

# Mathematical Foundations for Machine Learning

## Linear Algebra and Linear Regression

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# Today

## Linear algebra

- Primer and highlighting key aspects



## Linear regression

- Calculus and optimization



# Linear Algebra

# Linear Algebra

Convenient and concise way to work with math involving linear operations

$$3\theta_1 + 0\theta_2 + 5\theta_3 = 36$$

$$4\theta_1 + 3\theta_2 + 2\theta_3 = 46$$

$$2\theta_1 + 2\theta_2 + 1\theta_3 = 25$$

$$\underset{\substack{\uparrow \uparrow}}{V}\boldsymbol{\theta} = \boldsymbol{u} \quad V = \begin{bmatrix} 3 & 0 & 5 \\ 4 & 3 & 2 \\ 2 & 2 & 1 \end{bmatrix} \quad \boldsymbol{u} = \begin{bmatrix} 36 \\ 46 \\ 25 \end{bmatrix} \quad \boldsymbol{\theta} = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

Possible way to solve:  $\boldsymbol{\theta} = V^{-1}\boldsymbol{u}$

(Actually a pretty unstable way to solve in general. More on this later.)

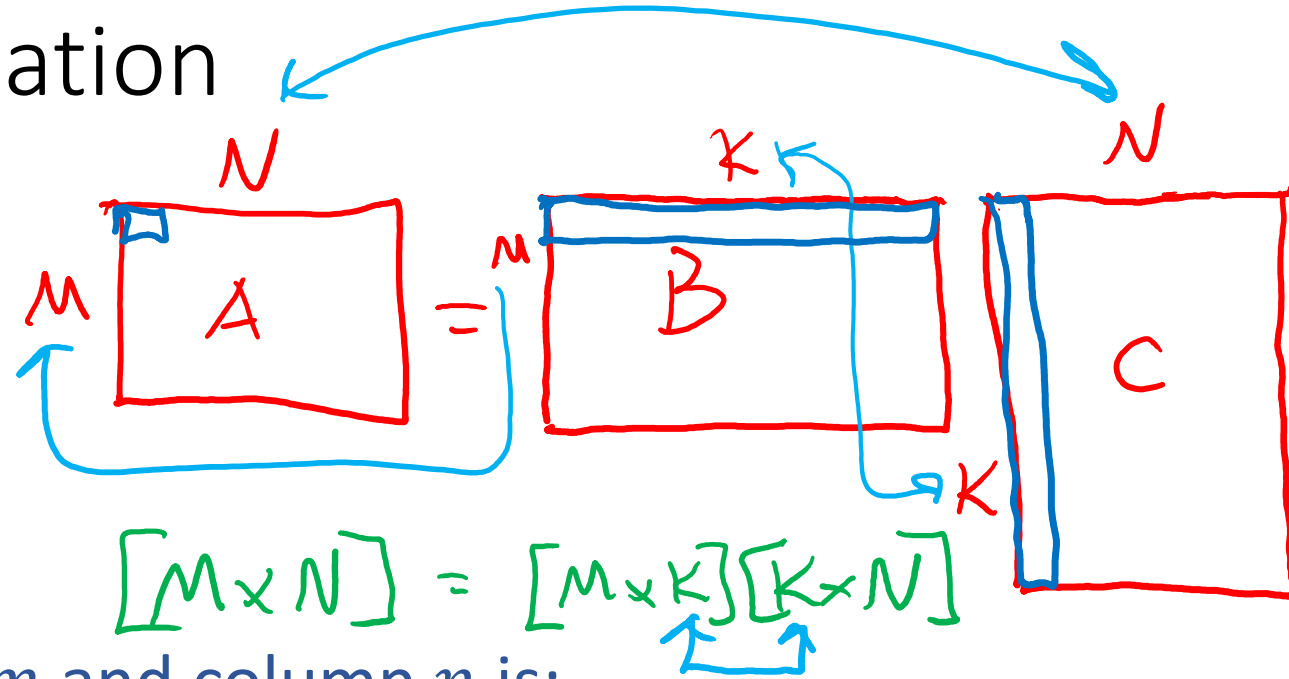
# Matrix Multiplication

$$A \in \mathbb{R}^{M \times N}$$

$$B \in \mathbb{R}^{M \times K}$$

$$C \in \mathbb{R}^{K \times N}$$

$$A = BC$$



The entry of  $A$  in row  $m$  and column  $n$  is:

$$A_{m,n} = \sum_{k=1}^K B_{m,k} C_{k,n}$$

i.e. multiply the elements of row  $m$  of  $B$  by the elements of column  $n$  of  $C$ , and then sum those products

