

# Linear Regression

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IIT Gandhinagar

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# Setup

# Linear Regression

- Output is continuous in nature.

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  - $F = ma$
  - $v = u + at$

# Task at hand

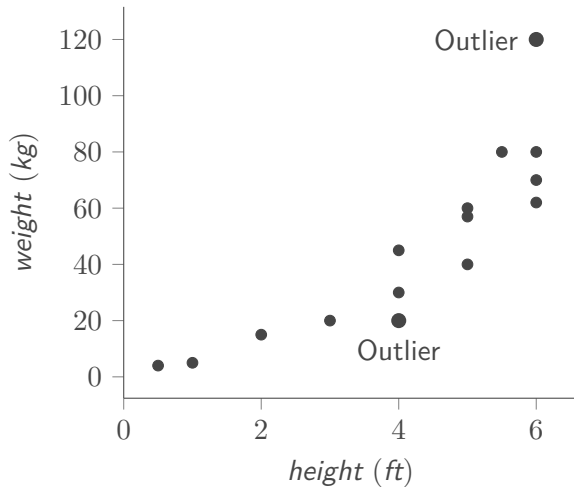
- TASK: Predict  $\text{Weight} = f(\text{height})$

Height	Weight
3	29
4	35
5	39
2	20
6	41
7	?
8	?
1	?

The first part of the dataset is the training points. The latter ones are testing points.



# Scatter Plot



# Matrix representation of the expression

- $weight_1 \approx \theta_0 + \theta_1 \cdot height_1$
- $weight_2 \approx \theta_0 + \theta_1 \cdot height_2$
- $weight_N \approx \theta_0 + \theta_1 \cdot height_N$

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$$weight_i \approx \theta_0 + \theta_1 \cdot height_i$$

## Matrix representation of the expression

$$\begin{bmatrix} weight_1 \\ weight_2 \\ \dots \\ weight_N \end{bmatrix} = \begin{bmatrix} 1 & height_1 \\ 1 & height_2 \\ \dots & \dots \\ 1 & height_N \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix}$$

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$$\hat{\mathbf{y}}_{n \times 1} = \mathbf{X}_{n \times d} \boldsymbol{\theta}_{d \times 1}$$

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- $\theta_0$  - Bias Term/Intercept Term
- $\theta_1$  - Slope

## Extension to multiple dimensions

In the previous example  $y = f(x)$ , where  $x$  is one-dimensional.



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$$\text{Demand} = f(\# \text{ occupants, Temperature})$$

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Examples in multiple dimensions.

One example is to predict the water demand of the IITGN campus

$$\text{Demand} = f(\# \text{ occupants, Temperature})$$

$$\text{Demand} = \text{Base Demand} + K_1 * \# \text{ occupants} + K_2 * \text{Temperature}$$

# Intuition

We hope to:

- Learn  $f$ :  $Demand = f(\#occupants, Temperature)$
- From training dataset
- To predict the condition for the testing set

# Linear Relationship

We have

- $x_i = \begin{bmatrix} \textit{Temperature}_i \\ \# \textit{Occupants}_i \end{bmatrix}$

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- and  $x_i' = \begin{bmatrix} 1 \\ Temperature_i \\ \#Occupants_i \end{bmatrix} = \begin{bmatrix} 1 \\ x_i \end{bmatrix}$
- Notice the transpose in the equation! This is because  $x_i$  is a column vector

## We can expect the following

- Demand increases, if # occupants increases, then  $\theta_2$  is likely to be positive

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- Demand increases, if  $\#$  occupants increases, then  $\theta_2$  is likely to be positive
- Demand increases, if temperature increases, then  $\theta_1$  is likely to be positive
- Base demand is independent of the temperature and the  $\#$  occupants, but, likely positive, thus  $\theta_0$  is likely positive.

