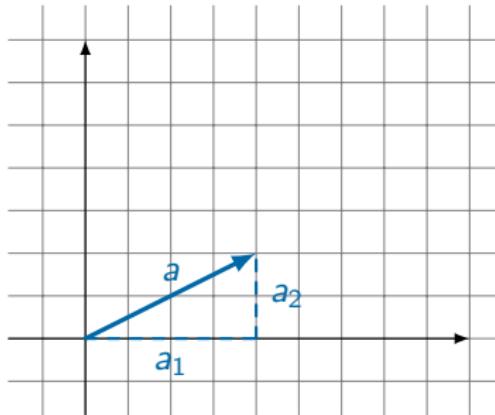
Vectors: scaling



Example:

$$-10 \times \begin{pmatrix} -1 \\ 6 \\ 3.14 \end{pmatrix} = \begin{pmatrix} 10 \\ -60 \\ -31.4 \end{pmatrix}$$

Vectors: length

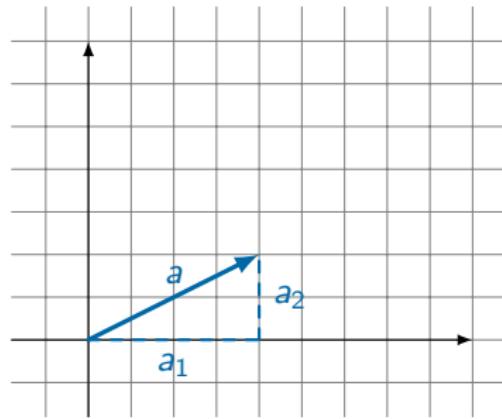


Length: $\|a\|$

$$\left\| \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_d \end{pmatrix} \right\| = \sqrt{a_1^2 + a_2^2 + \dots + a_d^2}$$

- ▶ For $d = 2$ this is the Pythagorean theorem

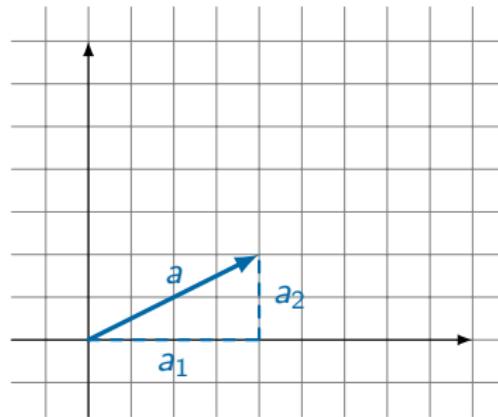
Vectors: length



Example:

$$\left\| \begin{pmatrix} 2 \\ 3 \\ -2 \end{pmatrix} \right\| = ?$$

Vectors: length



Example:

$$\left\| \begin{pmatrix} 2 \\ 3 \\ -2 \end{pmatrix} \right\| = \sqrt{4 + 9 + 4} = \sqrt{17} \approx 4.12$$

Outline

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Vectors: addition, scaling, length

Matrices: addition, scaling, transpose

Vectors and matrices: multiplication

Identity matrix and matrix inverse

Reading the Least Squares Formula

Matrices: scaling

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

- ▶ NB Vectors are $n \times 1$ matrices

Matrices: scaling

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Scaling: $c \times A$

$$c \times A = \begin{pmatrix} ca_{1,1} & ca_{1,2} & \dots & ca_{1,d} \\ ca_{2,1} & ca_{2,2} & \dots & ca_{2,d} \\ \vdots & & & \\ ca_{n,1} & ca_{n,2} & \dots & ca_{n,d} \end{pmatrix}$$

- ▶ Per coordinate, like for vectors

Matrices: scaling

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Example:

$$2 \times \begin{pmatrix} 5 & 4 & 3 \\ 2 & 1 & 0 \end{pmatrix} = \begin{pmatrix} ? & ? & ? \\ ? & ? & ? \end{pmatrix}$$

Matrices: scaling

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Example:

$$2 \times \begin{pmatrix} 5 & 4 & 3 \\ 2 & 1 & 0 \end{pmatrix} = \begin{pmatrix} 10 & 8 & 6 \\ 4 & 2 & 0 \end{pmatrix}$$

Matrices: addition

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Matrices: addition

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Addition: $A + B$

$$A + B = \begin{pmatrix} a_{1,1} + b_{1,1} & a_{1,2} + b_{1,2} & \dots & a_{1,d} + b_{1,d} \\ a_{2,1} + b_{2,1} & a_{2,2} + b_{2,2} & \dots & a_{2,d} + b_{2,d} \\ \vdots & & & \\ a_{n,1} + b_{n,1} & a_{n,2} + b_{n,2} & \dots & a_{n,d} + b_{n,d} \end{pmatrix}$$

