Introduction to Vector Space Models

Vector span, Subspaces, and Basis Vectors

Part 1: Vector Span and Subspaces

Linear Combinations (Algebraically)

A <u>linear combination</u> is constructed from a set of vectors $\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_p$ by multiplying each vector by a constant and adding the result:

$$\mathbf{c} = \mathbf{a}_1 \mathbf{v}_1 + \mathbf{a}_2 \mathbf{v}_2 + \ldots + \mathbf{a}_p \mathbf{v}_p = \sum_{i=1}^n \mathbf{a}_i \mathbf{v}_i$$

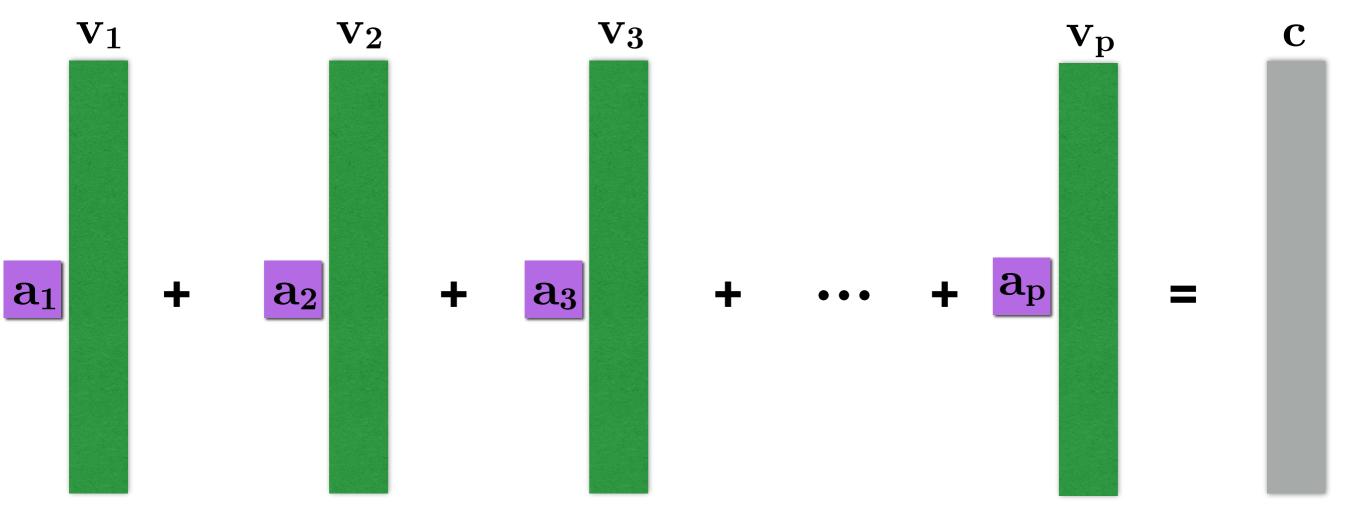
Linear Combinations (Algebraically)

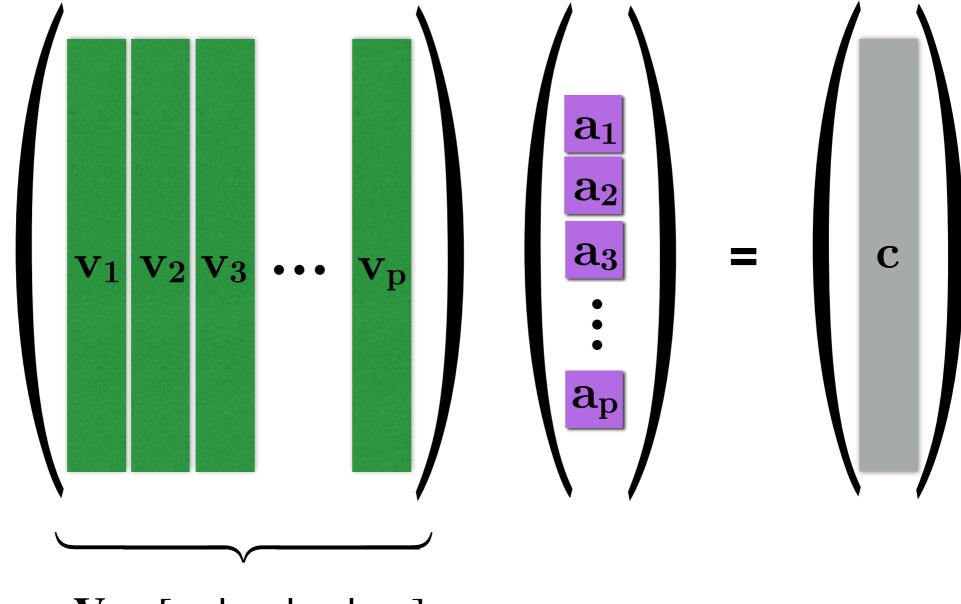
A <u>linear combination</u> is constructed from a set of vectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_p$ by multiplying each vector by a constant and adding the result:

$$\mathbf{c} = a_1 \mathbf{v}_1 + a_2 \mathbf{v}_2 + \ldots + a_p \mathbf{v}_p = \sum_{i=1}^n a_i \mathbf{v}_i$$

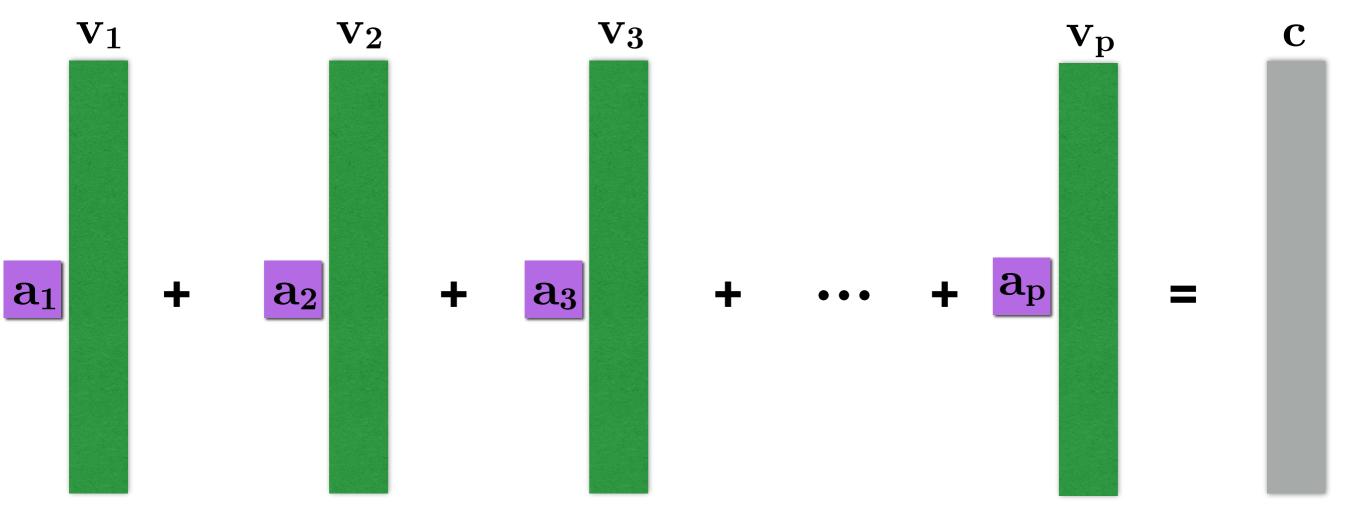
alternatively, we could write

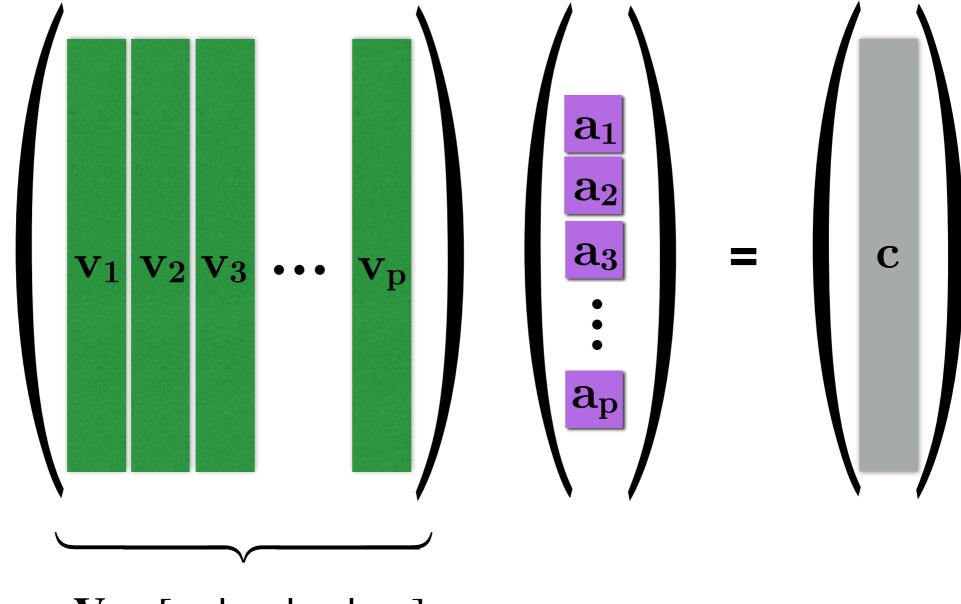
cernatively, we could write
$$\mathbf{c} = \mathbf{V}\mathbf{a} \quad \text{where} \quad \mathbf{V} = [\mathbf{v}_1 | \mathbf{v}_2 | \dots | \mathbf{v}_p] \quad \text{and} \quad \mathbf{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$





$$\mathbf{V} = [\mathbf{v}_1 \,|\, \mathbf{v}_2 \,|\, \dots \,|\, \mathbf{v}_p]$$

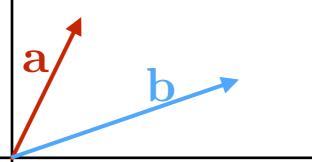




$$\mathbf{V} = [\mathbf{v}_1 \,|\, \mathbf{v}_2 \,|\, \dots \,|\, \mathbf{v}_p]$$

Linear Combinations

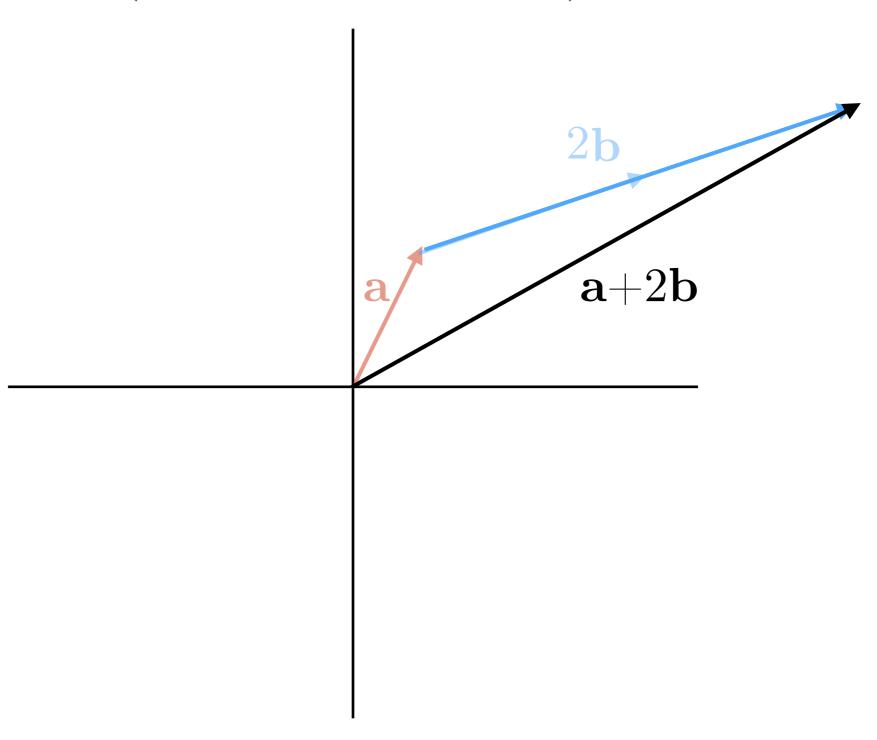
(Geometrically)



a+2b

Linear Combinations

(Geometrically)



(Algebraically)

A group of vectors, $\{\mathbf{v}_{1},\mathbf{v}_{2},...,\mathbf{v}_{n}\}$ are <u>linearly</u> <u>dependent</u> if there exists corresponding scalars, $\{\alpha_{1},\alpha_{2},...,\alpha_{n}\}$ not all equal to zero such that:

$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \ldots + \alpha_n \mathbf{v}_n = 0$$

(Algebraically)

A group of vectors, $\{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_n\}$ are <u>linearly</u> <u>dependent</u> if there exists corresponding scalars, $\{\alpha_1, \alpha_2, ..., \alpha_n\}$ not all equal to zero such that:

$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \ldots + \alpha_n \mathbf{v}_n = 0$$

For example, if $2\mathbf{v}_1 - 2\mathbf{v}_2 + 4\mathbf{v}_3 = 0$

Then,
$$\mathbf{v}_1 = \mathbf{v}_2 - 2\mathbf{v}_3$$

 $\#\mathbf{PerfectMulticollinearity}$

(Algebraically)

A group of vectors, $\{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_n\}$ are <u>linearly</u> <u>dependent</u> if there exists corresponding scalars, $\{\alpha_1, \alpha_2, ..., \alpha_n\}$ not all equal to zero such that:

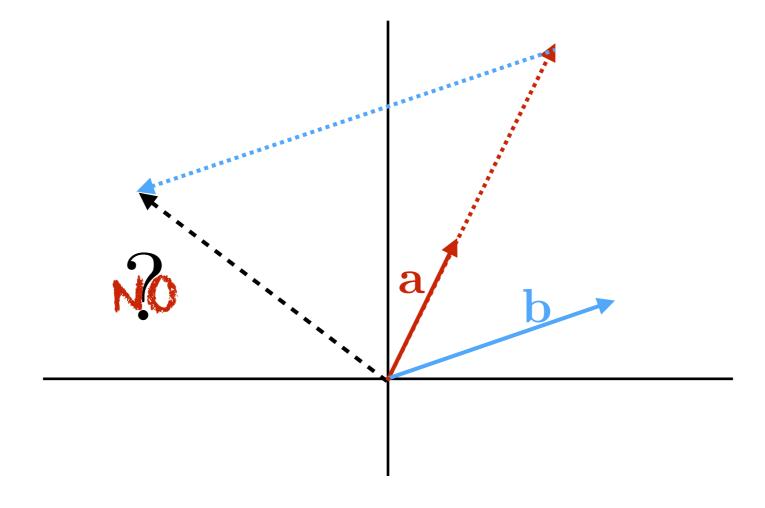
$$\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \ldots + \alpha_n \mathbf{v}_n = 0$$
#PerfectMulticollinearity

 $\{\mathbf{v}_{1},\mathbf{v}_{2},...,\mathbf{v}_{n}\}\ are\ \underline{\mathbf{linearly\ independent}}\ if\ the\ above\ equation\ has\ only\ the\ trivial\ solution\ (all\ \alpha_{i}=0)$

(Geometrically)

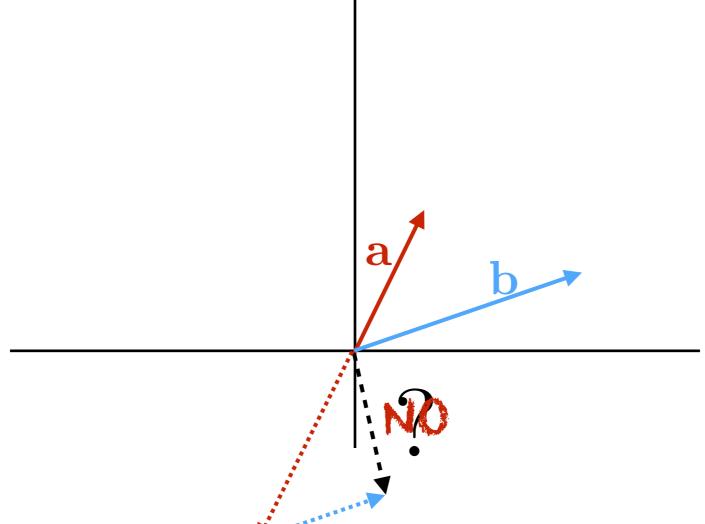
- ► Two vectors are <u>linearly dependent</u> if they are multiples of each other point in same (or opposite) direction
- ▶ More than two vectors are <u>linearly dependent</u> if at least one is a linear combination of the others

(Geometrically)



Can I add a third vector that is linearly *in*dependent of **a** and **b**?