# Normal Equation

# Generalized Linear Regression Format

- Assuming  $N$  samples for training



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$$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} 1 & x_{1,1} & x_{1,2} & \dots & x_{1,M} \\ 1 & x_{2,1} & x_{2,2} & \dots & x_{2,M} \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 1 & x_{N,1} & x_{N,2} & \dots & x_{N,M} \end{bmatrix}_{N \times (M+1)} \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_M \end{bmatrix}_{(M+1) \times 1}$$

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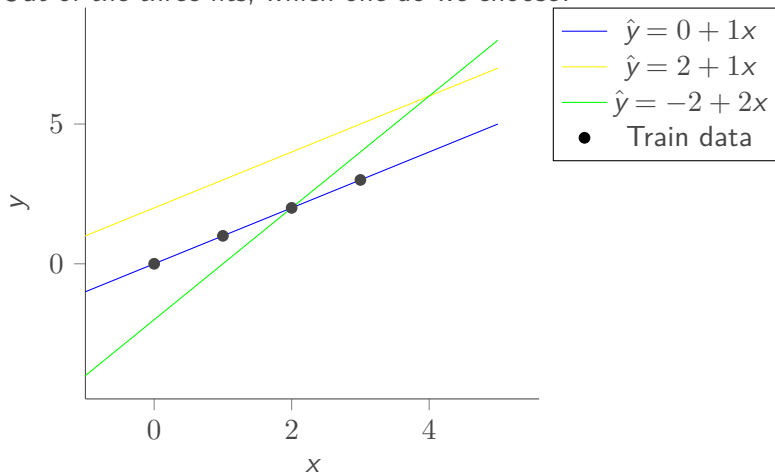
$$\hat{\mathbf{y}} = \mathbf{X}\boldsymbol{\theta}$$

# Relationships between feature and target variables

- There could be different  $\theta_0, \theta_1 \dots \theta_M$ . Each of them can represents a relationship.
- Given multiples values of  $\theta_0, \theta_1 \dots \theta_M$  how to choose which is the best?
- Let us consider an example in 2d

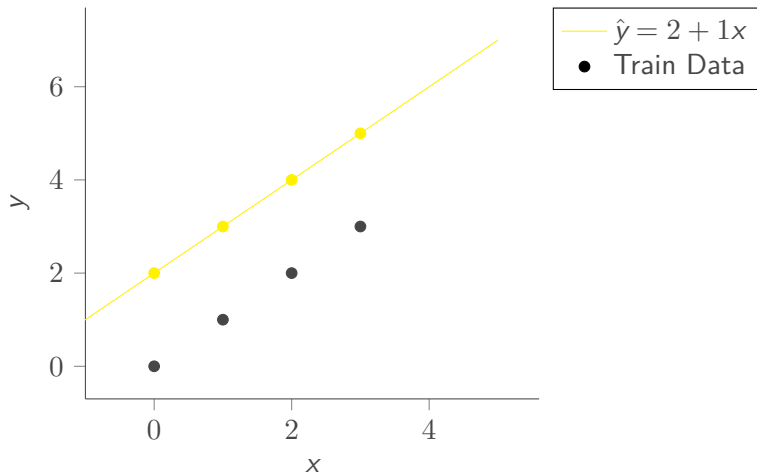
# Relationships between feature and target variables

Out of the three fits, which one do we choose?



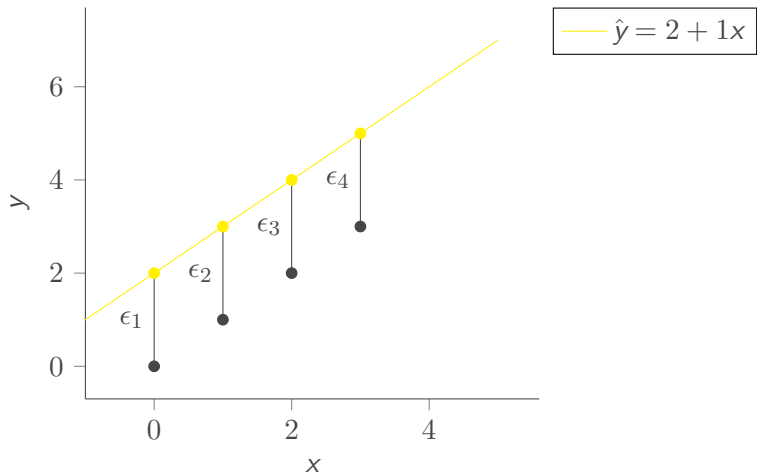
# Relationships between feature and target variables

We have  $\hat{y} = 2 + 1x$  as one relationship.