Width of  $B$  must match height of  $C$

# Poll 1

What is the resulting dimension of  $Z$ , where  $Z = \mathbf{u}\mathbf{v}^T$  and  $\mathbf{u} \in \mathbb{R}^{7 \times 1}$  and  $\mathbf{v} \in \mathbb{R}^{7 \times 1}$ ?

Select ALL that apply

A.  $Z \in \mathbb{R}$

B.  $Z \in \mathbb{R}^{49}$

C.  $Z \in \mathbb{R}^{7 \times 1}$

D.  $Z \in \mathbb{R}^{1 \times 7}$

E.  $Z \in \mathbb{R}^{1 \times 1}$

☒ F.  $Z \in \mathbb{R}^{7 \times 7}$  95%

G. I have no idea

# Vectors

$$\mathbf{u} \in \mathbb{R}^{M \times 1}$$

Column vector of length  $M$

$$\mathbf{v} \in \mathbb{R}^{1 \times M}$$

Row vector of length  $M$

$$\mathbf{z} \in \mathbb{R}^M$$

Ambiguous. In this course, assume column vector unless stated otherwise.

$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_M \end{bmatrix}$$

# Vectors

$$\mathbf{u} \in \mathbb{R}^M$$

$$\mathbf{v} \in \mathbb{R}^M \quad \text{Note these are both column vectors}$$

## Multiplication of vectors of the same length

Dot product (inner product):

- $y = \mathbf{u} \cdot \mathbf{v} = \mathbf{u}^T \mathbf{v} = \sum_{i=1}^M u_i v_i \quad y \in \mathbb{R}$
- A dot product is an **inner product** (inner product is a more general term)

Outer product (~~inner product~~):

- $Y = \mathbf{u} \otimes \mathbf{v} = \underline{\mathbf{u}\mathbf{v}^T} \quad Y \in \mathbb{R}^{M \times M} \quad Y_{i,j} = u_i v_j$



# Vectors

$$\mathbf{u} \in \mathbb{R}^M$$

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \cdot \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \rightarrow \text{sum of squares}$$

What happens when we do the dot product of a vector with itself?

$$\vec{u}^T u = \sum_{i=1}^M u_i^2$$

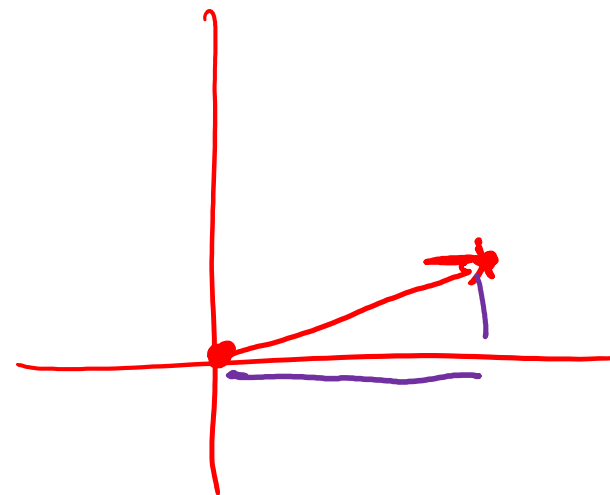
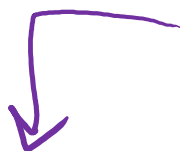
# Vectors

$$\mathbf{u} \in \mathbb{R}^M$$

Vector magnitude

$$|\mathbf{u}| = \sqrt{\sum_i^M u_i^2} = (\sum_i^M u_i^2)^{1/2} = (?)^{1/2}$$

$$\mathbf{u}^T \mathbf{u}$$
$$\mathbf{u} \cdot \mathbf{u}$$



L2 norm (Euclidean norm)

