Principal Components Analysis (PCA)

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c a technique for finding patterns in data of high dimension

Outline:

- 1. Eigenvectors and eigenvalues
- 2. PCA:
 - a) Getting the data
 - b) Centering the data
 - c) Obtaining the covariance matrix
 - d) Performing an eigenvalue decomposition of the covariance matrix
 - e) Choosing components and forming a feature vector
 - f) Deriving the new data set

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 $\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix}$ $\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix}$

$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix} * \begin{bmatrix} 1 \\ 3 \end{bmatrix}$$
$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix} * \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 11 \\ 5 \end{bmatrix}$$
$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix}$$

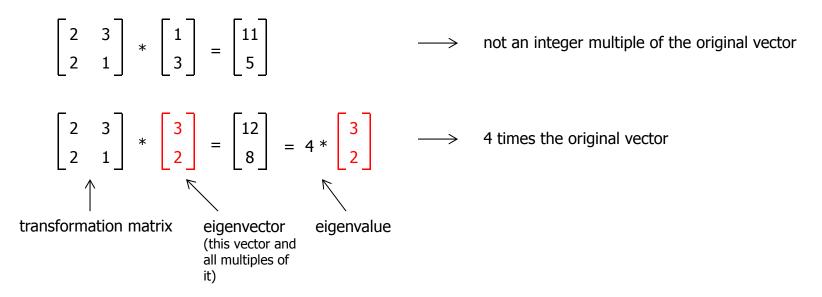
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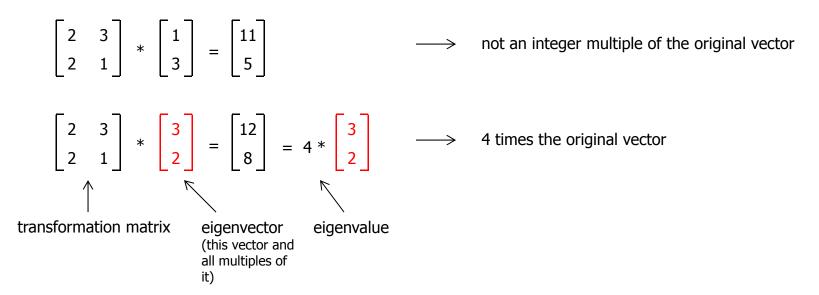
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$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix} * \begin{bmatrix} 3 \\ 2 \end{bmatrix} = \begin{bmatrix} 12 \\ 8 \end{bmatrix}$$

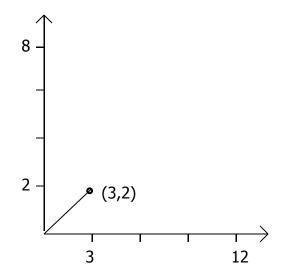
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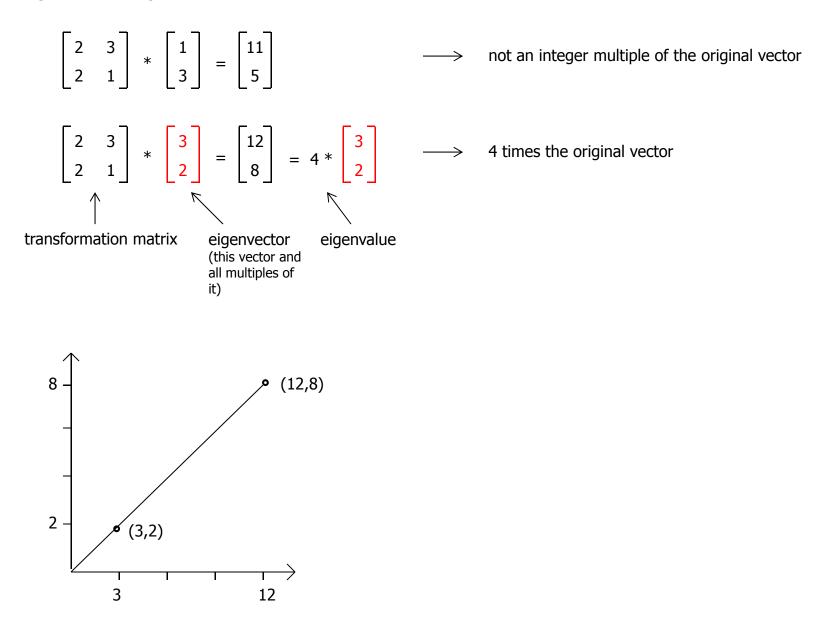
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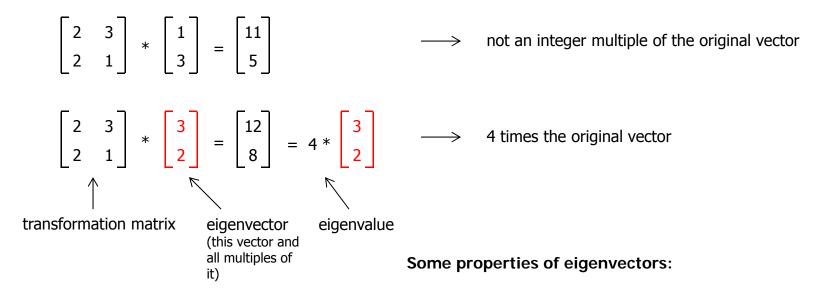
$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix} * \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 11 \\ 5 \end{bmatrix} \longrightarrow \text{ not an integer multiple of the original vector}$$
$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix} * \begin{bmatrix} 3 \\ 2 \end{bmatrix} = \begin{bmatrix} 12 \\ 8 \end{bmatrix} = 4 * \begin{bmatrix} 3 \\ 2 \end{bmatrix} \longrightarrow 4 \text{ times the original vector}$$