# Relationships between feature and target variables

How far is our estimated  $\hat{y}$  from ground truth  $y$ ?





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- $\theta_0, \theta_1$ : The parameters of the linear regression
- $\epsilon_i = y_i - \hat{y}_i$
- $\epsilon_i = y_i - (\theta_0 + x_i \cdot \theta_1)$



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- minimize  $|\epsilon_1| + |\epsilon_2| + \dots + |\epsilon_n|$  -  $L_1$  Norm

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Objective: minimize  $\epsilon_1^2 + \epsilon_2^2 + \cdots + \epsilon_N^2$

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Objective: Minimize  $\boldsymbol{\epsilon}^\top \boldsymbol{\epsilon}$

# Derivation of Normal Equation

$$\boldsymbol{\epsilon} = \mathbf{y} - \mathbf{X}\boldsymbol{\theta}$$

$$\boldsymbol{\epsilon}^\top \boldsymbol{\epsilon} = (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^\top (\mathbf{y} - \mathbf{X}\boldsymbol{\theta})$$

$$= \mathbf{y}^\top \mathbf{y} - 2\mathbf{y}^\top \mathbf{X}\boldsymbol{\theta} + \boldsymbol{\theta}^\top \mathbf{X}^\top \mathbf{X}\boldsymbol{\theta}$$

This is what we wish to minimize

# Minimizing the objective function

$$\frac{\partial \epsilon^\top \epsilon}{\partial \theta} = 0$$

- $\frac{\partial}{\partial \theta} \mathbf{y}^\top \mathbf{y} = 0$
- $\frac{\partial}{\partial \theta} (-2\mathbf{y}^\top \mathbf{X}\theta) = -2\mathbf{X}^\top \mathbf{y}$
- $\frac{\partial}{\partial \theta} (\theta^\top \mathbf{X}^\top \mathbf{X}\theta) = 2\mathbf{X}^\top \mathbf{X}\theta$

Substitute the values in the top equation

# Normal Equation derivation

$$\mathbf{0} = -2\mathbf{X}^\top \mathbf{y} + 2\mathbf{X}^\top \mathbf{X} \boldsymbol{\theta}$$

$$\mathbf{X}^\top \mathbf{y} = \mathbf{X}^\top \mathbf{X} \boldsymbol{\theta}$$

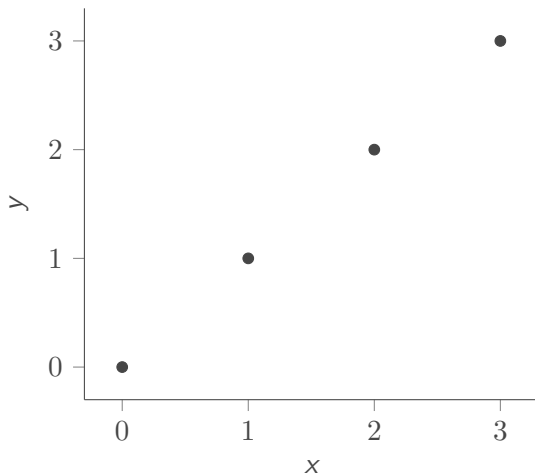
$$\hat{\boldsymbol{\theta}}_{OLS} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}$$

## Worked out example

x	y
0	0
1	1
2	2
3	3

Given the data above, find  $\theta_0$  and  $\theta_1$ .

# Scatter Plot



## Worked out example

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

$$\mathbf{X}^\top = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 \end{bmatrix}$$

$$\mathbf{X}^\top \mathbf{X} = \begin{bmatrix} 4 & 6 \\ 6 & 14 \end{bmatrix}$$

Given the data above, find  $\theta_0$  and  $\theta_1$ .