(Geometrically)



Can I add a third vector that is linearly *in*dependent of **a** and **b**?

(Definition)

The <u>span</u> of a single vector **v** is the set of all scalar multiples of **v**:

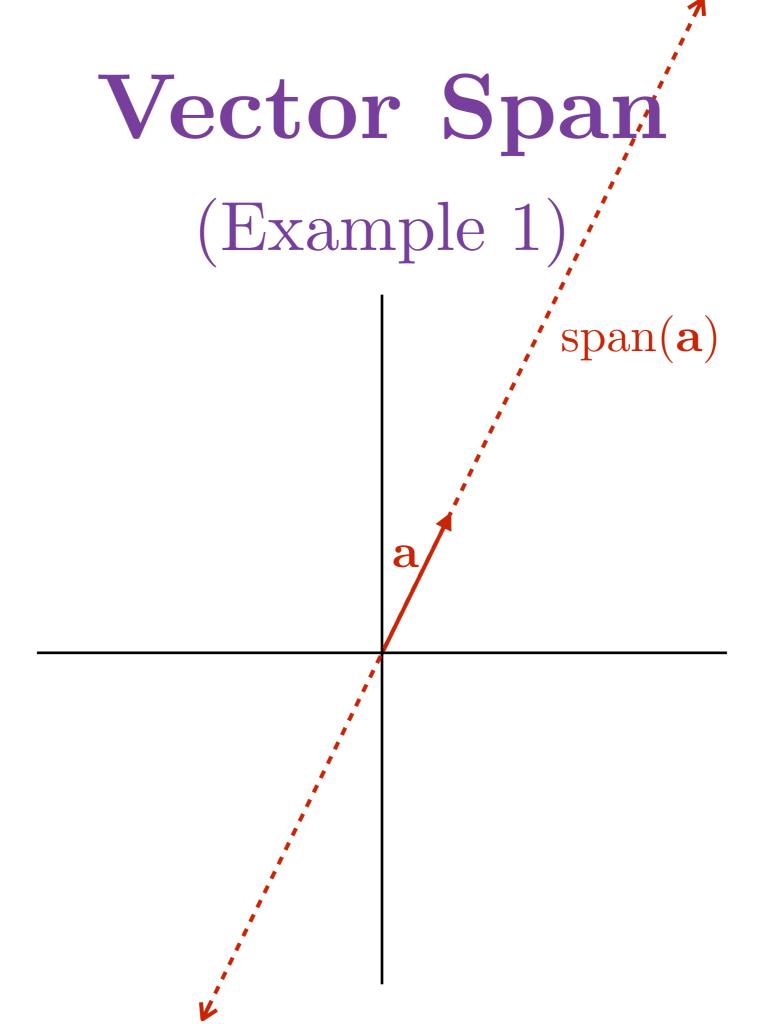
 $span(\mathbf{v}) = \{\alpha \mathbf{v} \text{ for all constants } \alpha\}$

▶ The <u>span</u> of a collection of vectors $V = \{v_1, v_2, ..., v_p\}$ is the set of *all* linear combinations of these vectors:

$$span(\mathbf{V}) = \{\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \dots + \alpha_p \mathbf{v}_p \text{ for all constants } \alpha_1, \alpha_2, \dots, \alpha_p\}$$

(Example 1)

a/



(Example 2)

a/b

(Example 2)



a/b

(Example 2)/

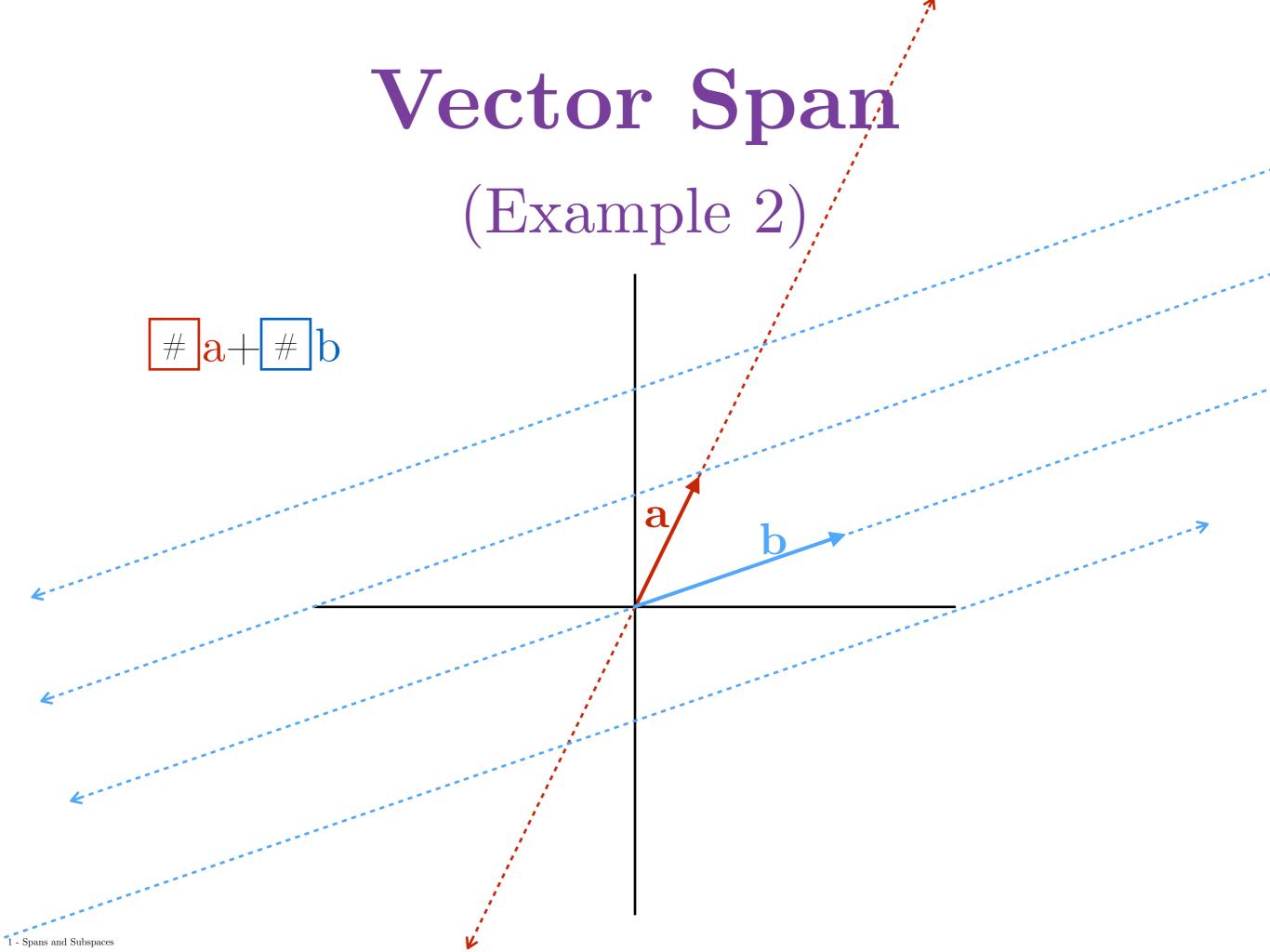


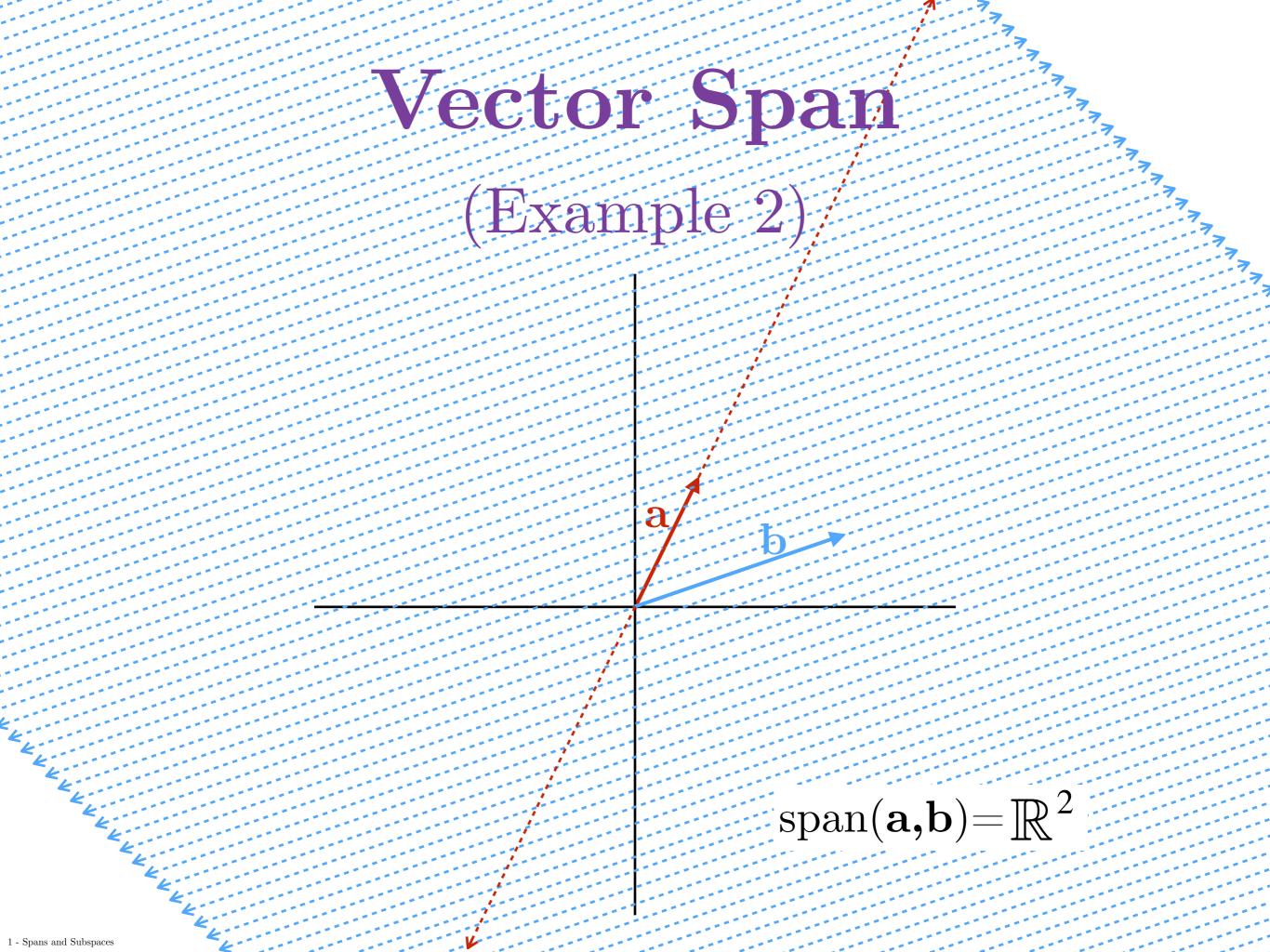
1 - Spans and Subspaces

(Example 2)



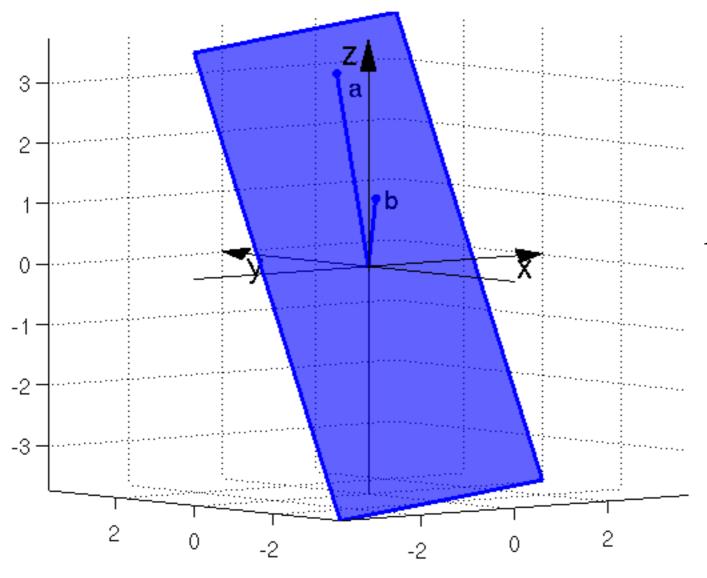
a/b





(Example 3)

What is the span of two linearly independent vectors in \mathbb{R}^3 ?



The plane (hyperplane) that contains both vectors. (A 2-dimensional <u>subspace</u> of \mathbb{R}^3)

Subspace

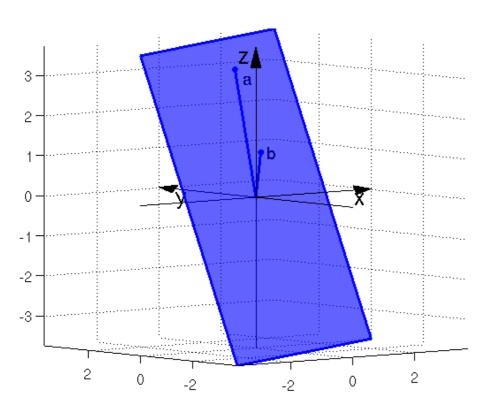
(Definition)

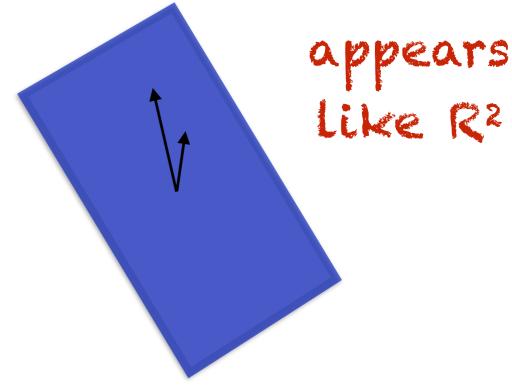
- A <u>subspace</u> S of \mathbb{R}^n is thought of as a "flat" (having no curvature) surface within \mathbb{R}^n . It is a collection of vectors which satisfies the following conditions:
 - The origin (0 vector) is contained in S.
 - If \mathbf{x} and \mathbf{y} are in S then $\mathbf{x}+\mathbf{y}$ also in S.
 - If \mathbf{x} is in S then $\alpha \mathbf{x}$ is in S for any scalar α .

Subspace

(Definition)

In other words, it is an infinite subset of vectors (points) from a larger space (\mathbb{R}^n) that when taken alone, appears like \mathbb{R}^p , p < n





The <u>dimension</u> of the subspace is the minimum number of vectors it takes to span the space. (Think: # of axes)

Hyperplane

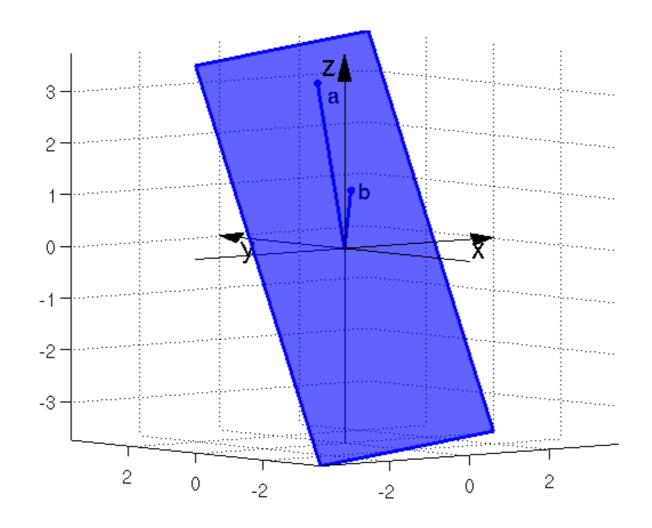
(Definition)

- A <u>hyperplane</u> is a subspace that has one less dimension than its ambient space.
- In 3-dimensional space a hyperplane would be a 2-dimensional plane.
- In 4-dimensional space, a hyperplane would be a 3-dimensional plane (helps to keep same picture in mind: a "flat" subspace in 4D!)

Hyperplane

(Definition)

• A <u>hyperplane</u> cuts the ambient space into two parts, one 'above' it and one 'below it'



Practice

Is the vector
$$\mathbf{x} = \begin{pmatrix} 4 \\ 3 \end{pmatrix}$$
 in the $span \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\}$?