- ▶ Per coordinate, like for vectors

Matrices: addition

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Example:

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

Matrices: addition

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Example:

$$\begin{pmatrix} -9 & -8 \\ 4 & 5 \\ 3 & 3 \end{pmatrix} + \begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix} = \text{Not possible!}$$

(because dimensions do not match)

Matrices: addition

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Example:

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Matrices: addition

An $n \times d$ matrix

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Example:

$$\begin{pmatrix} -9 & -8 \\ 4 & 5 \\ 3 & 3 \end{pmatrix} + \begin{pmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{pmatrix} = \begin{pmatrix} -8 & -4 \\ 6 & 10 \\ 6 & 9 \end{pmatrix}$$

Matrices: transpose

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Transpose A^T : Flip the matrix coordinates ($A_{ij}^T = A_{ji}$)

Image by Lucas Vieira,

<https://commons.wikimedia.org/w/index.php?curid=21897854>

Matrices: transpose

An $n \times d$ matrix

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & & & \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

Transpose A^T : Flip the matrix coordinates ($A_{ij}^T = A_{ji}$)

NB This changes every matrix row into a column and vice versa.

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Vectors and matrices: multiplication

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Reading the Least Squares Formula

Vectors: Multiplication

The Inner Product $\langle a, b \rangle$ between two vectors:

$$\langle a, b \rangle = a_1 b_1 + a_2 b_2 + \dots + a_d b_d$$

- ▶ E.g. $f(x) = \theta_0 + x_1 \theta_1 + \dots + x_d \theta_d = \theta_0 + \langle x, \theta \rangle$

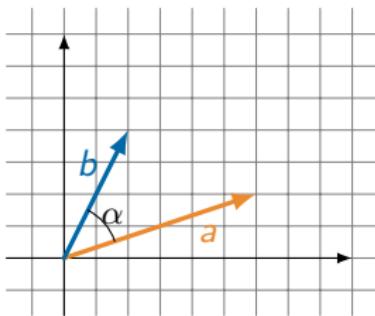
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- E.g. $f(x) = \theta_0 + x_1 \theta_1 + \dots + x_d \theta_d = \theta_0 + \langle x, \theta \rangle$

Interpretation:



If α is the angle between the two vectors, then

$$\langle a, b \rangle = \cos(\alpha) \times \|a\| \times \|b\|$$

Matrix times Vector: Multiplication

x : vector with d elements

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

$$\begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{pmatrix}$$

A : n rows, d columns

$C = A \times x = Ax$:
vector with n elements

Matrix times Vector: Multiplication

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{pmatrix}$$

Let a_i^T be the i -th row of A . Then

$$c_i = \langle a_i, x \rangle$$

Matrix times Vector: Multiplication

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{pmatrix}$$

Let a_i^T be the i -th row of A . Then

$$c_i = \langle a_i, x \rangle$$

Example: For any two vectors $v^T w = \langle v, w \rangle$

Matrix times Vector: Example

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_d \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{pmatrix}$$

Matrix times Vector: Example

$$\boxed{e_1} \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix} \begin{pmatrix} ? \\ ? \\ \vdots \\ ? \end{pmatrix}$$

$$\boxed{A}$$

$$\boxed{Ae_1}$$

Matrix times Vector: Example

e_1

$$\begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} \\ a_{2,1} \\ \vdots \\ a_{n,1} \end{pmatrix}$$

A

Ae_1

The **first column** of A tells us what Ae_1 should be.

Matrix times Vector: Example

e_2

$$\begin{pmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,d} \\ a_{2,1} & a_{2,2} & \dots & a_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \dots & a_{n,d} \end{pmatrix} \quad \begin{pmatrix} a_{1,2} \\ a_{2,2} \\ \vdots \\ a_{n,2} \end{pmatrix}$$

A

Ae_2

The *i-th column* of A tells us what Ae_i should be.

Motivation for Matrix times Vector Definition

The definitions of linear algebra ensure that it is **linear**:

$$A \left(a \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix} + b \begin{pmatrix} y_1 \\ \vdots \\ y_d \end{pmatrix} \right) = a A \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix} + b A \begin{pmatrix} y_1 \\ \vdots \\ y_d \end{pmatrix}$$

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Knowing Ae_1, \dots, Ae_d therefore **fully determines** Ax :

$$\begin{aligned} A \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix} &= A \left(x_1 \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + \dots + x_d \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{pmatrix} \right) \\ &= x_1(Ae_1) + x_2(Ae_2) + \dots + x_d(Ae_d) \end{aligned}$$

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So what is a matrix A ? You write down in column i what Ae_i should be, and then Ax is fully determined for any vector x by linearity.

