

# Building Features Using Normalization

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# Overview

**Normalization of feature vectors**

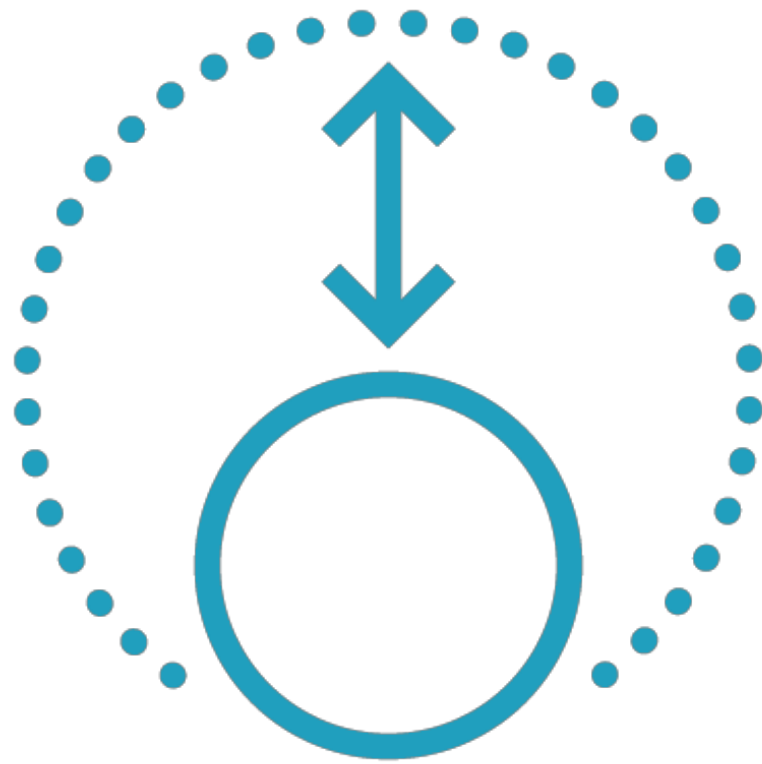
**Normalization and cosine similarity**

**L1, L2 and max norms for normalization**

# What is Normalization?

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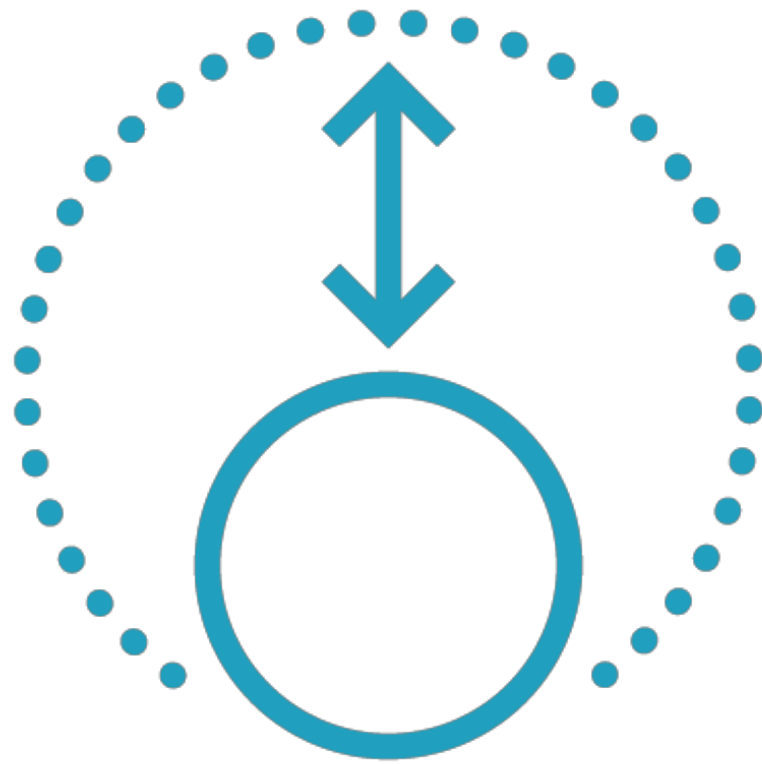