## Worked out example

$$(\mathbf{X}^\top \mathbf{X})^{-1} = \frac{1}{20} \begin{bmatrix} 14 & -6 \\ -6 & 4 \end{bmatrix}$$

$$\mathbf{X}^\top \mathbf{y} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 6 \\ 14 \end{bmatrix}$$

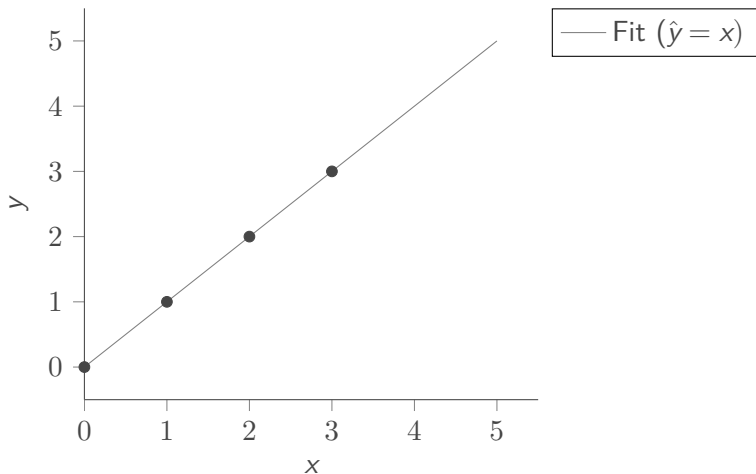


## Worked out example

$$\boldsymbol{\theta} = (\mathbf{X}^\top \mathbf{X})^{-1} (\mathbf{X}^\top \mathbf{y})$$

$$\begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix} = \frac{1}{20} \begin{bmatrix} 14 & -6 \\ -6 & 4 \end{bmatrix} \begin{bmatrix} 6 \\ 14 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

# Scatter Plot

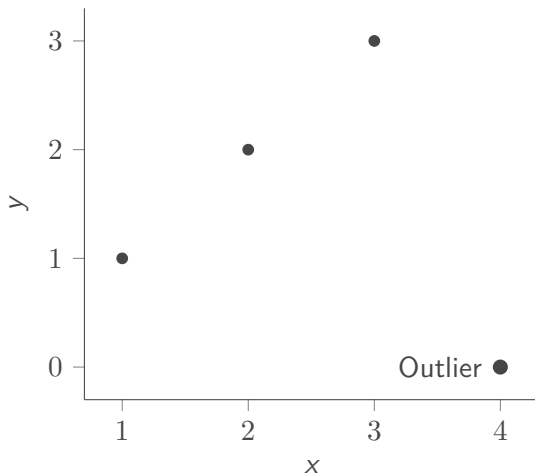


# Effect of outlier

x	y
1	1
2	2
3	3
4	0

Compute the  $\theta_0$  and  $\theta_1$ .

# Scatter Plot



## Worked out example

$$\mathbf{X} = \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix}$$

$$\mathbf{X}^\top = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 2 & 3 & 4 \end{bmatrix}$$

$$\mathbf{X}^\top \mathbf{X} = \begin{bmatrix} 4 & 10 \\ 10 & 30 \end{bmatrix}$$

Given the data above, find  $\theta_0$  and  $\theta_1$ .

## Worked out example

$$(\mathbf{X}^\top \mathbf{X})^{-1} = \frac{1}{20} \begin{bmatrix} 30 & -10 \\ -10 & 4 \end{bmatrix}$$

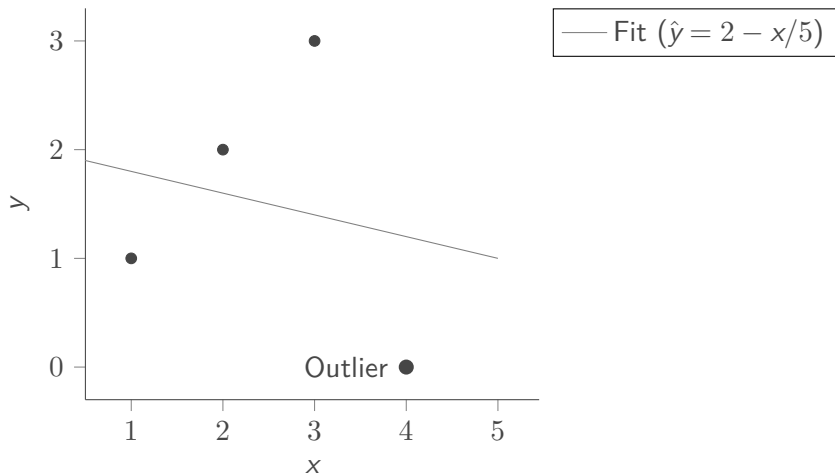
$$\mathbf{X}^\top \mathbf{y} = \begin{bmatrix} 6 \\ 14 \end{bmatrix}$$