Matrices: Multiplication

B : ***d* rows, *m* columns**

$$\begin{pmatrix} b_{1,1} & b_{1,2} & \dots & b_{1,m} \\ b_{2,1} & b_{2,2} & \dots & b_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{d,1} & b_{d,2} & \dots & b_{d,m} \end{pmatrix}$$

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$$\begin{pmatrix} c_{1,1} & c_{1,2} & \dots & c_{1,m} \\ c_{2,1} & c_{2,2} & \dots & c_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n,1} & c_{n,2} & \dots & c_{n,m} \end{pmatrix}$$

A : ***n* rows, *d* columns**

$C = A \times B = AB$:
***n* rows, *m* columns**

Matrices: Multiplication

$$\begin{pmatrix} b_{1,1} & b_{1,2} & \dots & b_{1,m} \\ b_{2,1} & b_{2,2} & \dots & b_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{d,1} & b_{d,2} & \dots & b_{d,m} \end{pmatrix}$$

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Let a_i^T be the i -th row of A and b_j the j -th column of B . Then

$$c_{i,j} = \langle a_i, b_j \rangle$$

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Let a_i^T be the i -th row of A and b_j the j -th column of B . Then

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Motivation: This ensures that $A(Bx) = (AB)x$ for any vector x .

E.g. $x = e_1$.

Examples

Inner product:

$$\left\langle \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 3 \\ 4 \end{pmatrix} \right\rangle =$$

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Matrix multiplication I:

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=

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Examples

Inner product:

$$\left\langle \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 3 \\ 4 \end{pmatrix} \right\rangle = 1 \times 3 + 2 \times 4 = 11$$

Matrix multiplication II:

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Examples

Inner product:

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Matrix multiplication II:

$$\begin{pmatrix} 1 & 2 \\ 2 & 3 \\ 3 & 4 \end{pmatrix} \begin{pmatrix} -1 & 2 \\ 1 & 1 \\ 0 & 3 \end{pmatrix} = \text{Not possible!}$$

(because dimensions do not match)

Outline

Intro: machine learning concepts for linear regression

Vectors: addition, scaling, length

Matrices: addition, scaling, transpose

Vectors and matrices: multiplication

Identity matrix and matrix inverse

Reading the Least Squares Formula

Identity Matrix

Is there a matrix which behaves like the number 1?

Yes, the **identity matrix** I !

B : **d rows, m columns**

$$\begin{pmatrix} b_{1,1} & b_{1,2} & \dots & b_{1,m} \\ b_{2,1} & b_{2,2} & \dots & b_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ b_{d,1} & b_{d,2} & \dots & b_{d,m} \end{pmatrix}$$

$$I = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{pmatrix} \quad \begin{pmatrix} c_{1,1} & c_{1,2} & \dots & c_{1,m} \\ c_{2,1} & c_{2,2} & \dots & c_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n,1} & c_{n,2} & \dots & c_{n,m} \end{pmatrix}$$

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$$c_{i,j} = b_{i,j} \quad \Rightarrow \quad I \times B = B$$

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$$c_{i,j} = b_{i,j} \implies I \times B = B$$

Likewise: $B \times I = B$

Matrix Inverse

A square matrix A has an **inverse** A^{-1} if

$$A^{-1} \times A = I = A \times A^{-1}$$

- ▶ Think of A^{-1} as “dividing by A ”
- ▶ The inverse is always unique (if it exists)

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- ▶ The inverse is always unique (if it exists)

Example:

$$\begin{pmatrix} -2 & 0 \\ 1 & 1 \end{pmatrix}^{-1} = \begin{pmatrix} -\frac{1}{2} & 0 \\ \frac{1}{2} & 1 \end{pmatrix}$$

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Reading the Least Squares Formula

$$\theta = (X^T X)^{-1} X^T y$$

- ▶ X^T is the **transpose** of X
- ▶ $(X^T X)^{-1}$ is the **inverse** of the matrix $X^T X$
- ▶ All other operations are **matrix multiplications**,
but we omit the \times symbol. E.g. $X^T X = X^T \times X$

Preparation for Next Lecture

The next lecture will be about **derivatives and optimization**.

To prepare, watch the following video:

[Math&Stuff - The Intuitive Concept of a Derivative](#)

References

-  Hastie, Trevor, Robert Tibshirani, and Jerome Friedman (2009). *The Elements of Statistical Learning*. 2nd ed. Springer.