Scaling to a certain range - **feature scaling**

Centering at 0 and scaling to unit variance - **standardization**

Transforming a vector to unit norm

# What is Normalization?



Scaling to a certain range - feature scaling

Centering at 0 and scaling to unit variance - standardization

**Transforming a vector to unit norm**

Norm refers to the  
**magnitude** of the vector

# Normalization and Cosine Similarity

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# Normalization

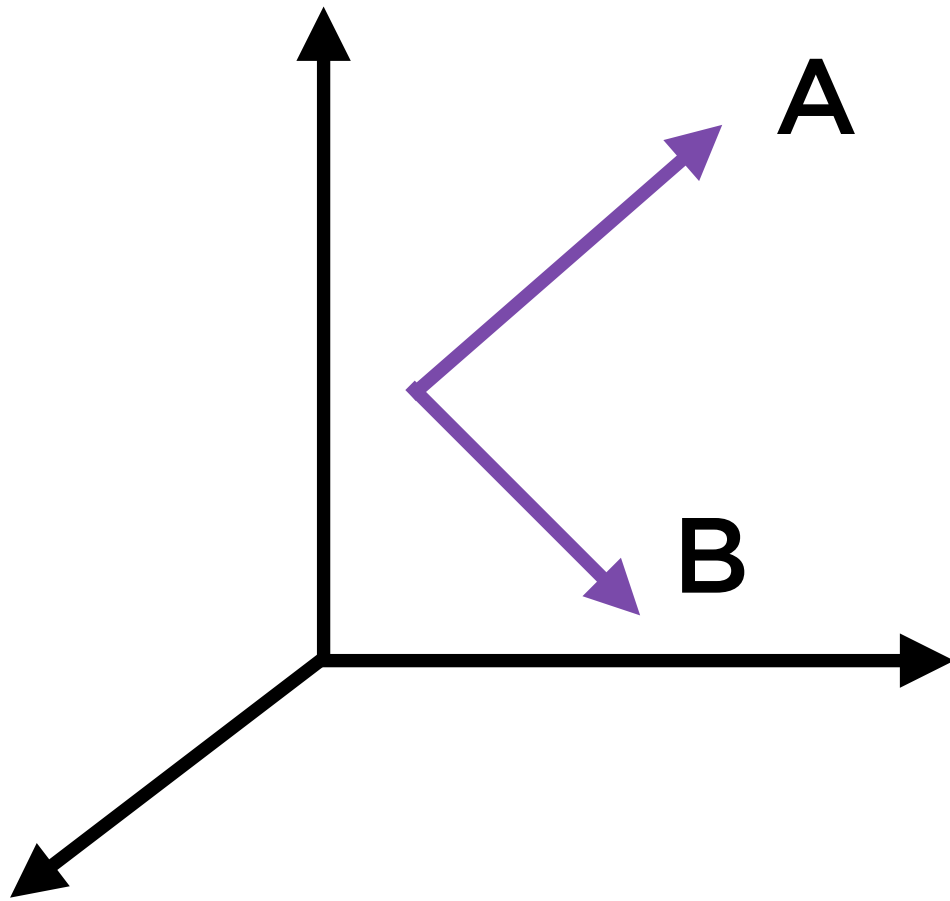
Process of scaling input vectors individually to unit norm (unit magnitude), often in order to simplify cosine similarity calculations.



# Cosine Similarity

Cosine similarity is a measure of similarity between two non-zero vectors, widely used in ML algorithms - especially in document modeling applications.