## Worked out example

$$\boldsymbol{\theta} = (\mathbf{X}^\top \mathbf{X})^{-1}(\mathbf{X}^\top \mathbf{y})$$

$$\begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix} = \begin{bmatrix} 2 \\ (-1/5) \end{bmatrix}$$

# Scatter Plot





# Basis Expansion

# Variable Transformation

Transform the data, by including the higher power terms in the feature space.

t	s
0	0
1	6
3	24
4	36

The above table represents the data before transformation

# Variable Transformation

Add the higher degree features to the previous table

t	$t^2$	s
0	0	0
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3	9	24
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Other transformations:  $\log(x)$ ,  $x_1 \times x_2$

# A big caveat: Linear in what?!<sup>1</sup>

1.  $\hat{s} = \theta_0 + \theta_1 * t$  is linear

---

<sup>1</sup><https://stats.stackexchange.com/questions/8689/what-does-linear-stand-for-in-linear-regression>

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1.  $\hat{s} = \theta_0 + \theta_1 * t$  is linear
2. Is  $\hat{s} = \theta_0 + \theta_1 * t + \theta_2 * t^2$  linear?

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2. Is  $\hat{s} = \theta_0 + \theta_1 * t + \theta_2 * t^2$  linear?
3. Is  $\hat{s} = \theta_0 + \theta_1 * t + \theta_2 * t^2 + \theta_3 * \cos(t^3)$  linear?

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4. Is  $\hat{s} = \theta_0 + \theta_1 * t + e^{\theta_2} * t$  linear?

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3. Is  $\hat{s} = \theta_0 + \theta_1 * t + \theta_2 * t^2 + \theta_3 * \cos(t^3)$  linear?
4. Is  $\hat{s} = \theta_0 + \theta_1 * t + e^{\theta_2} * t$  linear?
5. All except #4 are linear models!
6. Linear refers to the relationship between the parameters that you are estimating ( $\theta$ ) and the outcome

---

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# Basis Functions

- Linear regression only refers to linear in the parameters
- We can perform an arbitrary nonlinear transformation  $\phi(x)$  of the inputs  $x$  and then linearly combine the components of this transformation.
- $\phi : \mathbb{R}^D \rightarrow \mathbb{R}^K$  is called the basis function

# Basis Functions

Some examples of basis functions:

- Polynomial basis:  $\phi(x) = \{1, x, x^2, x^3, \dots\}$
- Fourier basis:  $\phi(x) = \{1, \sin(x), \cos(x), \sin(2x), \cos(2x), \dots\}$
- Gaussian basis:  
$$\phi(x) = \{1, \exp(-\frac{(x-\mu_1)^2}{2\sigma^2}), \exp(-\frac{(x-\mu_2)^2}{2\sigma^2}), \dots\}$$
- Sigmoid basis:  $\phi(x) = \{1, \sigma(x - \mu_1), \sigma(x - \mu_2), \dots\}$  where  
$$\sigma(x) = \frac{1}{1+e^{-x}}$$

# Geometric Interpretation

# Linear Combination of Vectors

Let  $\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3, \dots, \mathbf{v}_i$  be vectors in  $\mathbb{R}^D$ , where  $D$  denotes the dimensions.



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$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \alpha_3 \mathbf{v}_3 + \dots + \alpha_i \mathbf{v}_i$$

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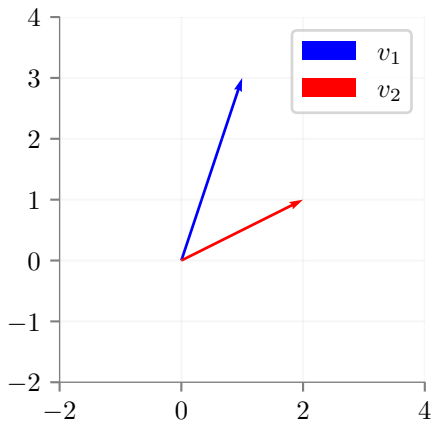
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If we stack the vectors  $v_1, v_2, \dots, v_i$  as columns of a matrix  $V$ , then the span of  $v_1, v_2, \dots, v_i$  is given as  $V\alpha$  where  $\alpha \in \mathbb{R}^i$