(More norms later)

$$\|\mathbf{u}\|_2 = \sqrt{\sum_i^M u_i^2} = (\sum_i^M \overset{\circ}{u_i^2})^{\overset{\circ}{1/2}} = (\mathbf{u}^T \mathbf{u})^{1/2}$$



L2 norm squared

$$\|\mathbf{u}\|_2^2 = \sum_i^M u_i^2 = \mathbf{u}^T \mathbf{u}$$

# Vectors

$$\mathbf{u} \in \mathbb{R}^M$$

$$\mathbf{v} \in \mathbb{R}^M$$

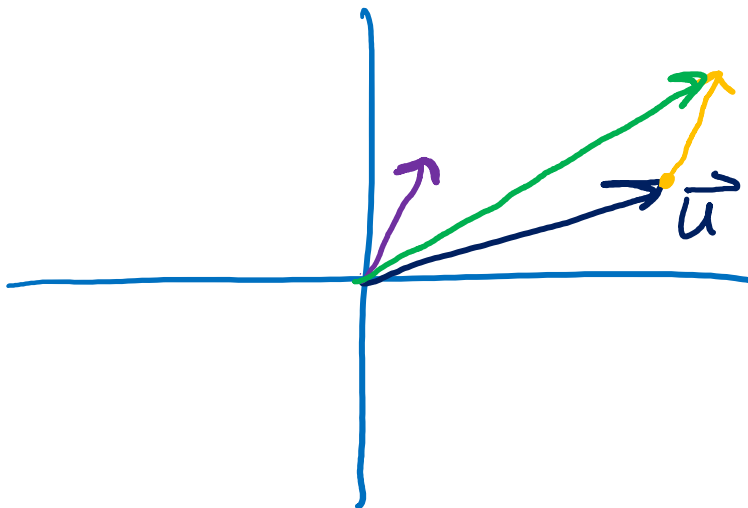
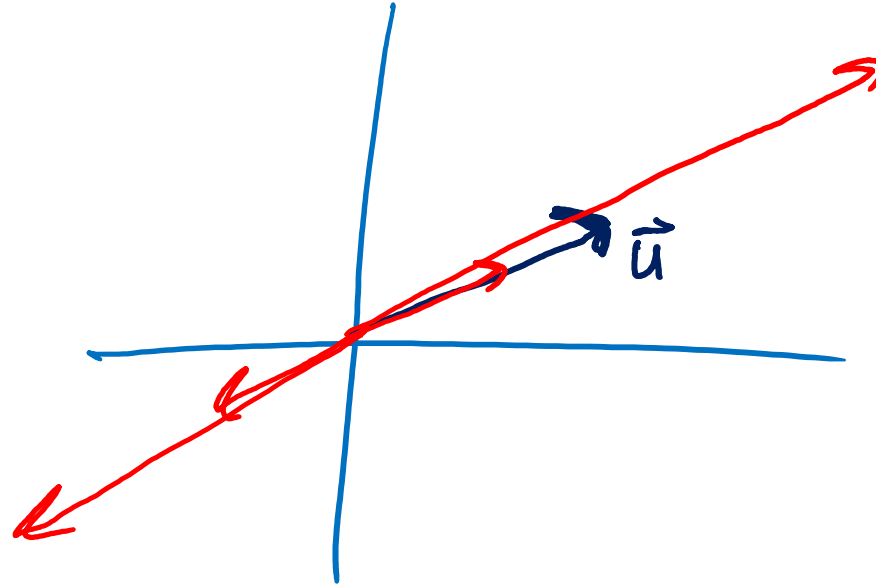
$$\alpha \in \mathbb{R}$$