# Orthogonal Vectors



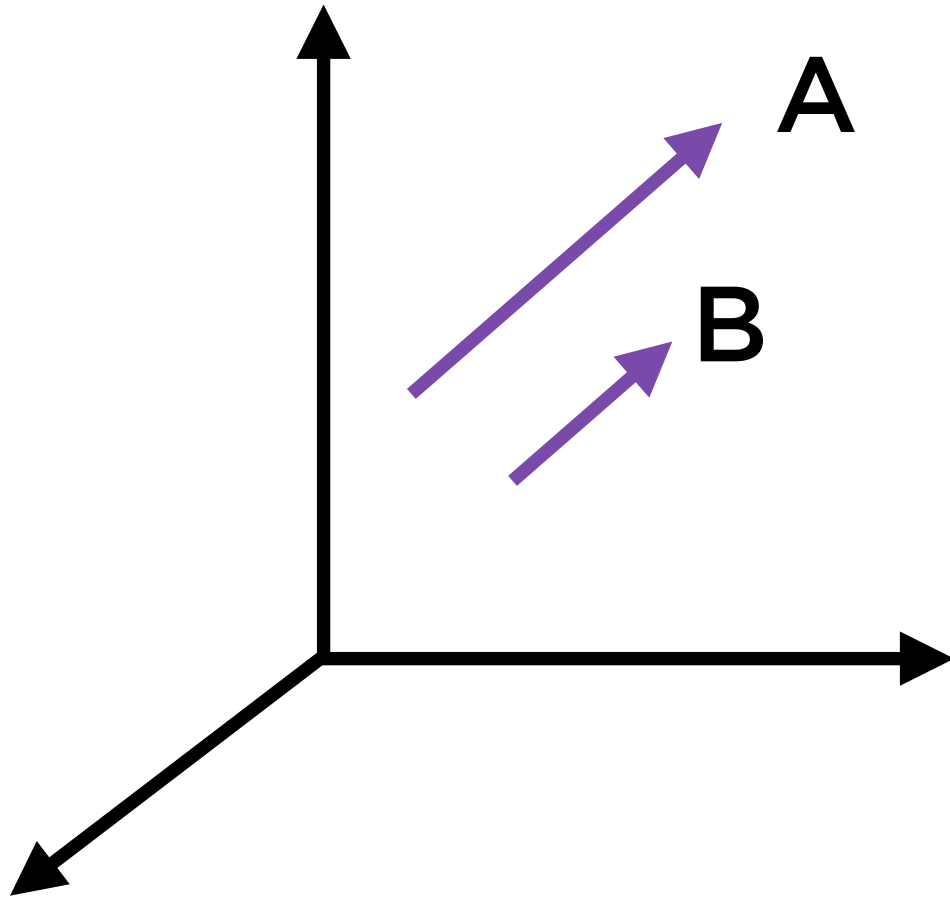
**Vectors A and B are at 90 degrees**

**Orthogonal vectors represent  
uncorrelated data**

**A and B are unrelated, independent**

**Cosine of 90 degrees = 0**

# Aligned Vectors



**Vectors A and B are parallel**

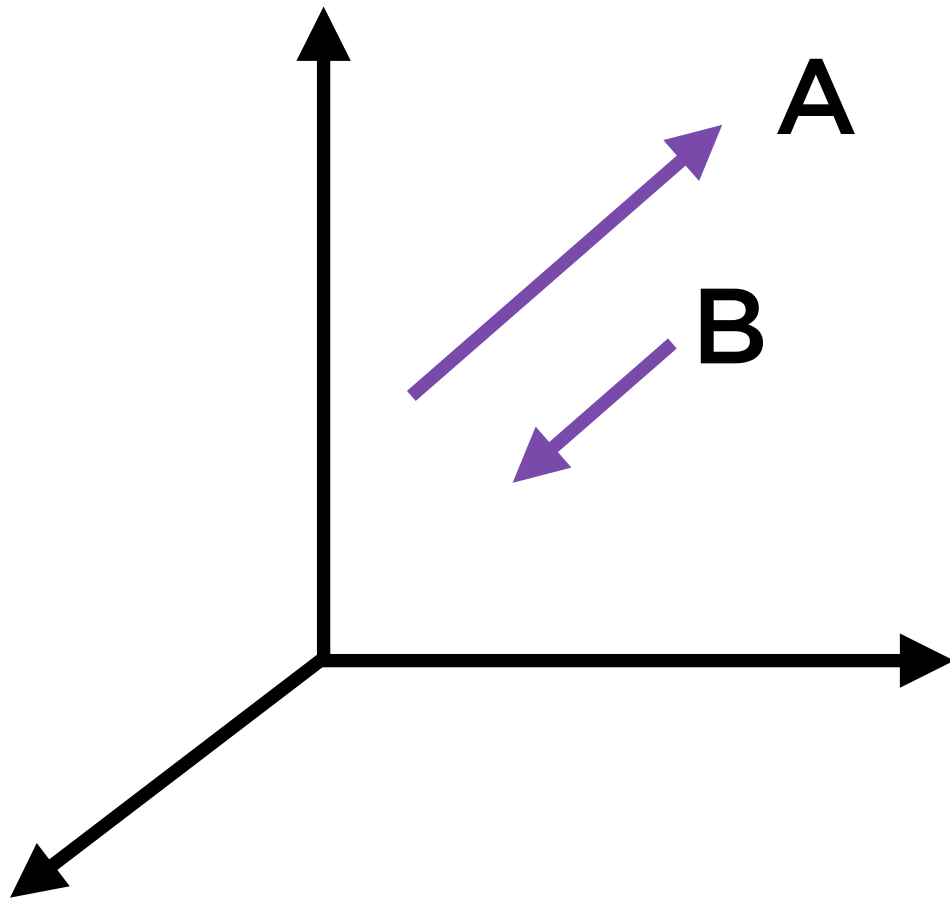
**Angle between them is 0 degrees**

**Perfectly aligned**

**Correlation of 1 (highest possible)**

**Cosine of 0 degrees = 1**

# Opposite Vectors



**Vectors A and B point in opposite directions**

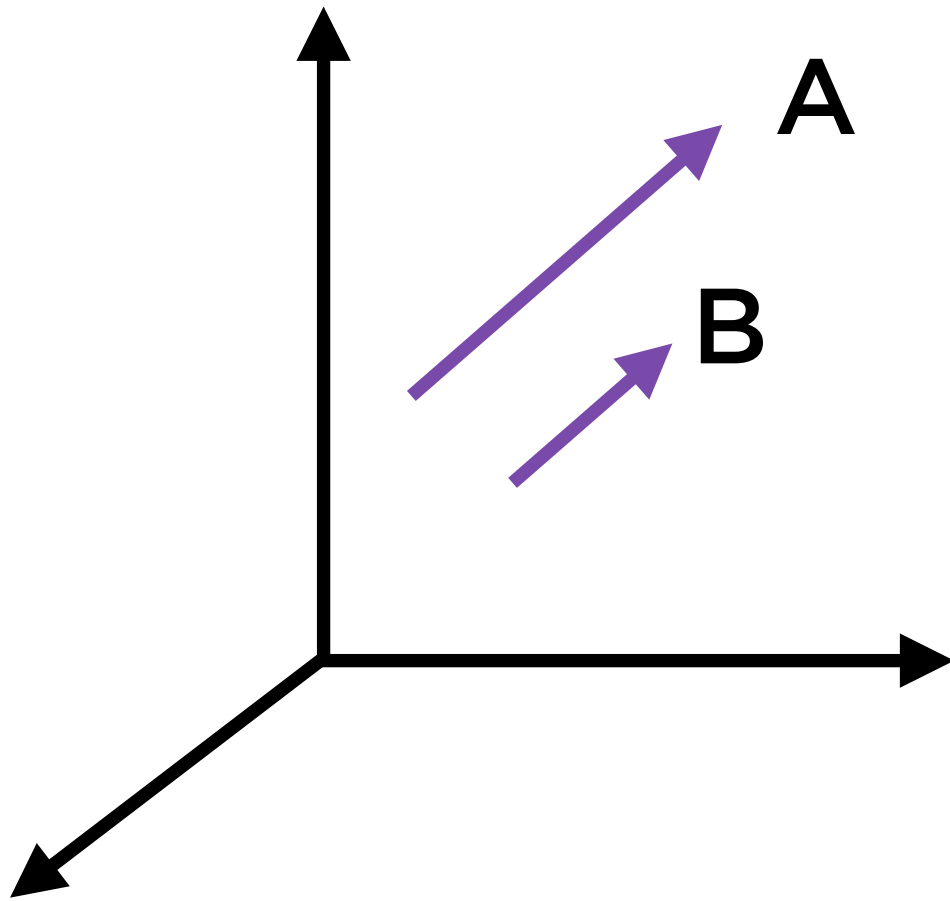
**Angle between them is 180 degrees**

**Perfectly opposed**

**Correlation of -1 (lowest possible)**

**Cosine of 180 degrees = -1**

# Cosine Similarity



**Quick and intuitive way to express alignment between two vectors**

**Each vector represents a single point**

**In three dimensions, a point is represented as**

$$(x_i, y_i, z_i)$$

# Cosine Similarity

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

$$\|\mathbf{A}\| = \sqrt{x_A^2 + y_A^2 + z_A^2}$$

$$\|\mathbf{B}\| = \sqrt{x_B^2 + y_B^2 + z_B^2}$$