Describe the span of one vector in \mathbb{R}^3

Describe the span of two linearly dependent vectors in \mathbb{R}^3

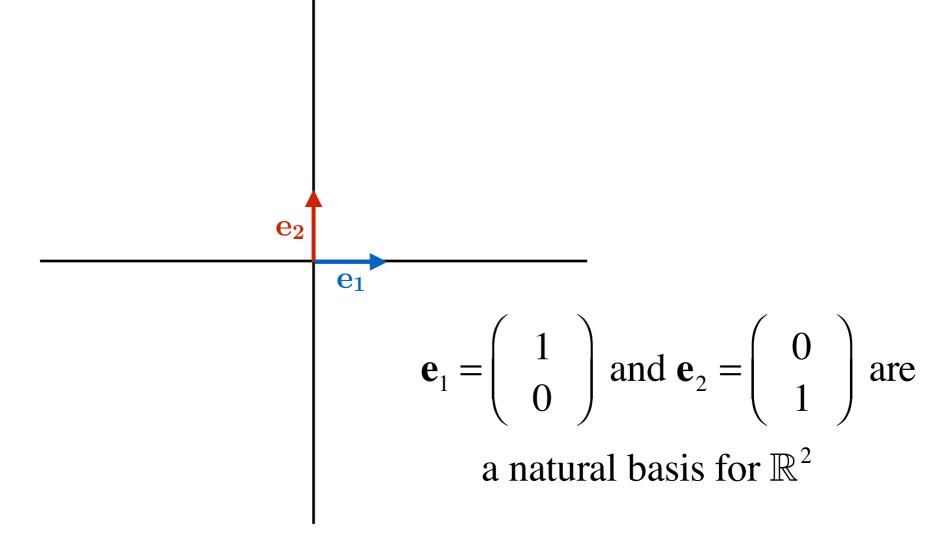
Compare the
$$span \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\}$$
 to the $span \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 \\ 2 \end{pmatrix} \right\}$

What is the dimension of the
$$span \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 \\ 2 \end{pmatrix} \right\}$$

Part 2: Basis and Coordinates

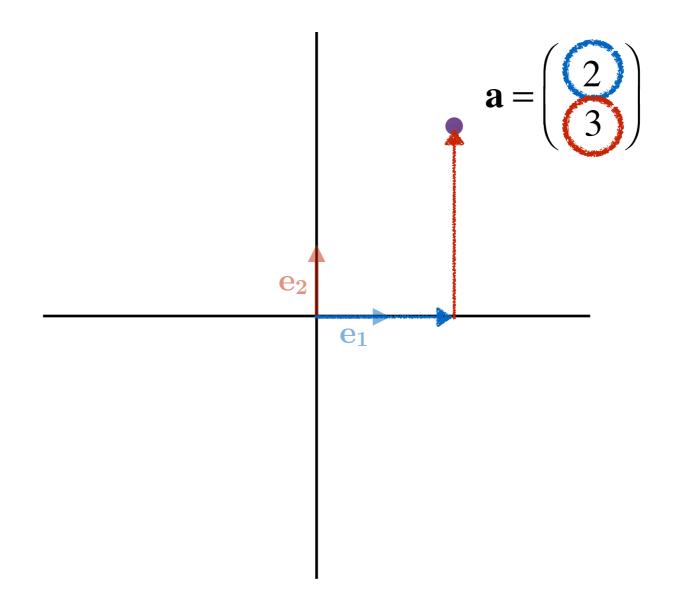
Basis and Coordinates

A collection of vectors makes a <u>basis</u> for a space (or a subspace) if they are linearly independent and span the space.



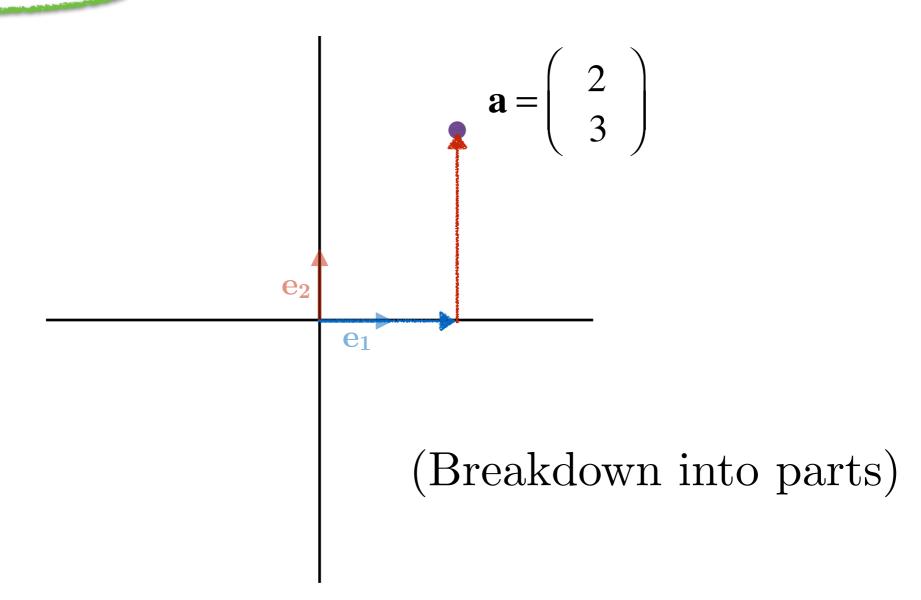
Basis and Coordinates

• Coordinate pairs are represented in a basis. Each coordinate tells you how far to move along each basis direction.

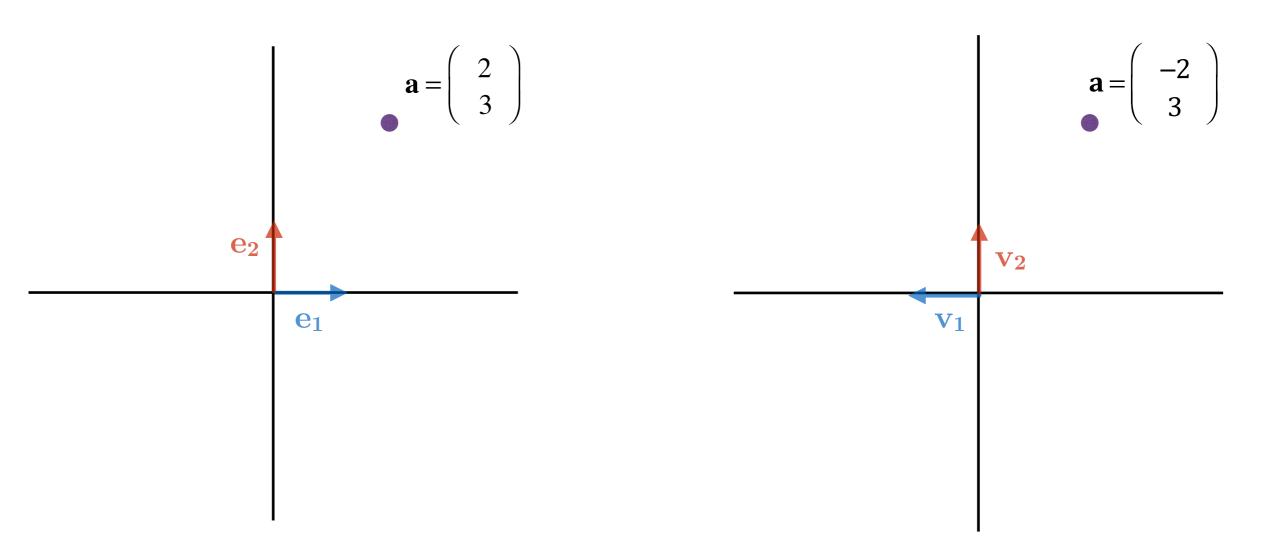


Basis and Coordinates

Coordinate pairs are represented in a basis. Each
 coordinate tells you how far to move along each
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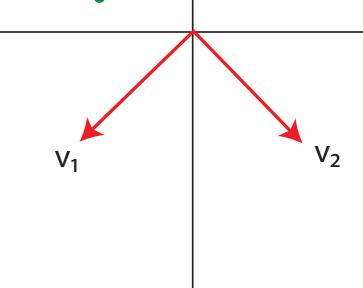
Change of Basis



$$2\mathbf{e}_{1} + 3\mathbf{e}_{2} = -2\mathbf{v}_{1} + 3\mathbf{v}_{2}$$

Practice

In the following picture, what would be the signs (+/-) of the coordinates of the green point in the basis $\{\mathbf{v}_1,\mathbf{v}_2\}$?



Find the coordinates of the vector
$$\mathbf{x} = \begin{pmatrix} 4 \\ 3 \end{pmatrix}$$
 in the basis $\left\{ \begin{pmatrix} -1 \\ -1 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right\}$.

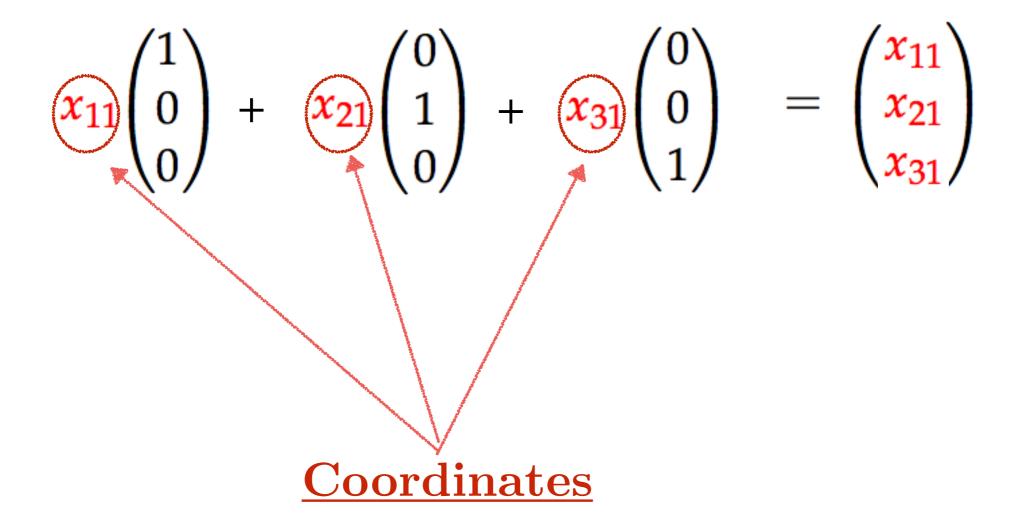
Draw a picture to confirm your answer matches your intuition.

Part 3: A Change of Basis

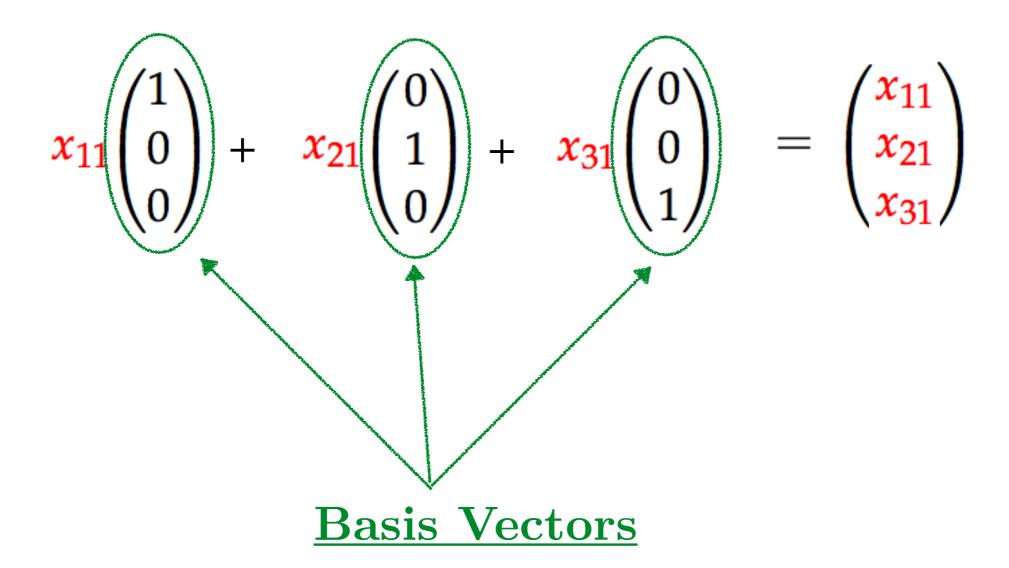
Basis and Coordinates

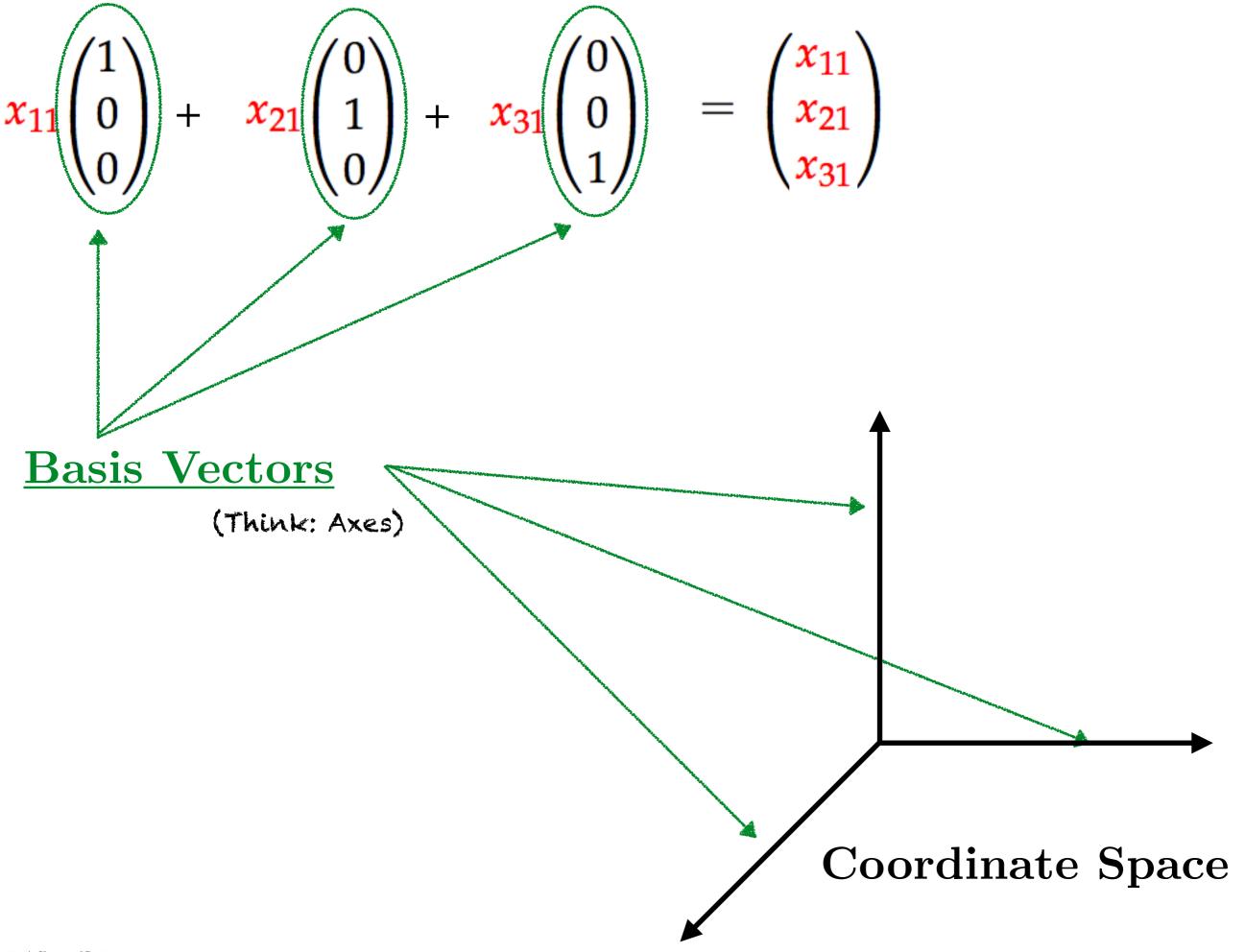
$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix} = \begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix}$$

Basis and Coordinates

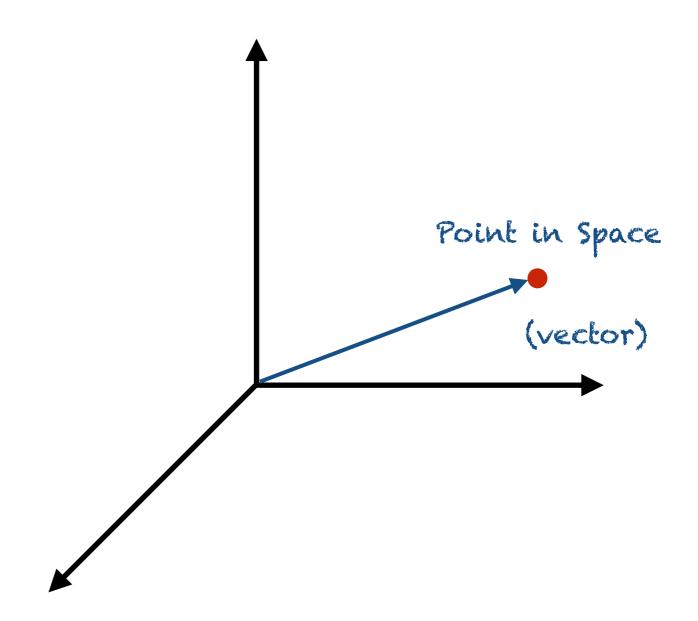


Bases and Coordinates





$$x_{11} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} + x_{21} \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} + x_{31} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix}$$