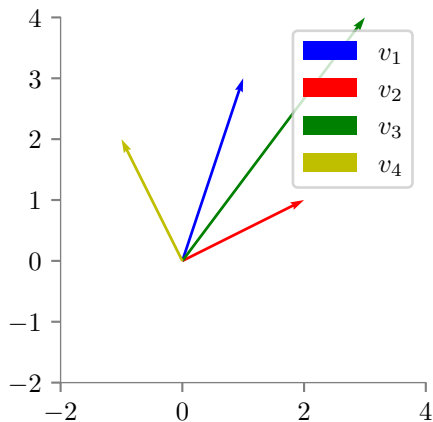
# Example

Find the span of  $\left( \begin{bmatrix} 1 \\ 3 \end{bmatrix}, \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right)$





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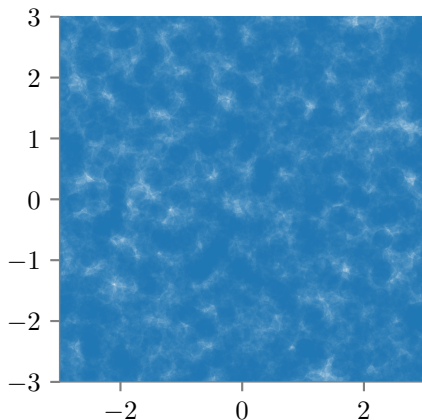


We have  $v_3 = v_1 + v_2$

We have  $v_4 = v_1 - v_2$

# Example

Simulating the above example in python using different values of  $\alpha_1$  and  $\alpha_2$



$$\text{Span}((v_1, v_2)) \in \mathcal{R}^2$$

## Example

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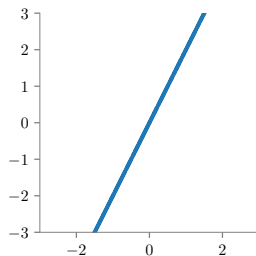
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Span of the above set is along the line  $y = 2x$

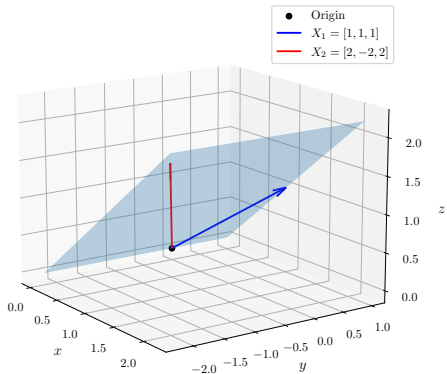


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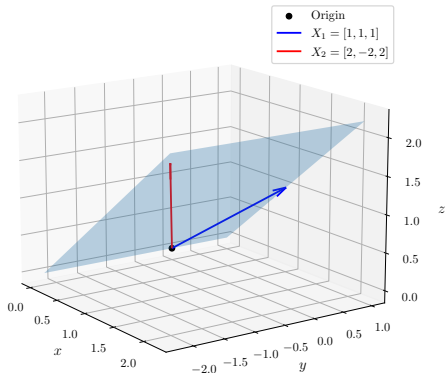
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Find the span of  $\left( \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \\ 2 \end{bmatrix} \right)$



The span is the plane  $z = x$  or  $x_3 = x_1$

# Geometric Interpretation

Consider  $\mathbf{X}$  and  $\mathbf{y}$  as follows.

$$\mathbf{X} = \begin{pmatrix} 1 & 2 \\ 1 & -2 \\ 1 & 2 \end{pmatrix}, \quad \mathbf{y} = \begin{pmatrix} 8.8957 \\ 0.6130 \\ 1.7761 \end{pmatrix}$$

- We are trying to learn  $\boldsymbol{\theta}$  for  $\hat{\mathbf{y}} = \mathbf{X}\boldsymbol{\theta}$  such that  $\|\mathbf{y} - \hat{\mathbf{y}}\|_2$  is minimised