$$\mathbf{A} \cdot \mathbf{B} = x_A x_B + y_A y_B + z_A z_B$$

# Cosine Similarity

$$\cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

$$\|A\| = \sqrt{x_A^2 + y_A^2 + z_A^2}$$

$$\|B\| = \sqrt{x_B^2 + y_B^2 + z_B^2}$$

$$A \cdot B = x_A x_B + y_A y_B + z_A z_B$$

Simplifying this calculation can simplify the computation of cosine similarity

# Normalization

Pre-convert A and B to unit norm vectors to simplify calculation

$$\mathbf{a} = \frac{\mathbf{A}}{||\mathbf{A}||} = \frac{(x_A, y_A, z_A)}{\text{sqrt}(x_A^2 + y_A^2 + z_A^2)}$$

$$\mathbf{b} = \frac{\mathbf{B}}{||\mathbf{B}||} = \frac{(x_B, y_B, z_B)}{\text{sqrt}(x_B^2 + y_B^2 + z_B^2)}$$



# Normalization

$$(x_A, y_A, z_A)$$

$$a = \frac{A}{||A||} = \frac{(x_A, y_A, z_A)}{\text{sqrt}(x_A^2 + y_A^2 + z_A^2)}$$

# Normalization

$(x_A, y_A, z_A)$

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# Cosine Similarity

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

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$$\mathbf{A} \cdot \mathbf{B} = x_A x_B + y_A y_B + z_A z_B$$