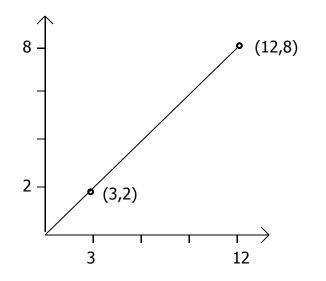


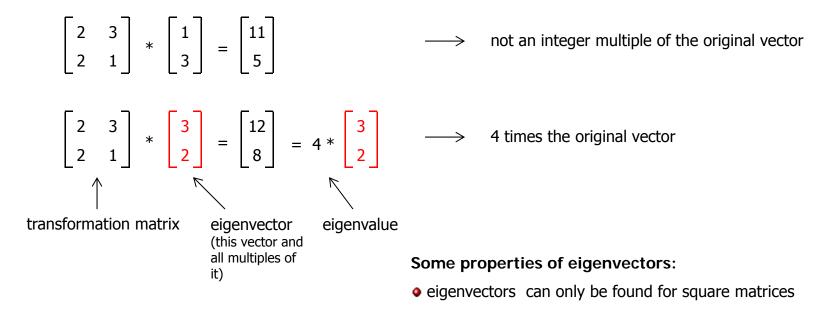


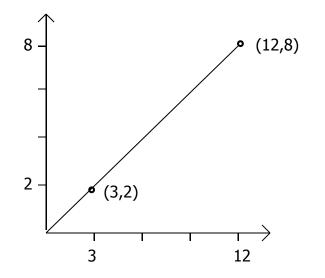