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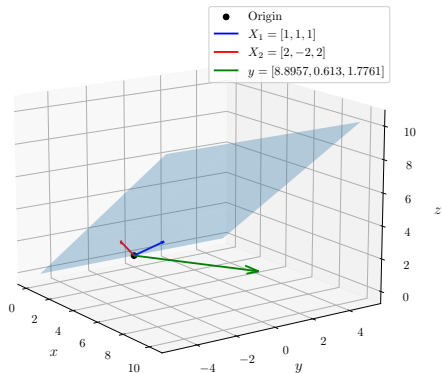
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- We wish to find  $\hat{\mathbf{y}}$  such that

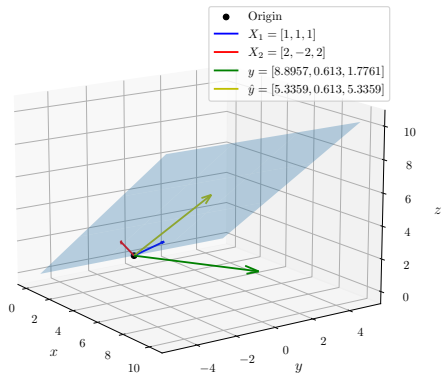
$$\arg \min_{\hat{\mathbf{y}} \in \text{SPAN}\{\bar{x}_1, \bar{x}_2, \dots, \bar{x}_D\}} \|\mathbf{y} - \hat{\mathbf{y}}\|_2$$

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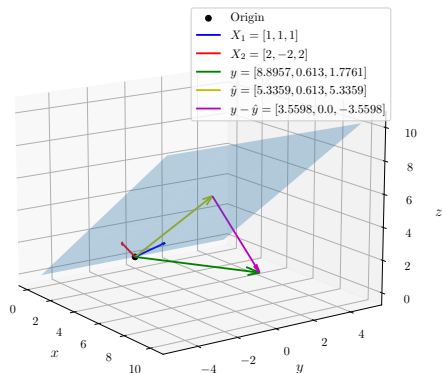


# Geometric Interpretation



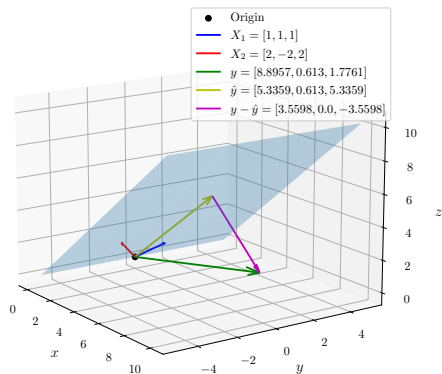
- We seek a  $\hat{y}$  in the span of the columns of  $\mathbf{X}$  such that it is closest to  $y$

# Geometric Interpretation



- This happens when  $y - \hat{y} \perp x_j \forall j$  or  $x_j^\top (y - \hat{y}) = 0$

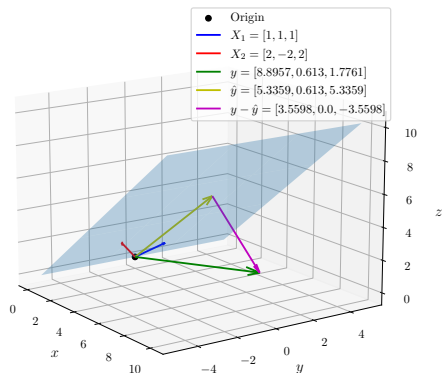
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- $X^\top (y - X\theta) = 0$
- $X^\top y = X^\top X\theta$  or  $\hat{\theta} = (X^\top X)^{-1} X^\top y$

# Dummy Variables and Multicollinearity

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The matrix  $\mathbf{X}$  is not full rank.

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Then this implies that  $S > W > E > N$

# Dummy Variables

N-1 Variable encoding

	Is it N?	Is it E?	Is it W?
N	1	0	0
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## N Variable encoding

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This introduces dependencies between them, and this can cause confusion in classifiers.

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Now,  $\theta_0$  can be interpreted as average person height.  $\theta_1$  as the amount that female height is above average and male height is below average.

# Practice and Review

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