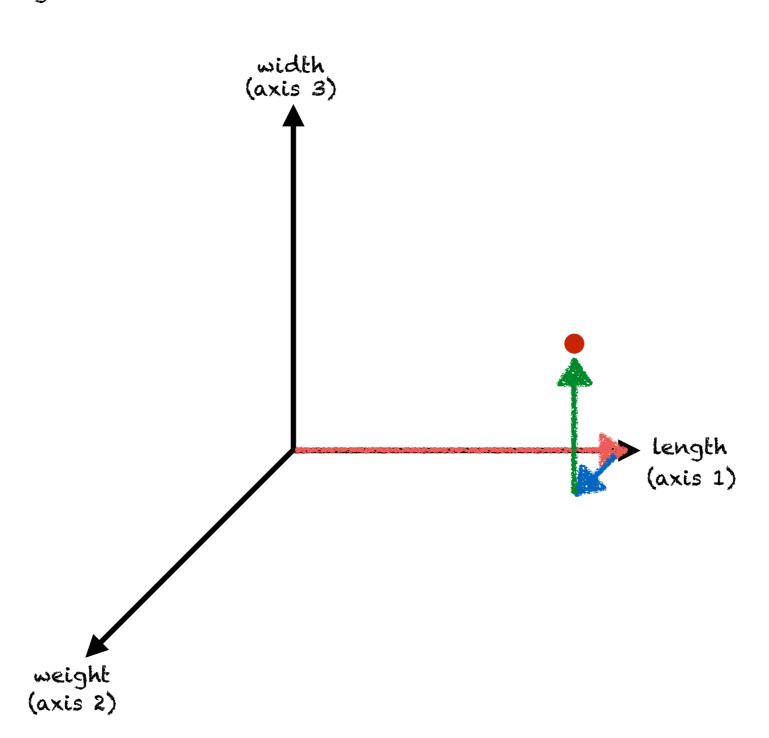


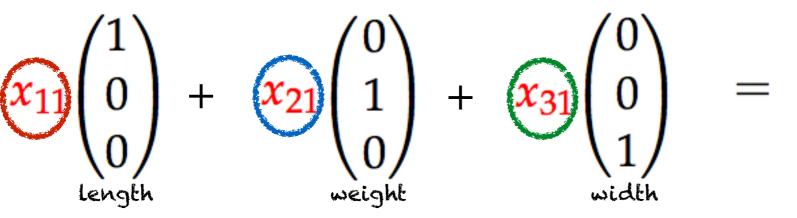
$$\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} x_{21} \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} x_{31} \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix}$$

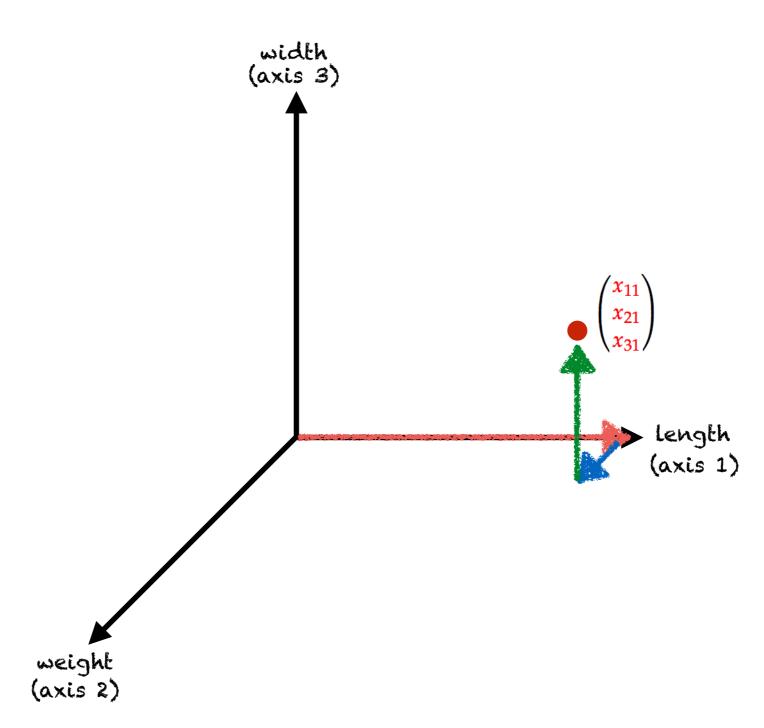
Coordinates give directions to a point along basis vectors.

For any set of data points, the basis vectors are the same. We compare the points by comparing their coordinates.

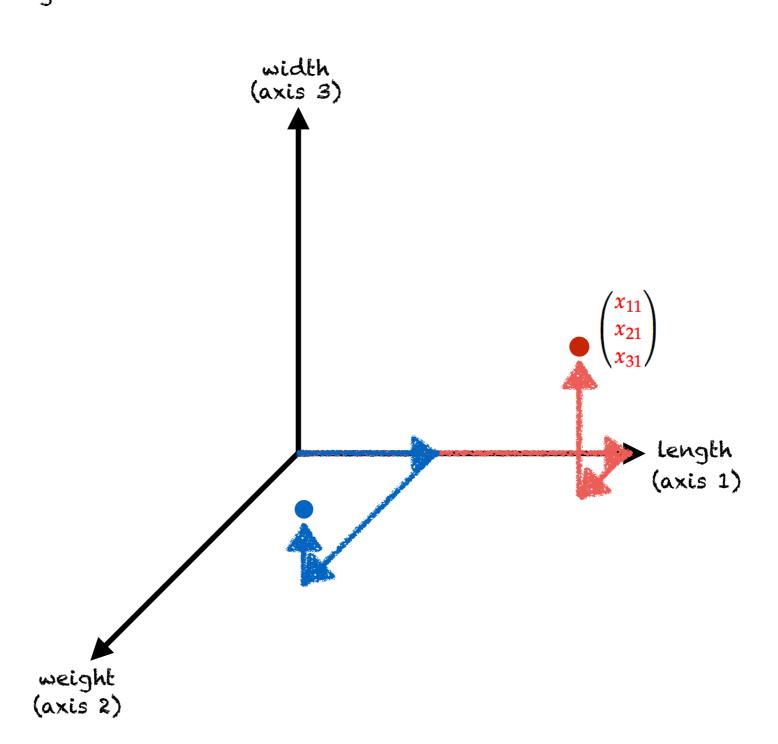
$$\begin{array}{c} x_{11} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} + \begin{array}{c} x_{21} \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} + \begin{array}{c} x_{31} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} & = \begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix}$$
weight width



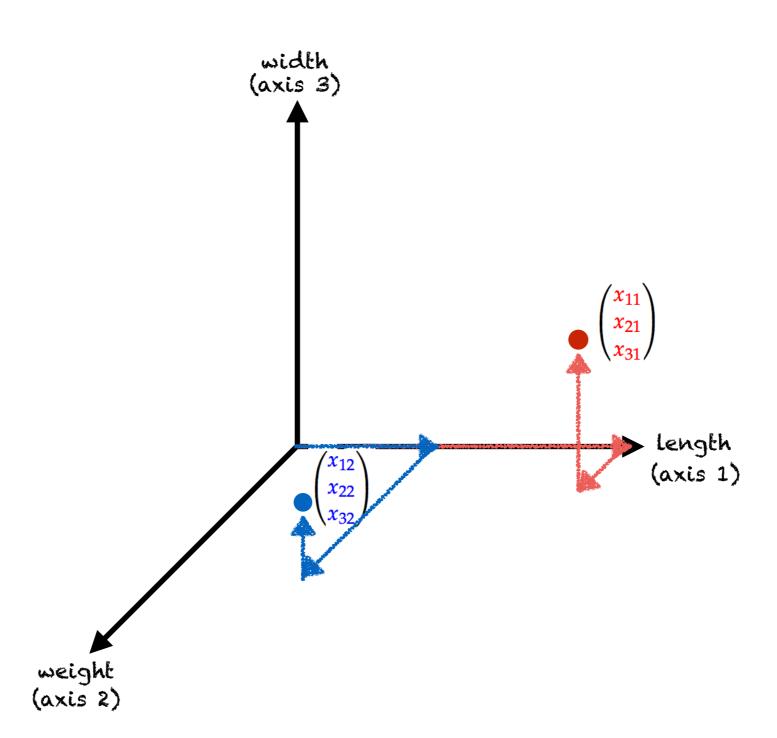




$$\begin{array}{c}
x_{12} \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \begin{array}{c} x_{22} \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} + \begin{array}{c} x_{32} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} & = \begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix} \\
& \text{weight} & \text{width} &
\end{array}$$



$$\begin{pmatrix}
x_{12} \\
0 \\
0 \\
0
\end{pmatrix} + \begin{pmatrix}
x_{22} \\
0 \\
0 \\
0
\end{pmatrix} + \begin{pmatrix}
x_{32} \\
0 \\
0 \\
1
\end{pmatrix} = \begin{cases}
0 \\
0 \\
1
\end{cases}$$
weight width



Compared to red point, blue point has:

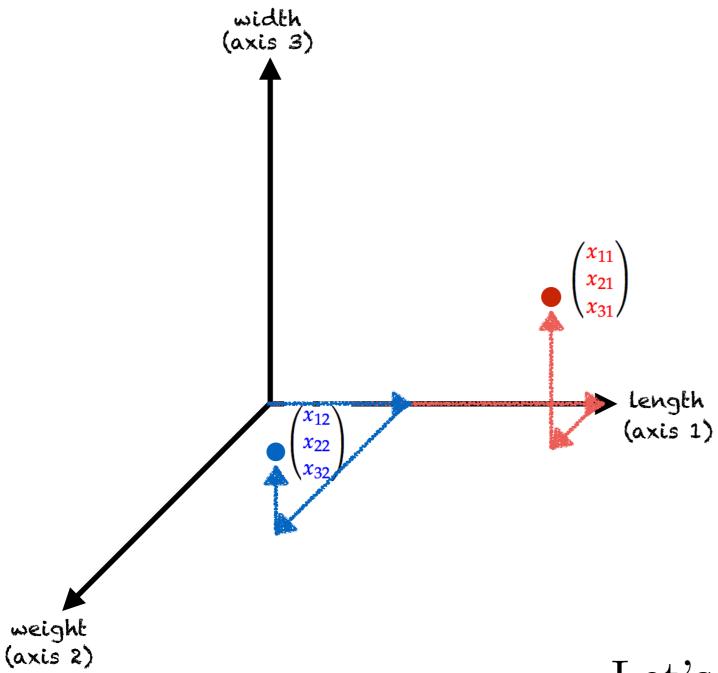


 x_{22}

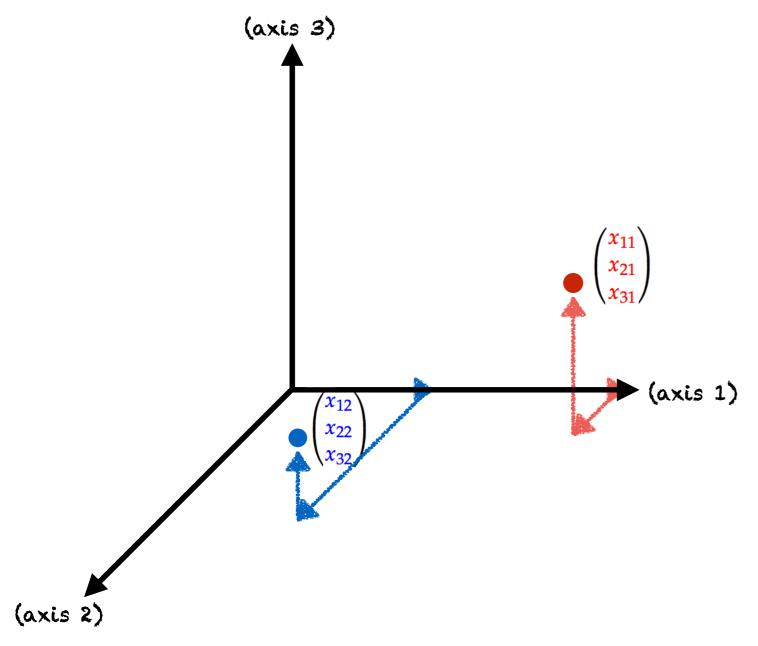
(axis 1)

Let's change the basis...

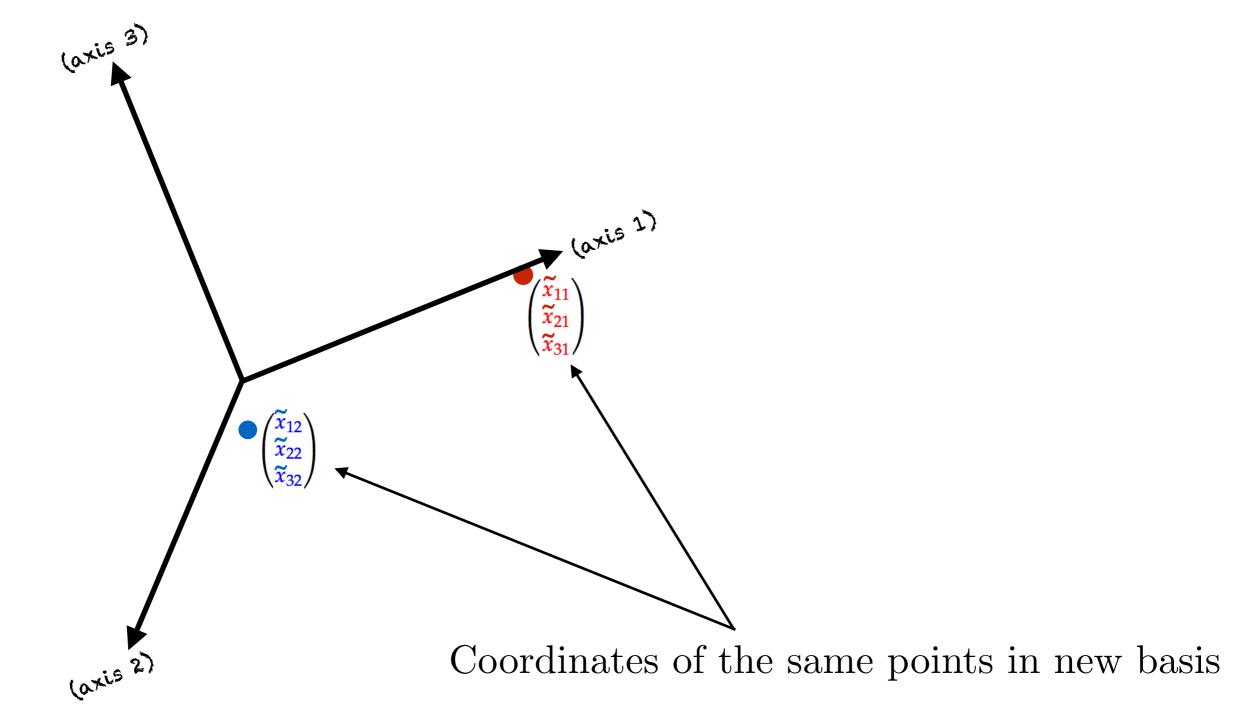
weight (axis 2)