# Cosine Similarity

$$\cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

$$\|A\| = 1$$

$$\|B\| = 1$$

$$A \cdot B = x_A x_B + y_A y_B + z_A z_B$$

Normalizing is a row-wise operation, while scaling is a column-wise operation

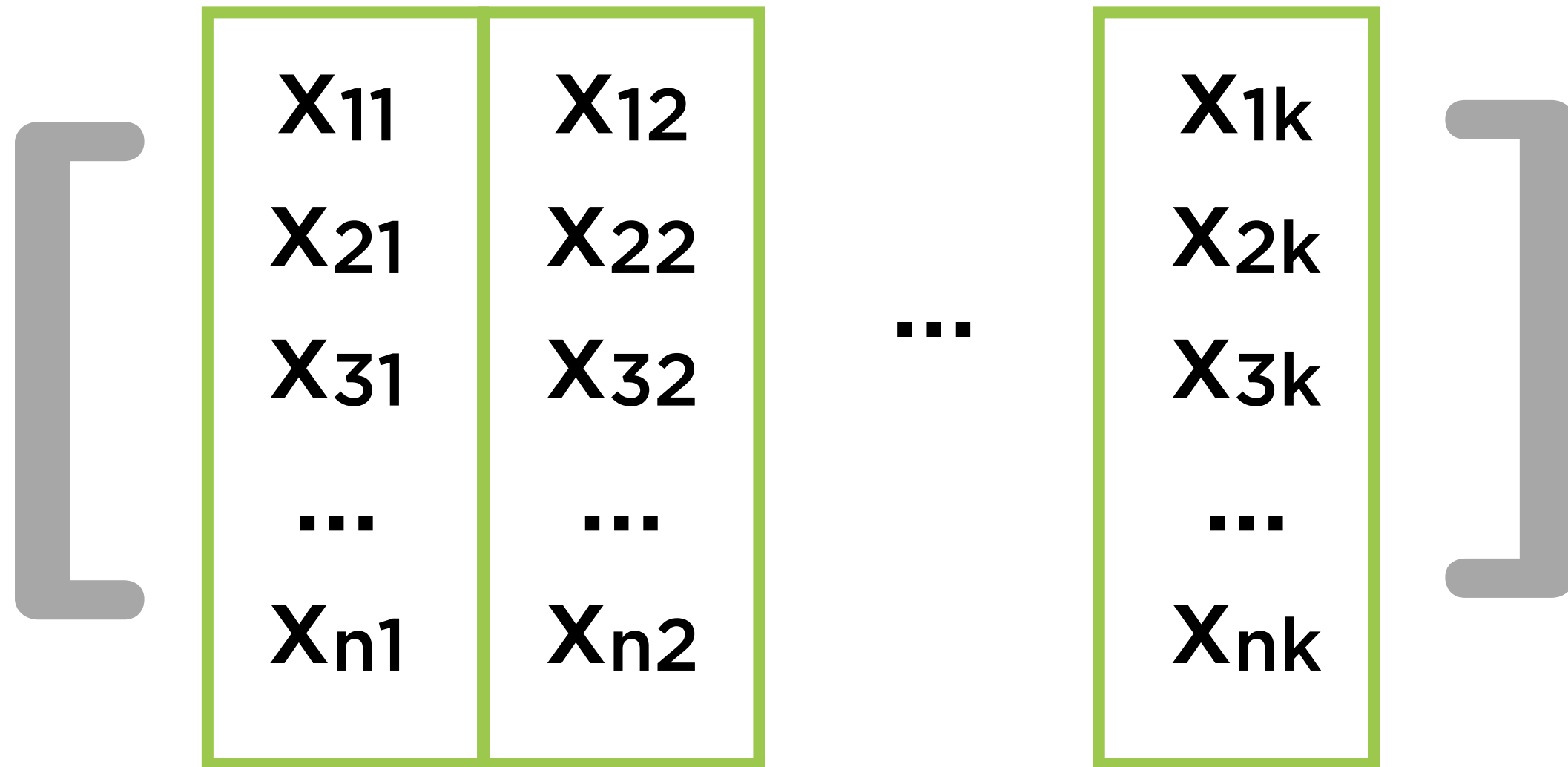


Data

$$\begin{bmatrix} X_{11} & X_{12} & \dots & X_{1k} \\ X_{21} & X_{22} & & X_{2k} \\ X_{31} & X_{32} & & X_{3k} \\ \dots & \dots & & \dots \\ X_{n1} & X_{n2} & & X_{nk} \end{bmatrix}$$