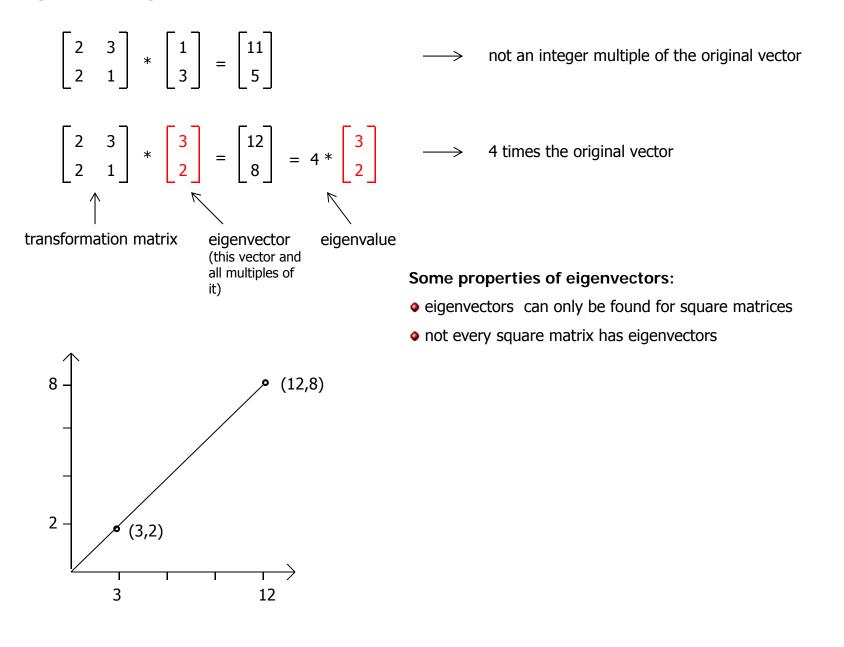


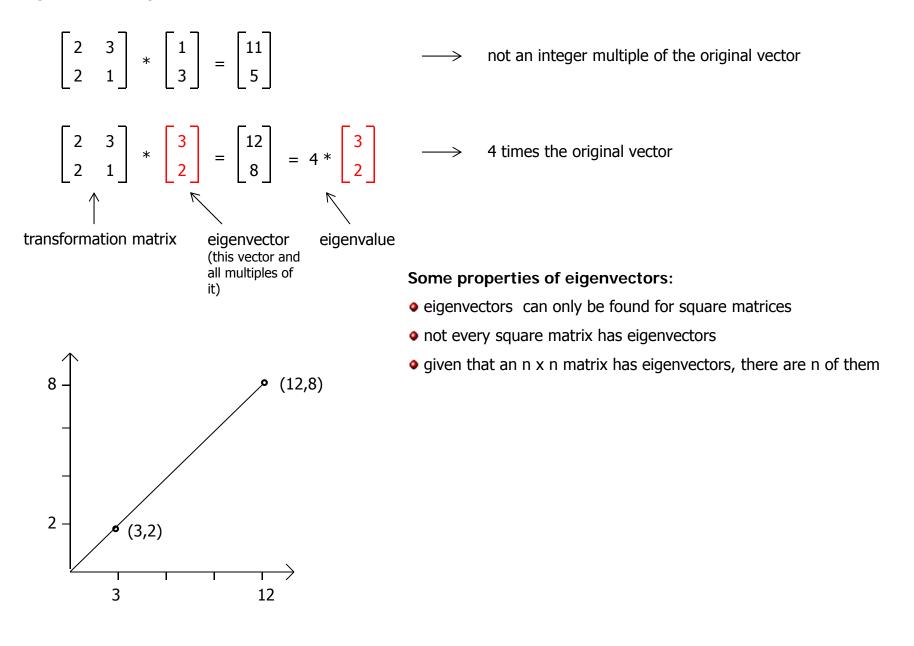