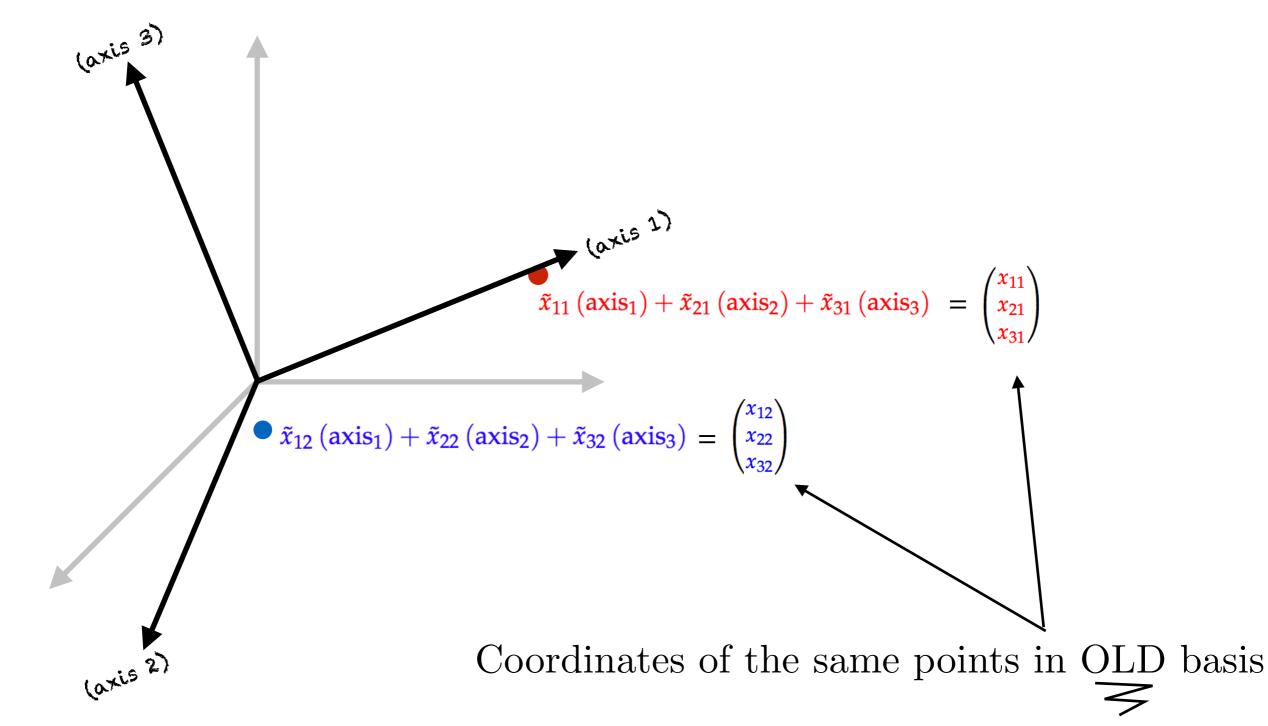


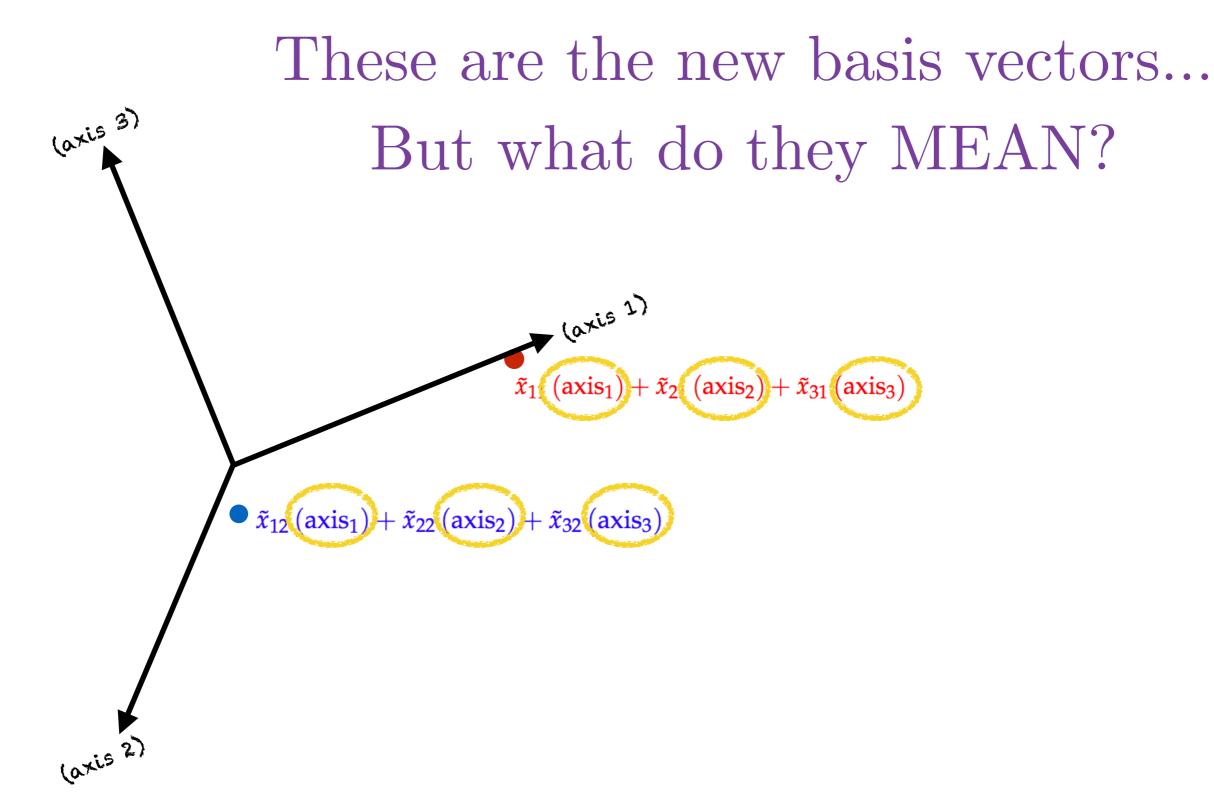
Let's change the basis...



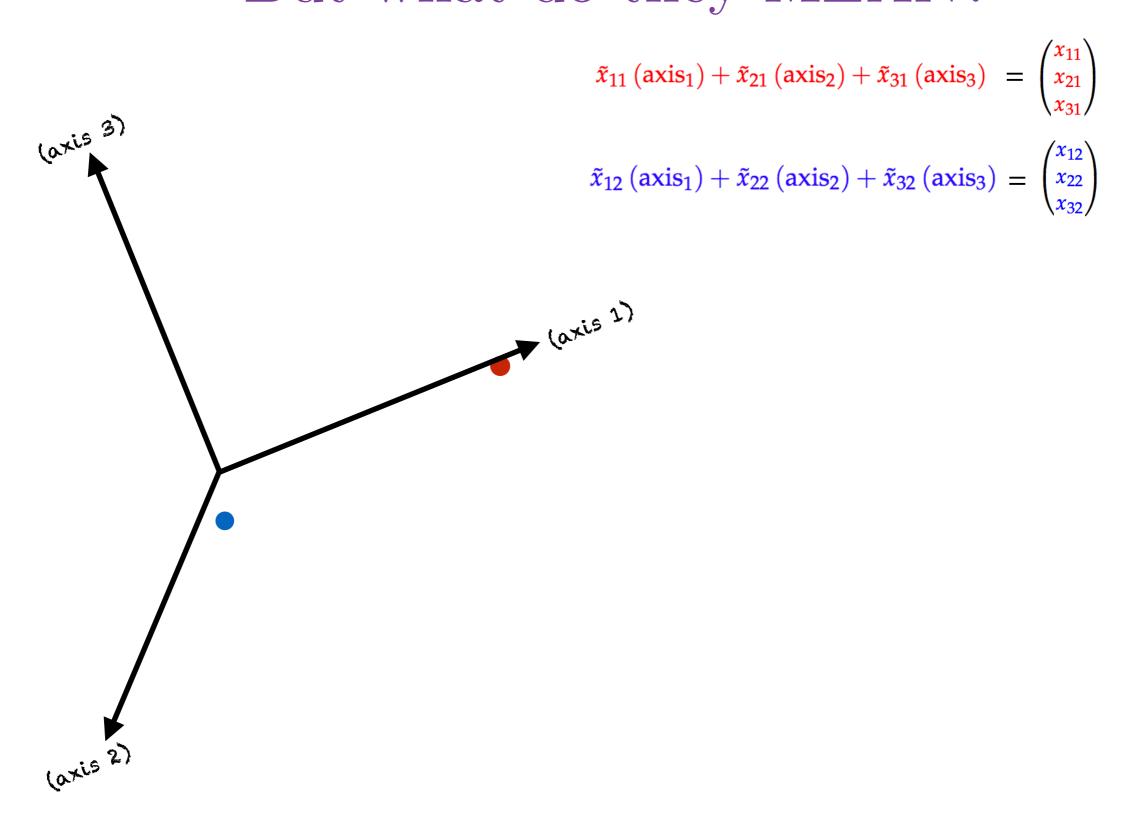
Let's change the basis...



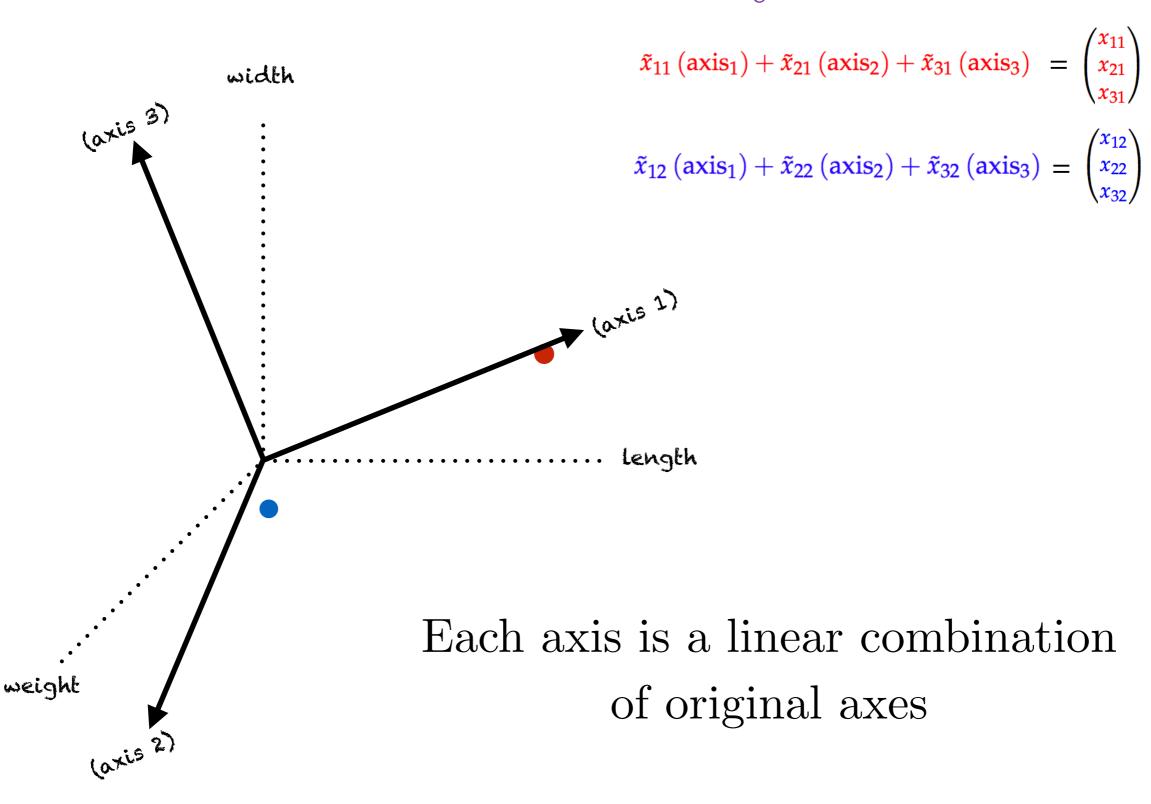




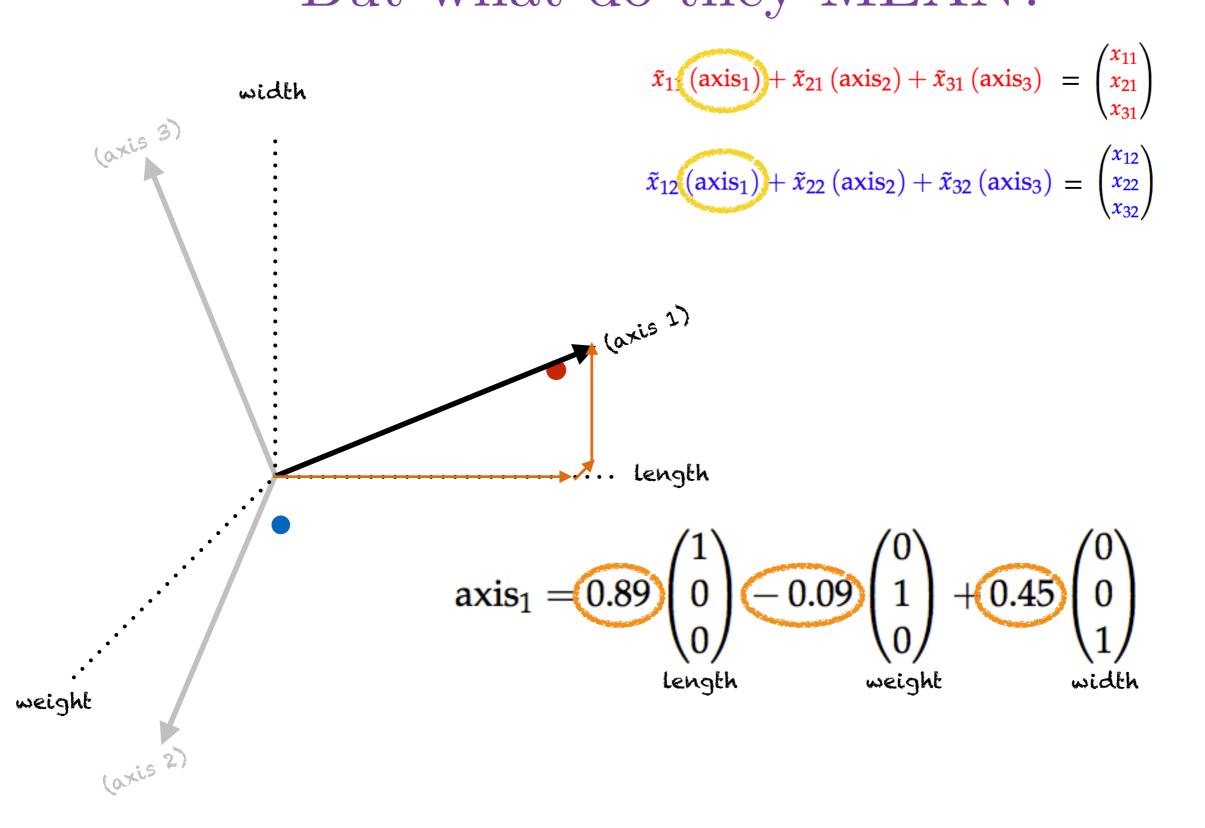
These are the new basis vectors... But what do they MEAN?



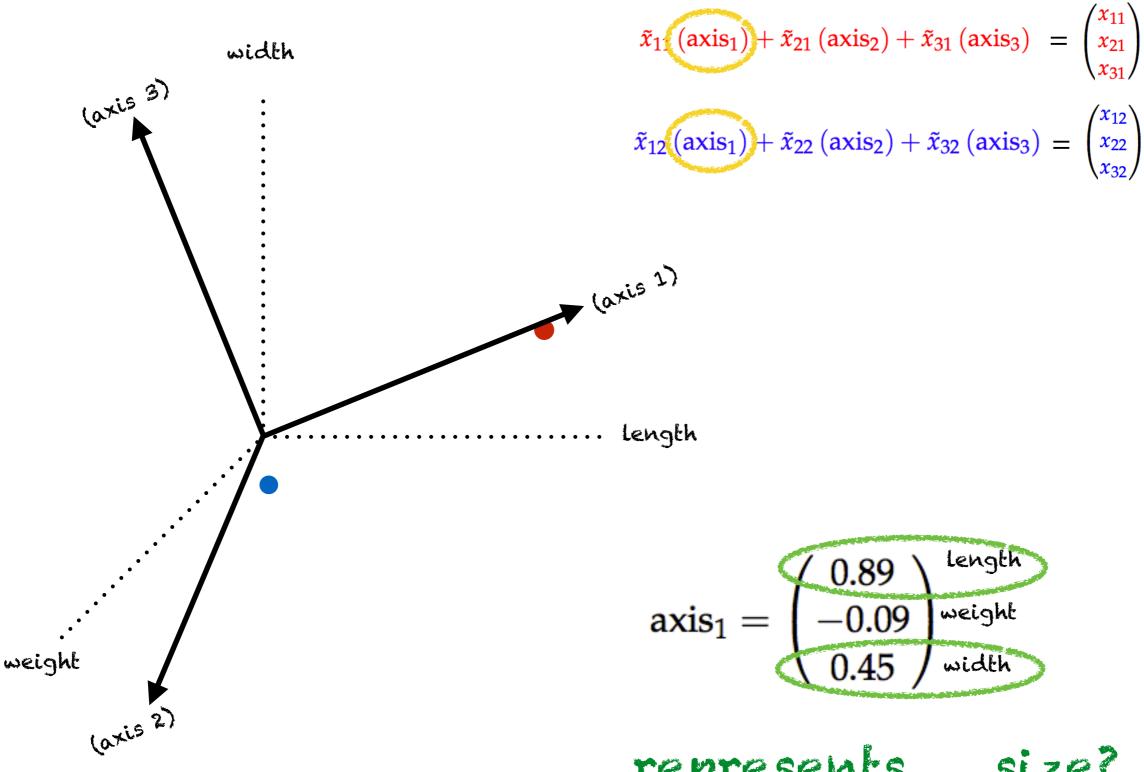
These are the new basis vectors... But what do they MEAN?