All of the numeric values in our dataset

# Columns Represent Features

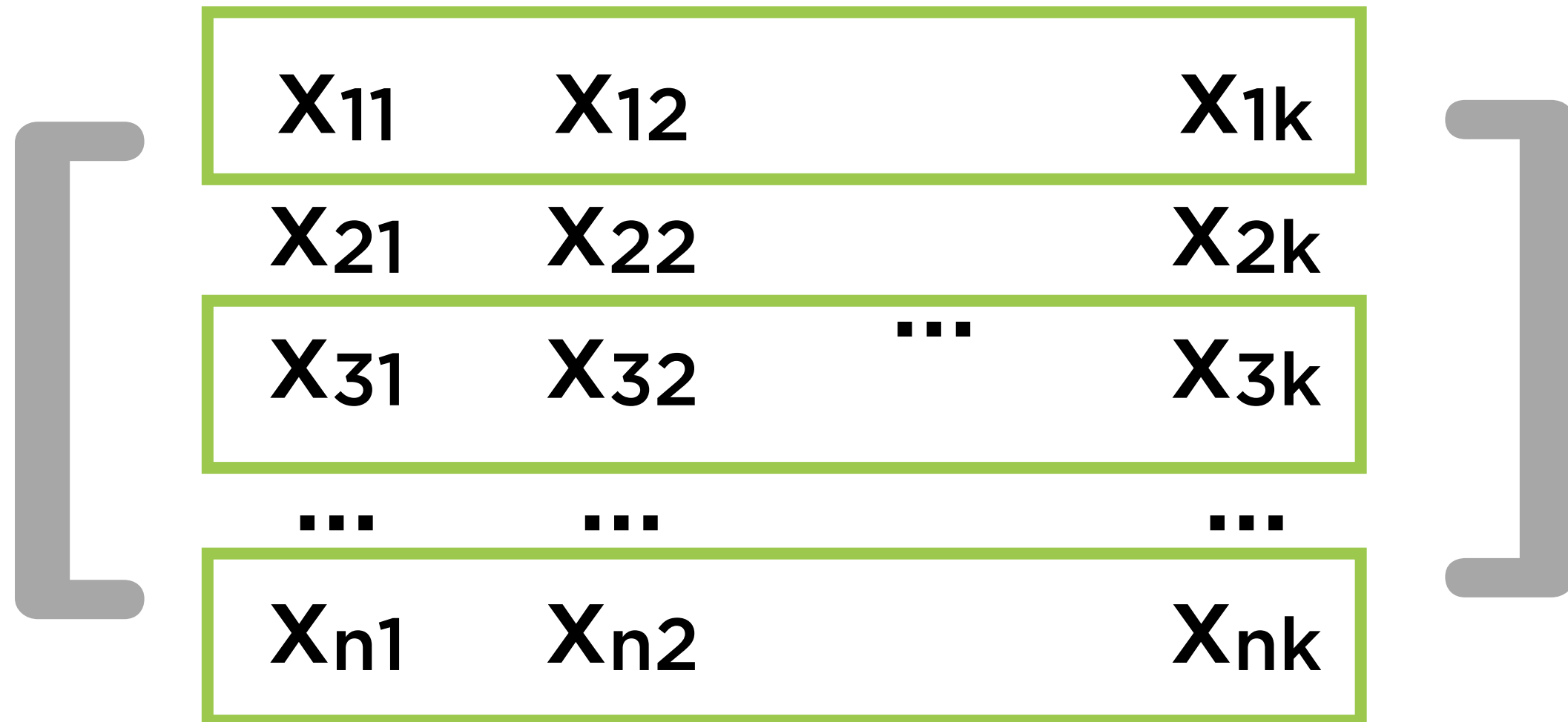


The diagram illustrates a data matrix where columns represent features. It consists of a large gray bracket on the left and a large gray bracket on the right. Between these brackets are three green-outlined boxes. The first box contains a vertical list of features:  $X_{11}$ ,  $X_{21}$ ,  $X_{31}$ ,  $\dots$ , and  $X_{n1}$ . The second box contains a vertical list of features:  $X_{12}$ ,  $X_{22}$ ,  $X_{32}$ ,  $\dots$ , and  $X_{n2}$ . To the right of the second box is an ellipsis ( $\dots$ ). The third box contains a vertical list of features:  $X_{1k}$ ,  $X_{2k}$ ,  $X_{3k}$ ,  $\dots$ , and  $X_{nk}$ .

$X_{11}$	$X_{12}$	$\dots$	$X_{1k}$
$X_{21}$	$X_{22}$		$X_{2k}$
$X_{31}$	$X_{32}$		$X_{3k}$
$\dots$	$\dots$		$\dots$
$X_{n1}$	$X_{n2}$		$X_{nk}$

Standardization and scaling apply to an individual feature

# Rows Represent Vectors



<b><math>X_{11}</math></b>	<b><math>X_{12}</math></b>		<b><math>X_{1k}</math></b>
<b><math>X_{21}</math></b>	<b><math>X_{22}</math></b>		<b><math>X_{2k}</math></b>
<b><math>X_{31}</math></b>	<b><math>X_{32}</math></b>	<b><math>\dots</math></b>	<b><math>X_{3k}</math></b>
<b><math>\dots</math></b>	<b><math>\dots</math></b>		<b><math>\dots</math></b>
<b><math>X_{n1}</math></b>	<b><math>X_{n2}</math></b>		<b><math>X_{nk}</math></b>

Normalization applies to vectors i.e. to a row which represents data for a single instance