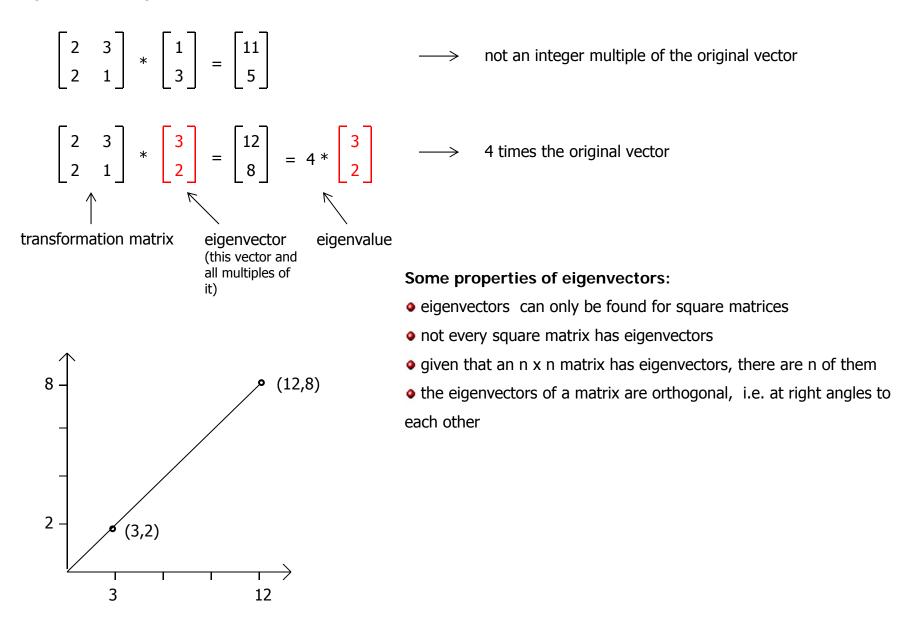


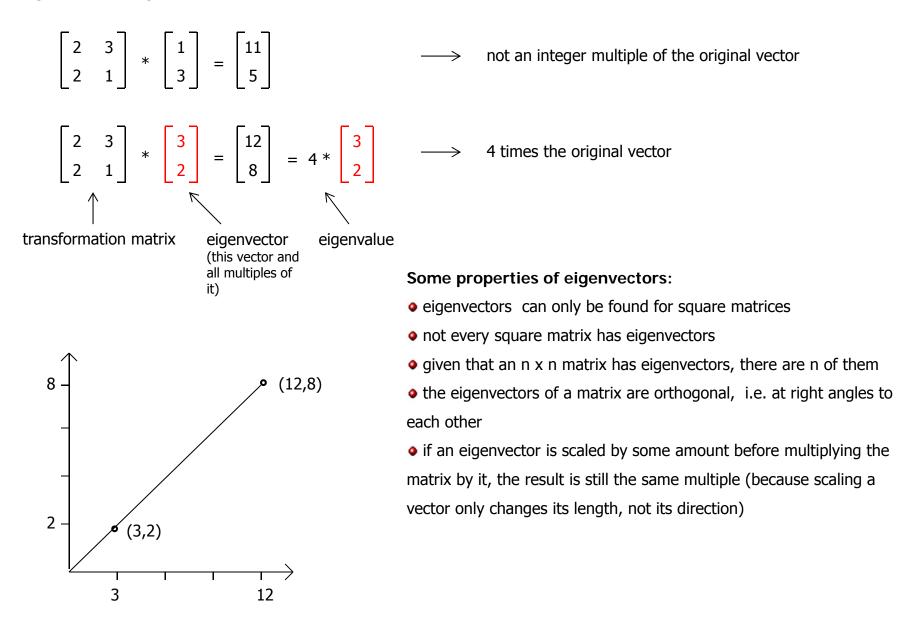


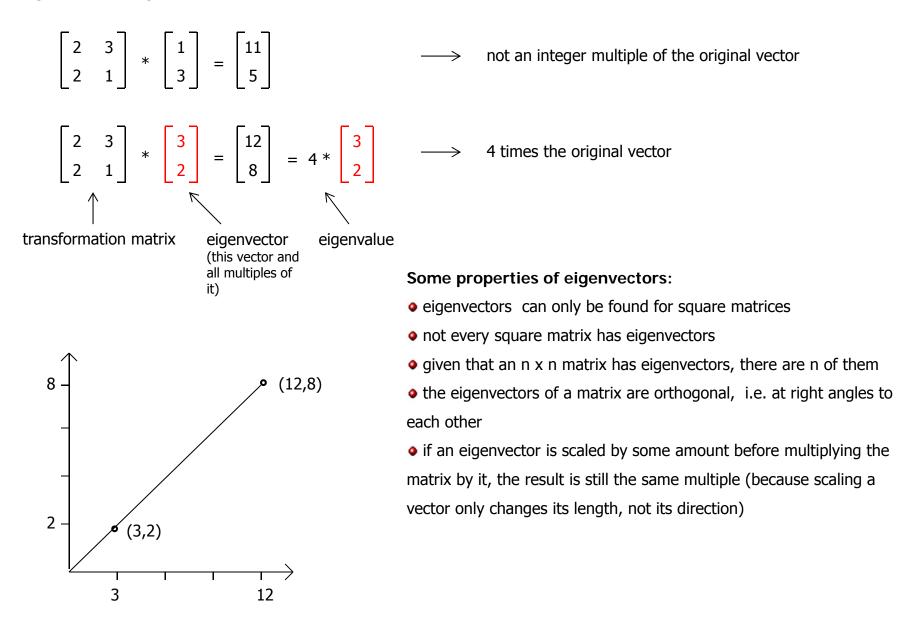