Scalar multiplication

$$\alpha \mathbf{u} = \begin{bmatrix} \alpha u_1 \\ \alpha u_2 \\ \vdots \\ \alpha u_M \end{bmatrix}$$

Vector addition

$$\mathbf{u} + \mathbf{v} = \begin{bmatrix} u_1 + v_1 \\ u_2 + v_2 \\ \vdots \\ u_M + v_M \end{bmatrix}$$



# Vectors

$$\mathbf{u}, \mathbf{v} \in \mathbb{R}^M$$

Linear combination of vectors

$$\mathbf{z} = \alpha \mathbf{u} + \beta \mathbf{v} = \begin{bmatrix} \alpha u_1 + \beta v_1 \\ \alpha u_2 + \beta v_2 \\ \vdots \\ \alpha u_M + \beta v_M \end{bmatrix} \text{ for any } \alpha, \beta \in \mathbb{R}$$

# Span

Set of all linear combination of a set of vectors

Given a set of vectors  $\mathcal{S} = \{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$ , where  $\mathbf{v}_i \in \mathbb{R}^M \forall i$   
 $span(\mathcal{S}) = \{w_1\mathbf{v}_1 + w_2\mathbf{v}_2 + w_3\mathbf{v}_3 \mid w_i \in \mathbb{R}\}$

Notation alert!



Span of a set of vectors is an example of a vector space. Vector space is a more general term.

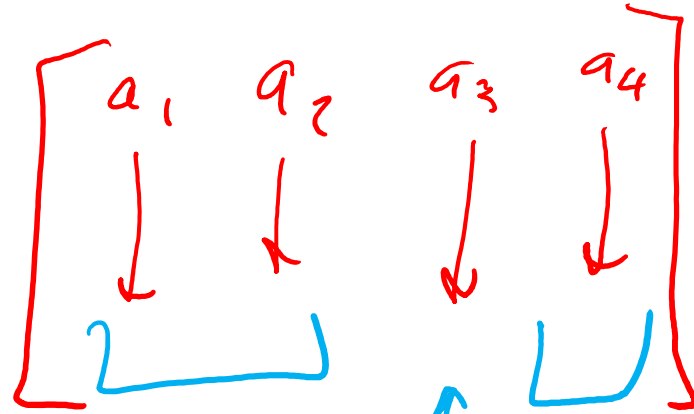
# Span, Dimensionality, and Rank

$$V = \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & v_3 \\ \downarrow & \downarrow & \downarrow \end{bmatrix}$$

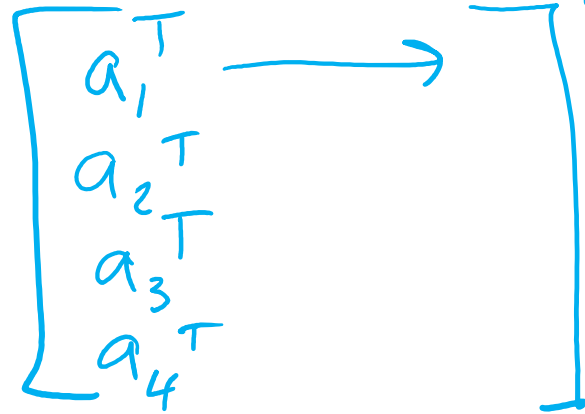
$\text{Rank}(V) \rightarrow$  dimension of vector space  
spanned by  $\{v_1, v_2, v_3\}$   
 $\uparrow \quad \uparrow \quad \uparrow$