Demo

**Normalization and cosine similarity**

# Types of Normalization

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# Different Norms

**L1**

Sum of absolute values of  
components of vector

**L2**

Traditional definition of  
vector magnitude

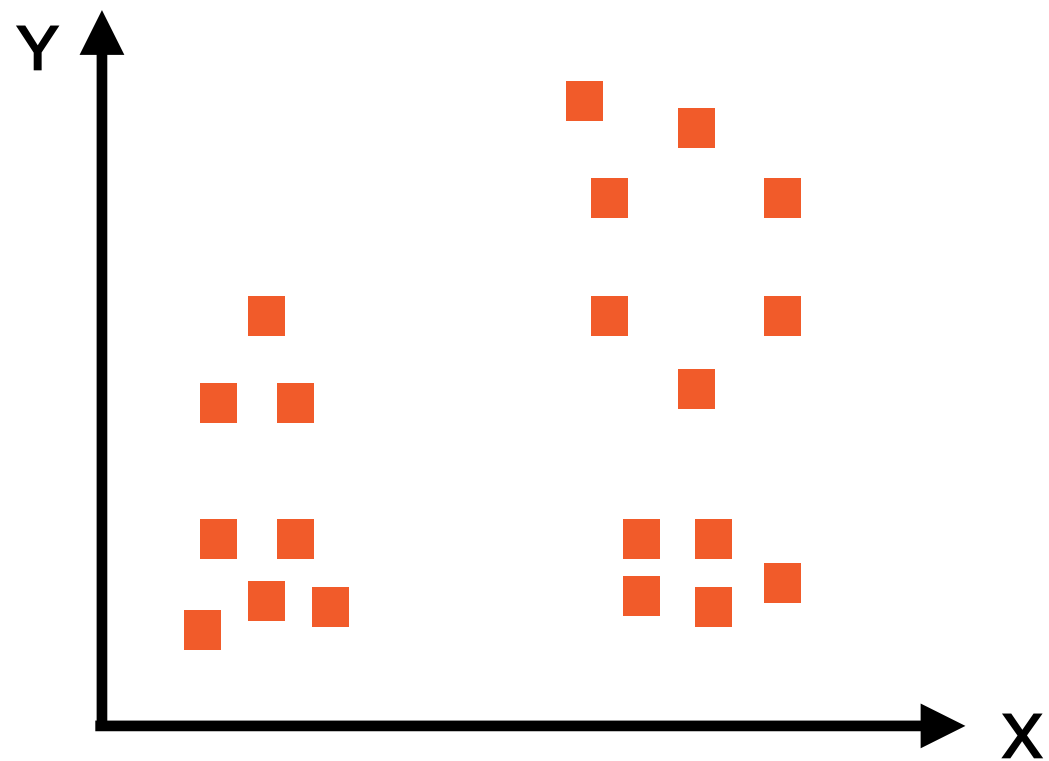
**max**

Largest absolute value of  
elements of vector

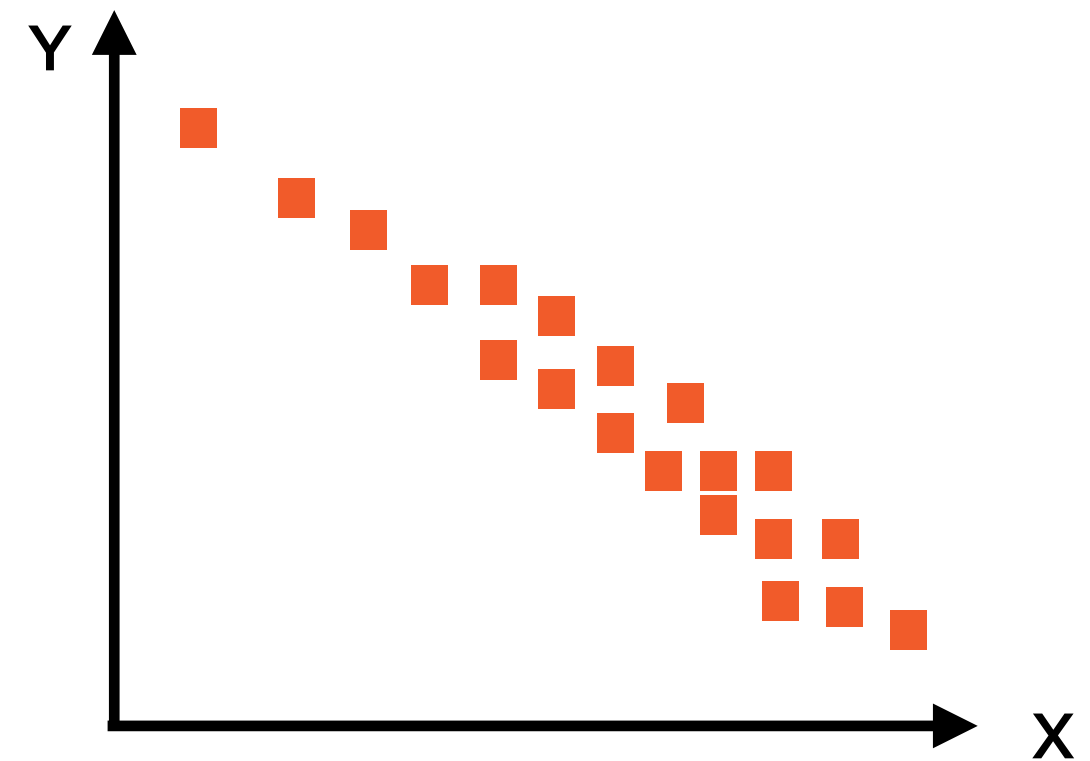
# L1-norm

$$X_{\text{new}} = \frac{(x, y, z)}{|x| + |y| + |z|}$$

# L1-norm



Before L1-norm