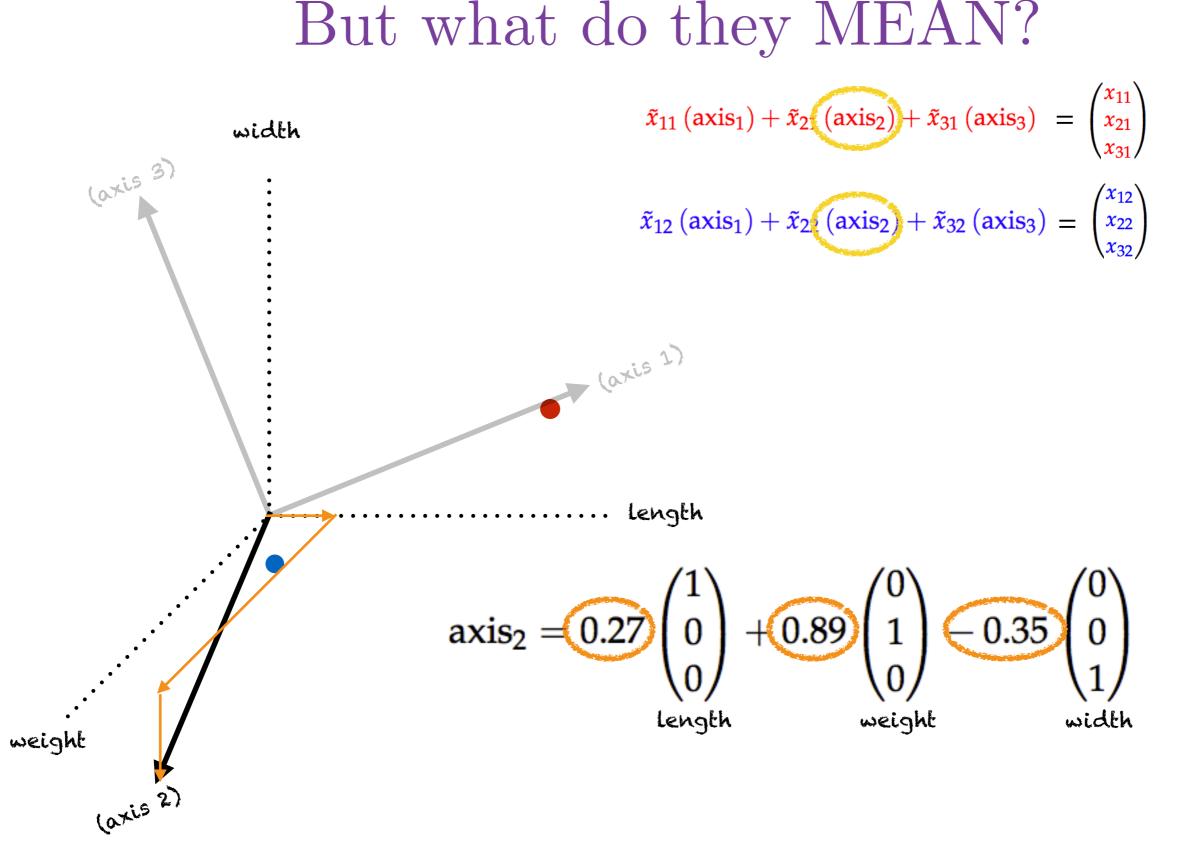
These are the new basis vectors... But what do they MEAN?



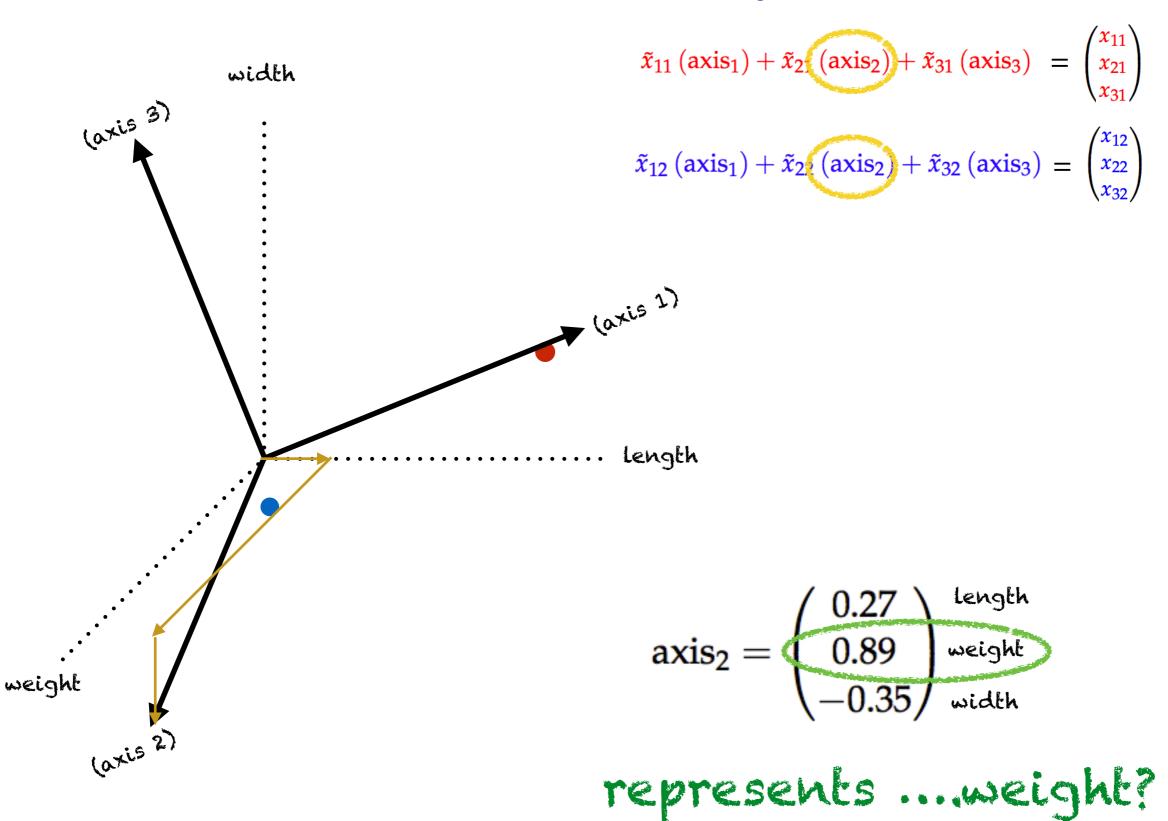
But what do they MEAN?



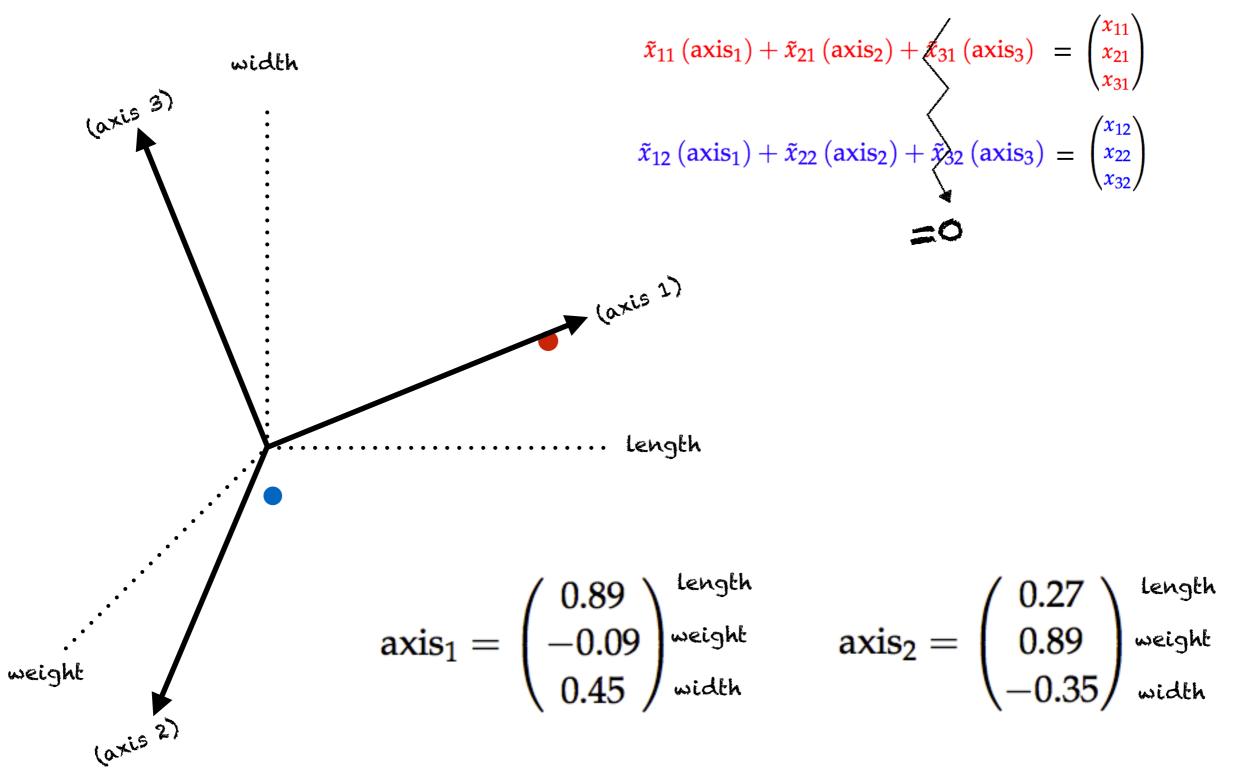
representssize?



But what do they MEAN?



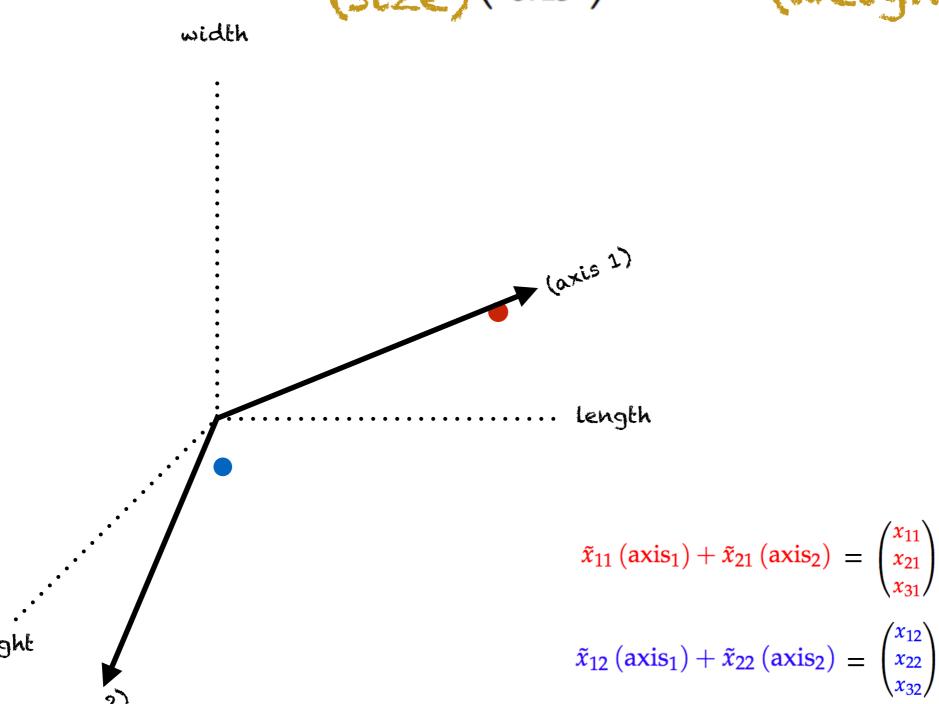
But what do they MEAN?



Let's ignore axis 3 for now...

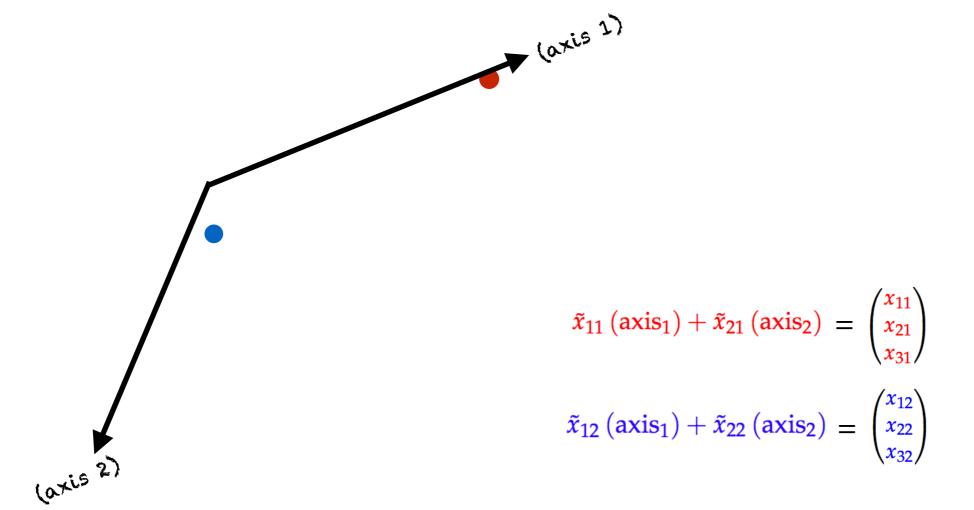
$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \end{pmatrix}$$
 weight width

$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix} \text{ weight } axis_2 = \begin{pmatrix} 0.27 \\ 0.89 \\ -0.35 \end{pmatrix} \text{ weight } weight \\ \text{weight } (size) \begin{pmatrix} 0.45 \\ 0.45 \end{pmatrix} \text{ width } weight$$



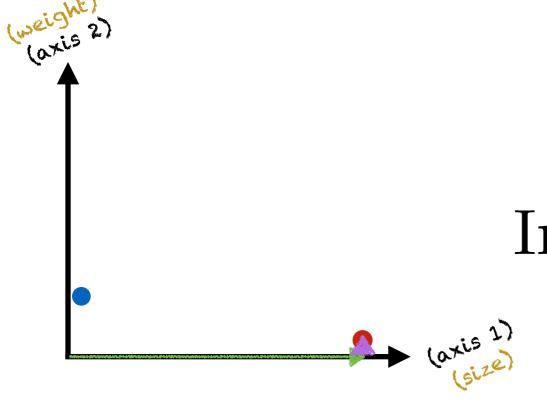
$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix}$$
 weight width

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$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix}$$
 beight width

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$$(\tilde{x}_{11}(axis_1) + \tilde{x}_{21}(axis_2) = \begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix}$$

Infer that the red point has:

large size

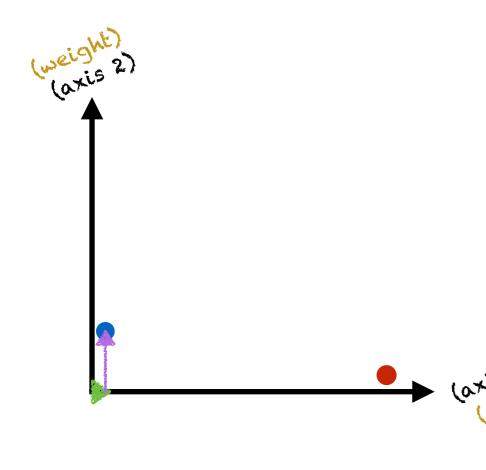
and

small weight

relative to blue point

$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix}$$
 weight width

$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix} \text{ weight } axis_2 = \begin{pmatrix} 0.27 \\ 0.89 \\ \text{weight } \\ \text{weight }$$



$$(\tilde{x}_{12})$$
axis₁) $+ \tilde{x}_{22}$ (axis₂) $= \begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix}$