# Span, Dimensionality, and Rank

$$A \in \mathbb{R}^{5 \times 4}$$



$$A' \in \mathbb{R}^{4 \times 5}$$



# Linear Regression



# Fitting a linear model

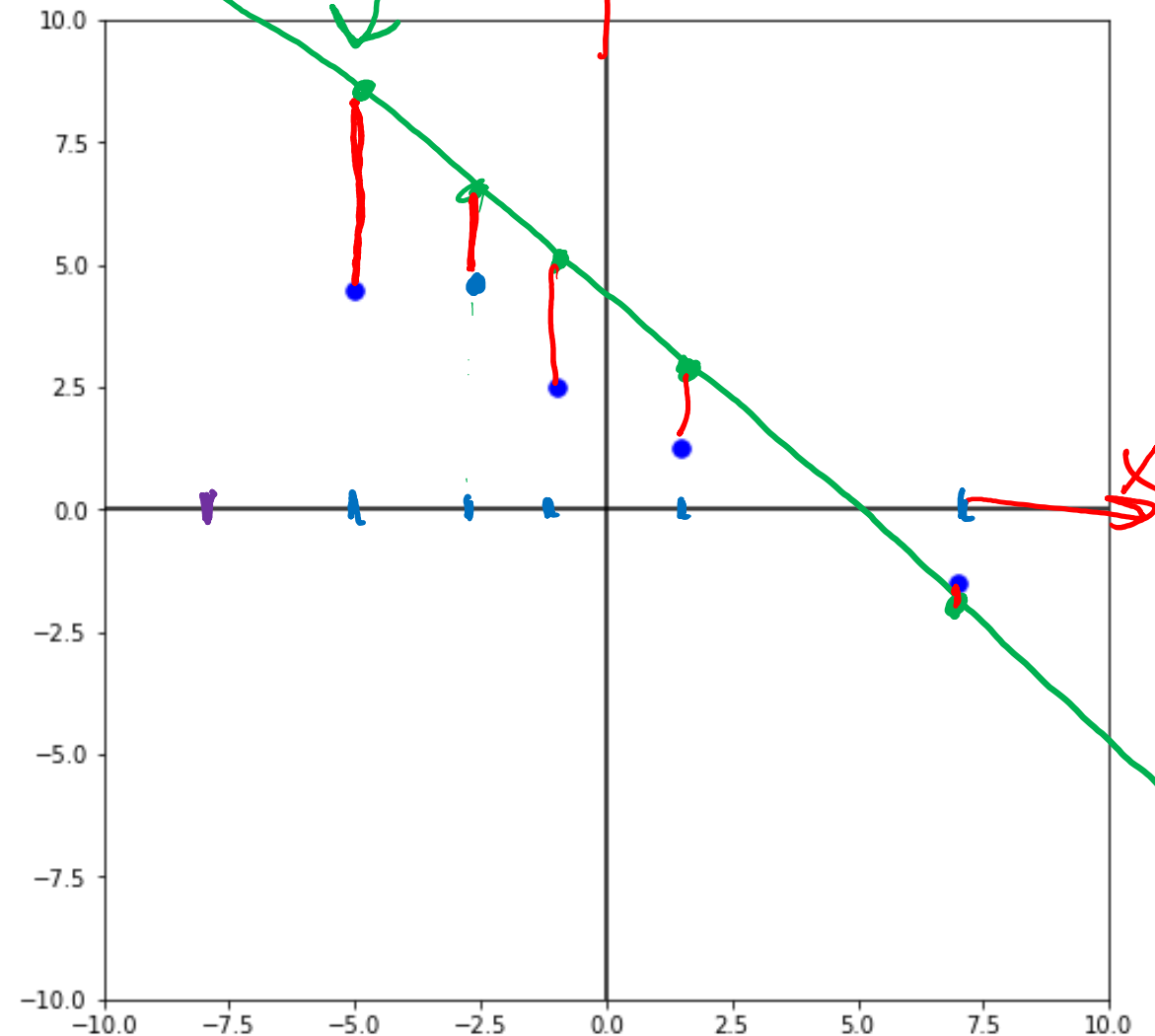
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$$\mathcal{D} = \{(x^{(i)}, y^{(i)})\}_{i=1}^4$$
$$= \{(-1, 2.5),$$
$$(7, -1.5),$$
$$(-5, 4.5),$$
$$(1.5, 1.25)\}$$

$$\sum_{i=1}^N \underbrace{(y^{(i)} - \hat{y}^{(i)})^2}_{\text{error}}$$

$$\hat{y} = mx + b$$

$$x_{\text{new}} = -8$$



# Jupyter Demo

m  -0.15  
b  28000