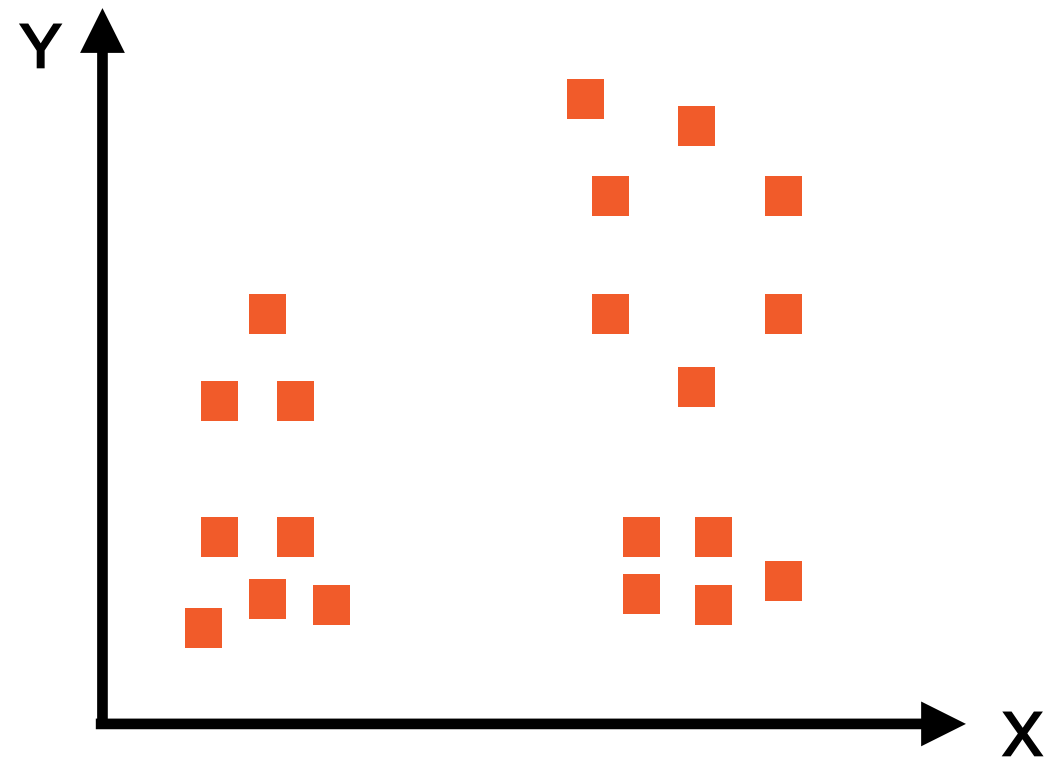
After L1-norm



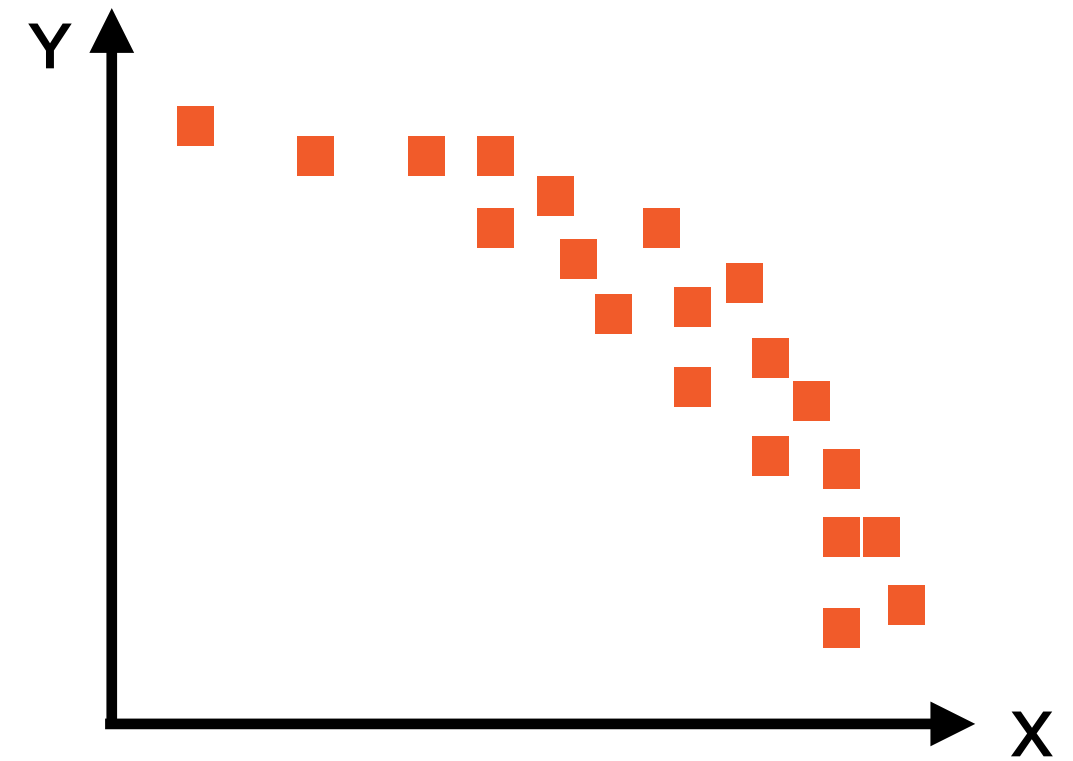
L2-norm

$$\mathbf{X}_{\text{new}} = \frac{(\mathbf{x}, y, z)}{\text{sqrt}(\mathbf{x}^2 + y^2 + z^2)}$$

# L2-norm



Before L2-norm



After L2-norm

max norm

$$X_{\text{new}} = \frac{(x, y, z)}{\max(\text{abs}(x, y, z))}$$

Demo

**Applying L1, L2 and max norms for  
normalization**

# Summary

**Normalization of feature vectors**

**Normalization and cosine similarity**

**L1, L2 and max norms for normalization**