Infer that the blue point has:

small size

and

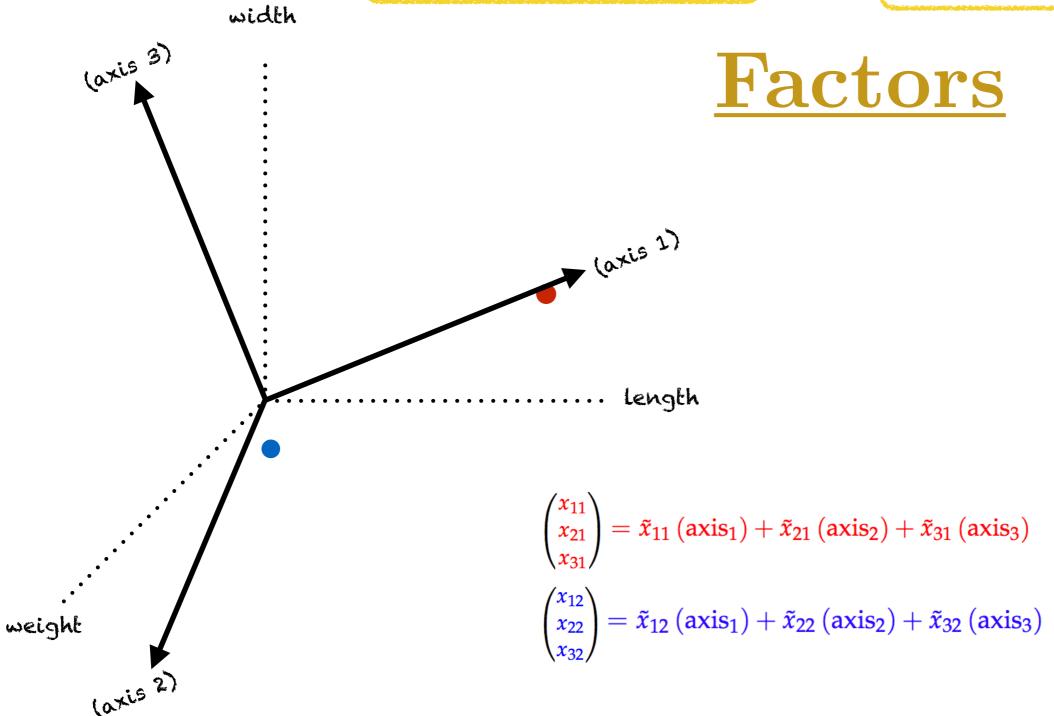
large weight

relative to red point

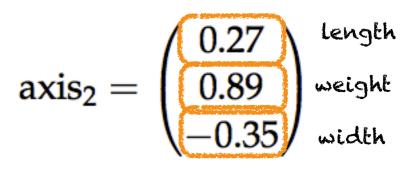
Some Terminology

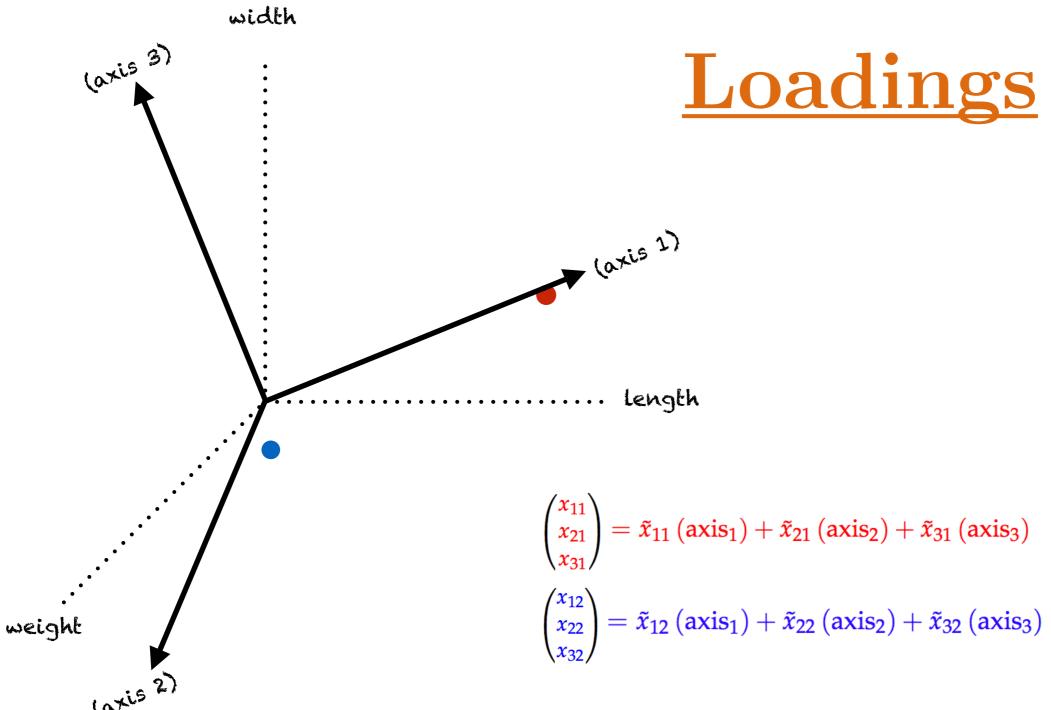
$$\mathrm{axis}_1 = \left(egin{array}{c} 0.89 \ -0.09 \ 0.45 \end{array}
ight)$$
 weight width

$$\mathsf{axis}_2 = egin{pmatrix} 0.27 \ 0.89 \ -0.35 \end{pmatrix}$$
 weight



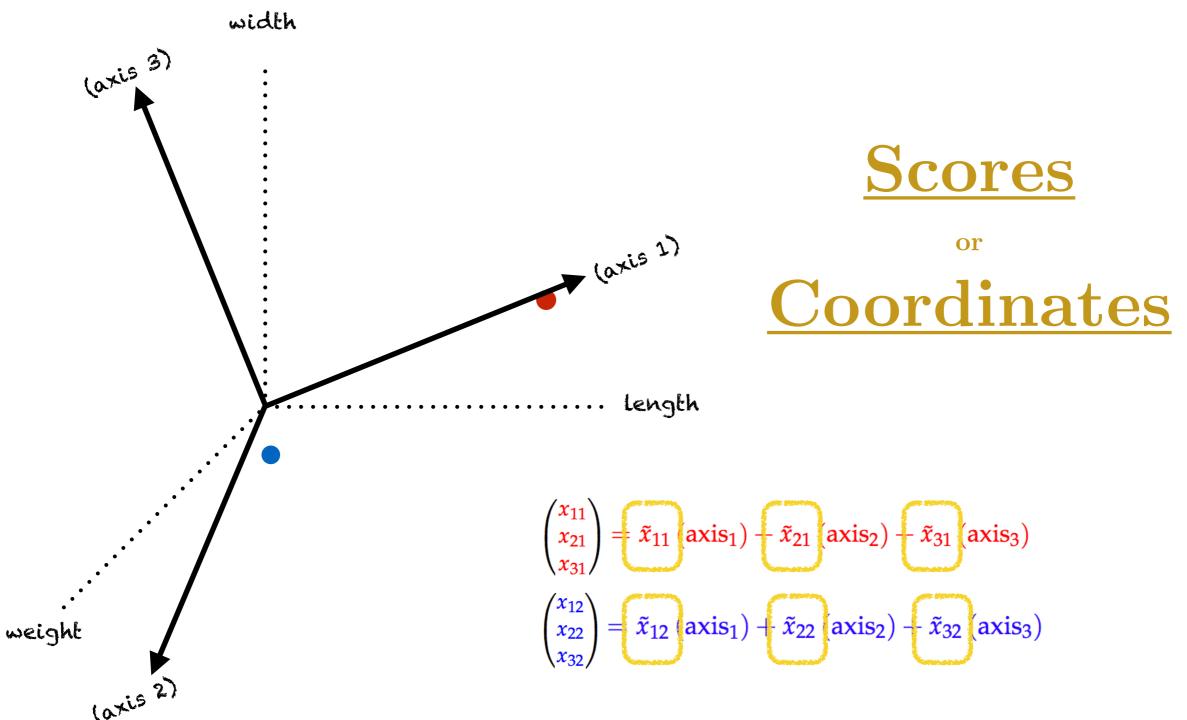
$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix}$$
 length weight width





$$\mathrm{axis}_1 = egin{pmatrix} 0.89 \ -0.09 \ 0.45 \end{pmatrix}$$
 weight width

$$\mathrm{axis}_2 = egin{pmatrix} 0.27 \ 0.89 \ -0.35 \end{pmatrix}$$
 weight

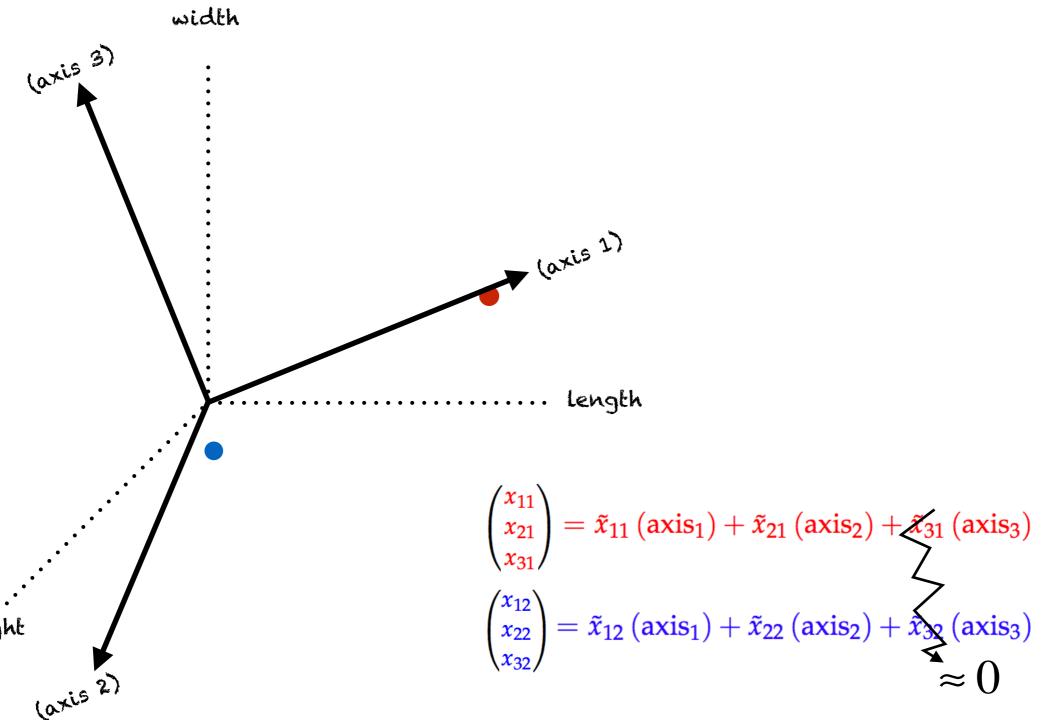


Part 4: One Step Further

Back to Matrix Multiplication

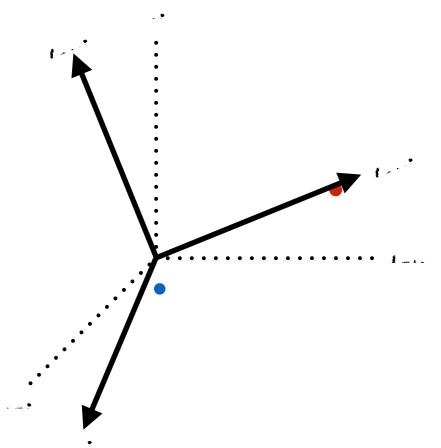
$$\mathrm{axis}_1 = egin{pmatrix} 0.89 \ -0.09 \ 0.45 \end{pmatrix}$$
 weight width

$$axis_2 = egin{pmatrix} 0.27 \\ 0.89 \\ -0.35 \end{pmatrix}$$
 weight width



$$\mathrm{axis}_1 = egin{pmatrix} 0.89 \ -0.09 \ 0.45 \end{pmatrix}$$
 weight width

$$axis_2 = egin{pmatrix} 0.27 \\ 0.89 \\ -0.35 \end{pmatrix}$$
 weight width

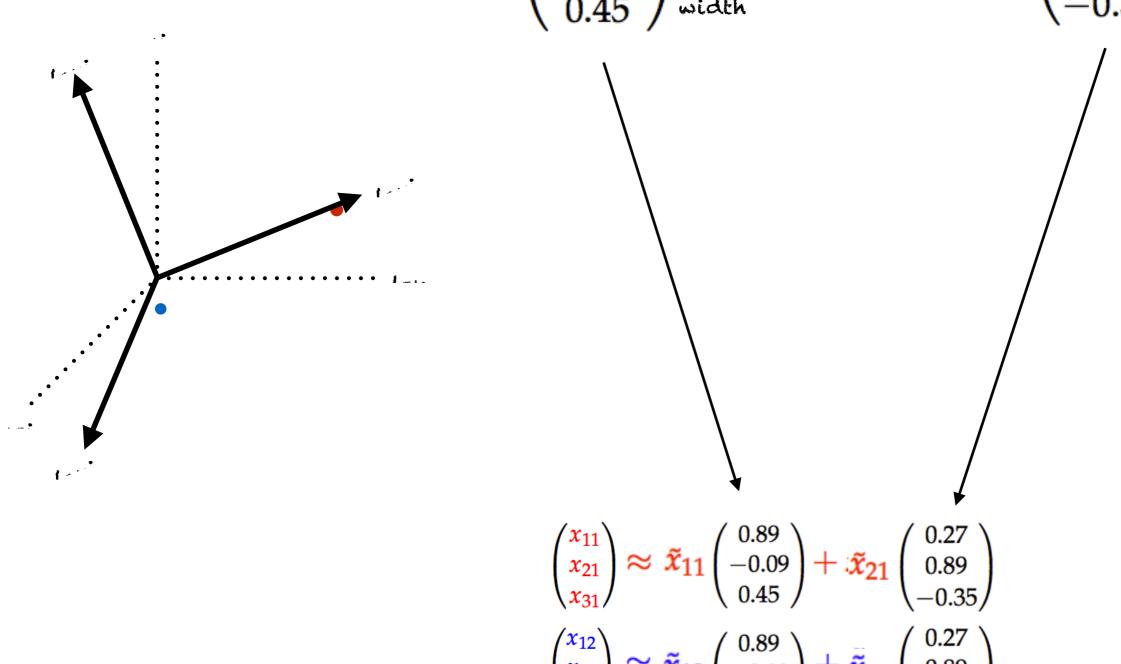


$$\begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix} \approx \tilde{x}_{11} (axis_1) + \tilde{x}_{21} (axis_2)$$

$$\begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix} \approx \tilde{x}_{12} (axis_1) + \tilde{x}_{22} (axis_2)$$

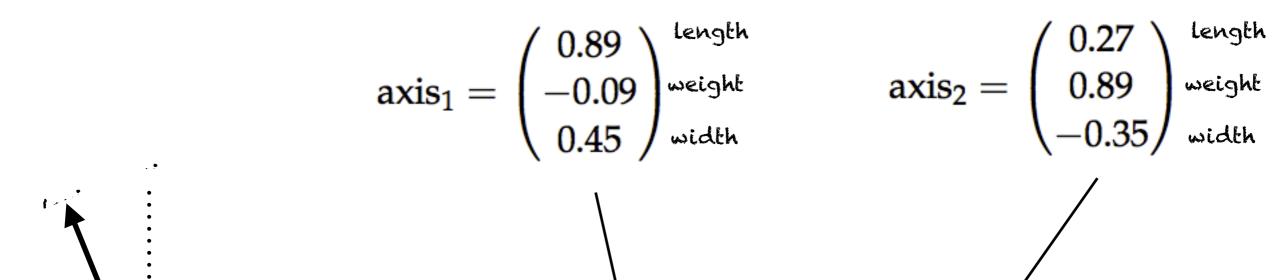
$$\begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix} \approx \tilde{x}_{12} (axis_1) + \tilde{x}_{22} (axis_2)$$

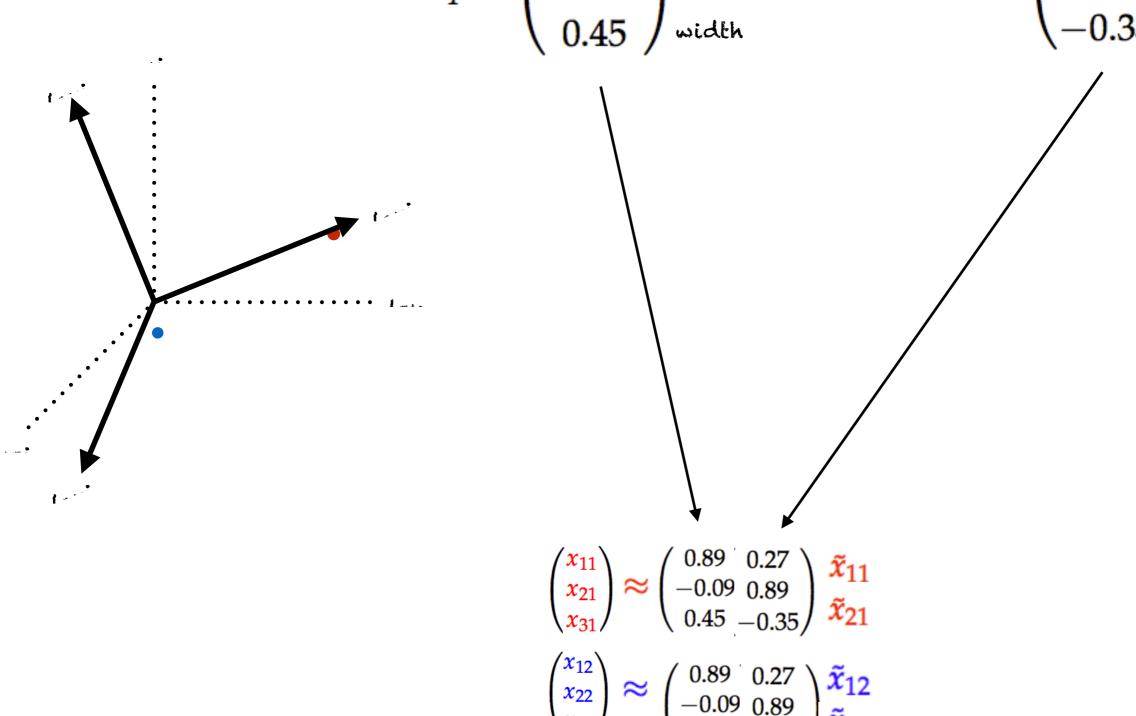
$${
m axis}_1=egin{pmatrix} 0.89 \ -0.09 \ 0.45 \end{pmatrix}$$
 bength weight width ${
m axis}_2=egin{pmatrix} 0.27 \ 0.89 \ -0.35 \end{pmatrix}$ width



$$\begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix} \approx \tilde{x}_{11} \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix} + \tilde{x}_{21} \begin{pmatrix} 0.27 \\ 0.89 \\ -0.35 \end{pmatrix}$$

$$\begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix} \approx \tilde{x}_{12} \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix} + \tilde{x}_{22} \begin{pmatrix} 0.27 \\ 0.89 \\ -0.35 \end{pmatrix}$$



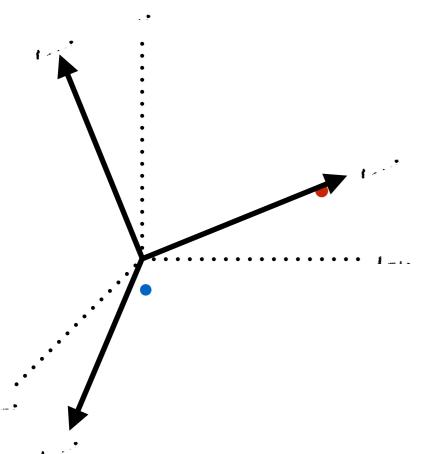


$$\begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \frac{\tilde{x}_{11}}{\tilde{x}_{21}}$$

$$\begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \frac{\tilde{x}_{12}}{\tilde{x}_{22}}$$

$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix}$$
 beight width

$$axis_2 = \begin{pmatrix} 0.27 \\ 0.89 \\ -0.35 \end{pmatrix}$$
 beight width



$$\begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \tilde{x}_{21}$$

$$\begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \tilde{x}_{12}$$
Step Further

$$\begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \tilde{x}_{21}$$
 Data Matrix Factors Scores
$$\begin{pmatrix} x_{11} \\ x_{21} \\ x_{21} \\ x_{22} \\ x_{32} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \tilde{x}_{12}$$

$$\tilde{x}_{12}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{23}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{24}$$

$$\tilde{x}_{22}$$

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$$\tilde{x}_{24}$$

$$\tilde{x}_{22}$$

$$\tilde{x}_{24}$$

$$\tilde{x}_{24}$$

$$\tilde{x}_{25}$$

$$\tilde{x}_{25}$$

$$\tilde{x}_{26}$$

$$\tilde{x}_{26}$$

$$\tilde{x}_{27}$$

$$\tilde{x}_{27}$$

$$\tilde{x}_{28}$$

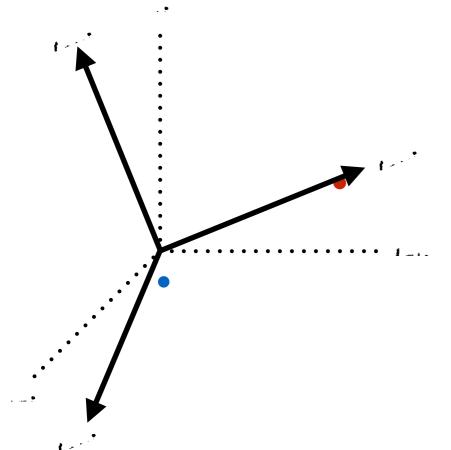
$$\tilde{x}_{28}$$

$$\tilde{x}_{29}$$

$$\tilde{x}_{29}$$

$$axis_1 = \begin{pmatrix} 0.89 \\ -0.09 \\ 0.45 \end{pmatrix}$$
 length weight width

$$axis_2 = egin{pmatrix} 0.27 \\ 0.89 \\ -0.35 \end{pmatrix}$$
 weight width



Interpretability of latent factors is a little subjective, but soon you will be more comfortable with the idea!

$$\begin{pmatrix} x_{11} \\ x_{21} \\ x_{31} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \tilde{x}_{11}$$

$$\begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \end{pmatrix} \approx \begin{pmatrix} 0.89 & 0.27 \\ -0.09 & 0.89 \\ 0.45 & -0.35 \end{pmatrix} \tilde{x}_{12}$$
Step Further

- One Step Fu

Part 5: A More Complete Example

(Nonnegative) Matrix Factorization for Text

(Factors in Text)

Document 1

My cat likes to eat dog food. It's insane. He won't eat tuna, but dog food? He's all over it.

Document 2

Check out this video of my dog chasing my cat around the house! He never gets tired! Simon! The cat is not a dog toy! Dumb dog.

Document 3

I **injured** my **ankle** playing football yesterday. It is bruised and swollen. Maybe **sprained**?

Document 4

So tired of being injured. My ankle just won't get better! I sprained it 2 months ago!

(Factors in Text)

		doc1	doc2	doc3	doc4
D _	"cat"	/ 1	2	0	0 \
	"dog"	2	3	0	0
	"tired"	0	1	0	1
В —	"injured"	0	0	1	1
	"ankle"	0	0	1	1
	"sprained"	0 /	0	1	1 /

In this example, our observations are the documents and the words are the variables

(Factors in Text)

$$\mathbf{B} = \begin{array}{c} \text{"cat"} \\ \text{"dog"} \\ \text{"tired"} \\ \text{"injured"} \\ \text{"ankle"} \\ \text{"sprained"} \end{array} \left(\begin{array}{cccccc} doc1 & doc2 & doc3 & doc4 \\ 1 & 2 & 0 & 0 \\ 2 & 3 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ \end{array} \right)$$

Basis (Elementary Axes) of our 6-dimensional space

(Factors in Text)

		doc1	doc2	doc3	doc4
	"cat"	/ 1	2	0	0
	"dog"	2	3	0	0
R _	"tired"	0	1	0	1
D —	"injured"	0	0	1	1
	"ankle"	0	0	1	1
	"sprained"	0 /	0	1	1

We can approximate this matrix using a matrix factorization

		Factor1	Factor2	-				
	"cat"	/ 1.0	0	\				
	"dog"	1.6	0	1	doc1	doc2	doc3	doc4
D ~	"tired"	0.4	0.4		(1.0)	1.7	0	0.0)
$\mathbf{B} \approx$	"injured"	0	0.8	١	0	0.1	0.9	1.1
	"ankle"	0	0.8	١	`			,
	"sprained"	0	0.8	J				

(Factors in Text)

		doc1	doc2	doc3	doc4
	"cat"	/ 1	2	0	0
	"dog"	2	3	0	0
R _	"tired"	0	1	0	1
D —	"injured"	0	0	1	1
	"ankle"	0	0	1	1
	"sprained"	0 /	0	1	1 ,

We can approximate this matrix using a matrix factorization

		doc1	doc2	doc3	doc4
	"cat"	/ 1	1.7	0	0 \
	"dog"	1.6	2.7	0	0
$\mathbf{B} \approx$	"tired"	0.4	0.72	0.36	0.44
D≈	"injured"	0	0	0.72	0.88
	"ankle"	0	0	0.72	0.88
	"sprained"	0 /	0	0.72	0.88

(Factors in Text)

		C	loc1	doc	2 doc3	doc4	1
D	"cat"	/	1	2	0	0	1
	"dog"		2	3	0	0	
	"tired"		0	1	0	1	
D —	"injured"		0	0	1	1	
	"ankle"		0	0	1	1	
	"sprained"		0	0	1	1	

How did I get this?
We'll talk about it later!

Factor1 Factor2 'cat" / 1.0 0

(Factors in Text)

$$\mathbf{B} \approx \begin{array}{c} \text{``cat''} & \text{$factor1$} & \text{Factor2} \\ \text{``dog''} & \text{1.0} & \text{0} \\ \text{``dog''} & \text{1.6} & \text{0} \\ \text{``tired''} & \text{0.4} & \text{0.4} \\ \text{``injured''} & \text{0} & \text{0.8} \\ \text{``ankle''} & \text{0} & \text{0.8} \\ \text{``sprained''} & \text{0} & \text{0.8} \\ \end{array} \right) \begin{array}{c} \text{doc1} & \text{doc2} & \text{doc3} & \text{doc4} \\ \text{0} & \text{0.10} & \text{0.00} \\ \text{0} & \text{0.11} & \text{0.9} & \text{1.11} \\ \end{array}$$

Each column of B (each document) can be written as a linear combination of factors. These linear combinations are the points' coordinate representations in the new basis.

(Factors in Text)

$$\mathbf{B} \approx \begin{array}{c} \text{``cat''} & 1.0 & 0 \\ \text{``dog''} & 1.6 & 0 \\ \text{``tired''} & 0.4 & 0.4 \\ \text{``injured''} & 0 & 0.8 \\ \text{``ankle''} & 0 & 0.8 \\ \text{``sprained''} & 0 & 0.8 \end{array} \right) \begin{array}{c} \text{doc1 doc2 doc3 doc4} \\ 1.0 & 1.7 & 0 & 0.0 \\ 0 & 0.1 & 0.9 & 1.1 \end{array} \right)$$

Each column of B (each document) can be written as a linear combination of factors. These linear combinations are the points' coordinate representations in the new basis.

$$\mathbf{B}_{\star 2} \approx 1.7 Factor_1 + 0.1 Factor_2$$
(doc 2)

(Factors in Text)

$$\mathbf{B} \approx \begin{array}{c} \text{``cat''} & 1.0 & 0 \\ \text{``dog''} & 1.6 & 0 \\ \text{``tired''} & 0.4 & 0.4 \\ \text{``injured''} & 0 & 0.8 \\ \text{``ankle''} & 0 & 0.8 \\ \text{``sprained''} & 0 & 0.8 \end{array} \right) \begin{array}{c} \text{doc1 doc2 doc3 doc4} \\ 1.0 & 1.7 & 0 & 0.0 \\ 0 & 0.1 & 0.9 & 1.1 \end{array} \right)$$

Each column of B (each document) can be written as a linear combination of factors. These linear combinations are the points' coordinate representations in the new basis.

$$\mathbf{B}_{\star 2} \approx 1.7 Factor_1 + 0.1 Factor_2$$
(doc 2)

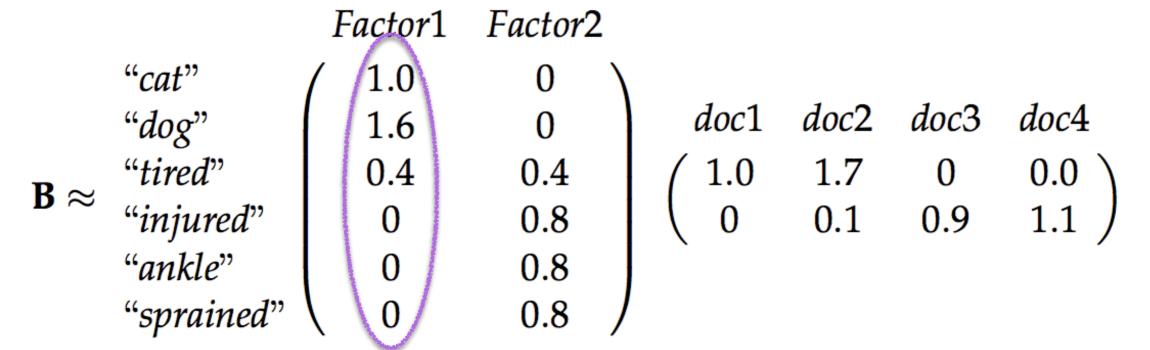
Conclude: document 2 more aligned with factor 1 than factor 2

(Factors in Text)

$$\mathbf{B} \approx \begin{array}{c} \text{``cat''} & \text{$factor 1$} \\ \text{``dog''} \\ \text{``tired''} \\ \text{``injured''} \\ \text{``ankle''} \\ \text{``sprained''} \end{array} \left(\begin{array}{c} 1.0 & 0 \\ 1.6 & 0 \\ 0.4 & 0.4 \\ 0 & 0.8 \\ 0 & 0.8 \end{array} \right) \begin{array}{c} \text{doc1 doc2 doc3 doc4} \\ \text{1.0} & 1.7 & 0 & 0.0 \\ 0 & 0.1 & 0.9 & 1.1 \end{array} \right)$$

$$\mathbf{B}_{\star 2} \approx 1.7 Factor_1 + 0.1 Factor_2$$
 How do we interpret factor 1?

(Factors in Text)



How do we interpret factor 1?

$$Factor_{1} = 1 \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ cat \end{pmatrix} + 1.6 \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ dog \end{pmatrix} + 0.4 \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ tired \end{pmatrix} + 0 \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ ankle \end{pmatrix} + 0 \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ o \\ ankle \end{pmatrix}$$

(Factors in Text)

Factor1 Factor2

	"cat"	/	1.0	0
$\mathbf{B} \approx$	"dog"		1.6	0
	"tired"		0.4	0.4
	"injured"		0	0.8
	"ankle"		0	0.8
	"sprained"		0	0.8

doc1 doc2 doc3 doc4 $\begin{pmatrix} 1.0 & 1.7 & 0 & 0.0 \\ 0 & 0.1 & 0.9 & 1.1 \end{pmatrix}$ Scores/Coordinates.Allow us to describe data observations

according to the new factors.

- Loadings.
- Allow us to interpret factors.
 - Factor 1: pets
 - ▶ Factor 2: injuries

- ▶ Document 1: about pets
- ▶ Document 2: about pets
- ▶ Document 3: about injuries
- Document 4: about injuries

Why a New Basis?

- We want to use a **subset of the new basis vectors** (i.e. new features/variables/axes) to **reduce the dimensionality** of the data and keep patterns
- We *hope* that the new features (being combinations of the old ones) will have some **interpretation**

- The interpretation of the new basis vectors (new features/variables) is subjective.
- We simply look at the loadings to find the variables with the highest loading values (in absolute value) and try to interpret their collective meaning.

• Original basis vectors (features/variables) were: height, weight, head_circumference, verbal_score, quant_score, household_income, house value.

Let's see if we can assign some meaning to our new basis vectors (features/variables)

Axis 1
$\left(0.7\right)$
0.8
0.5
0
0
0
0



• Original basis vectors (features/variables) were: height, weight, head_circumference, verbal_score, quant_score, household_income, house value.

Let's see if we can assign some meaning to our new basis vectors (features/variables)

	Axis 2
height	$\begin{pmatrix} 0 \end{pmatrix}$
weight	0
$head_circumference$	0
$verbal_score$	0.7
$quant_score$	0.8
$household_income$	0.2
$house_value$	$\left(\begin{array}{c} 0.1 \end{array}\right)$



Original basis vectors (features/variables) were: height, weight, head_circumference, verbal_score, quant_score, household_income, house value.

Let's see if we can assign some meaning to our new basis vectors (features/variables)

	Axis 3
height	$\begin{pmatrix} 0 \end{pmatrix}$
weight	0
$head_circumference$	0
$verbal_score$	0.1
$quant_score$	0.3
$household_income$	0.9
$house_value$	$\left(\begin{array}{c} 0.7 \end{array}\right)$



Major Ideas from Section

- ▶ linear combinations geometrically
- ▶ linear (in)dependence geometrically
- vector span
- subspace
- dimension of subspace
- hyperplane
- basis vectors
- coordinates in different bases
- (generic) factor analysis
- loadings
- scores/coordinates