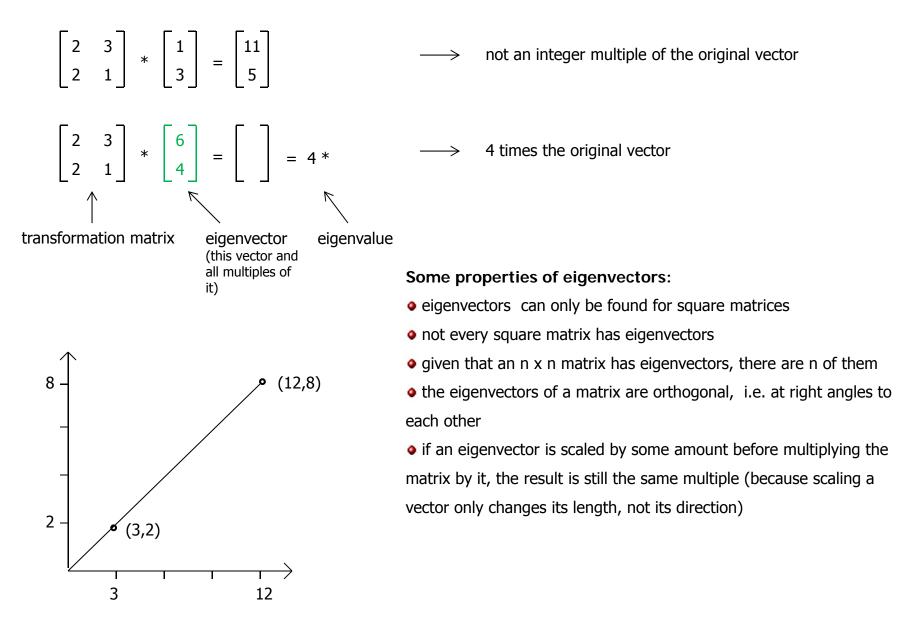


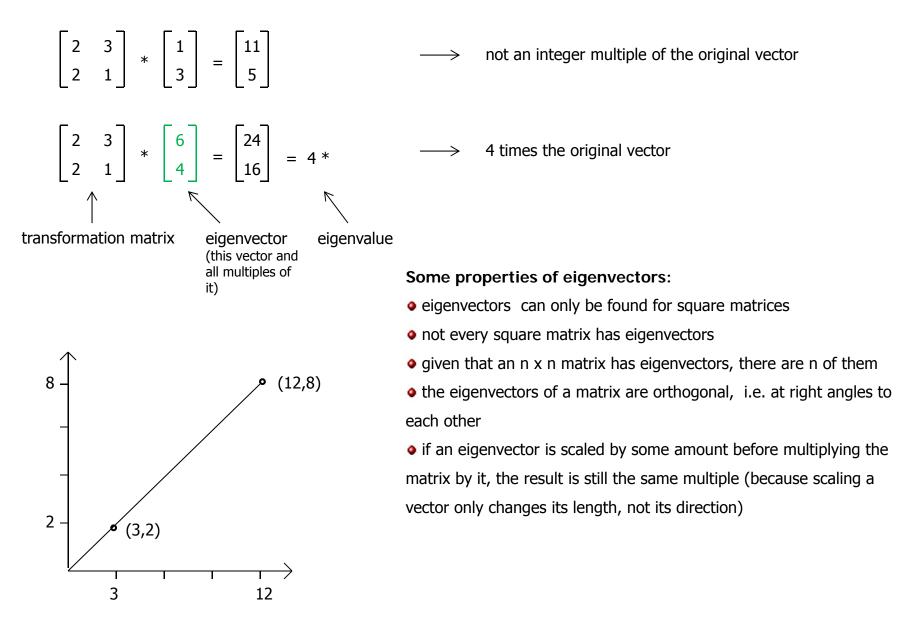


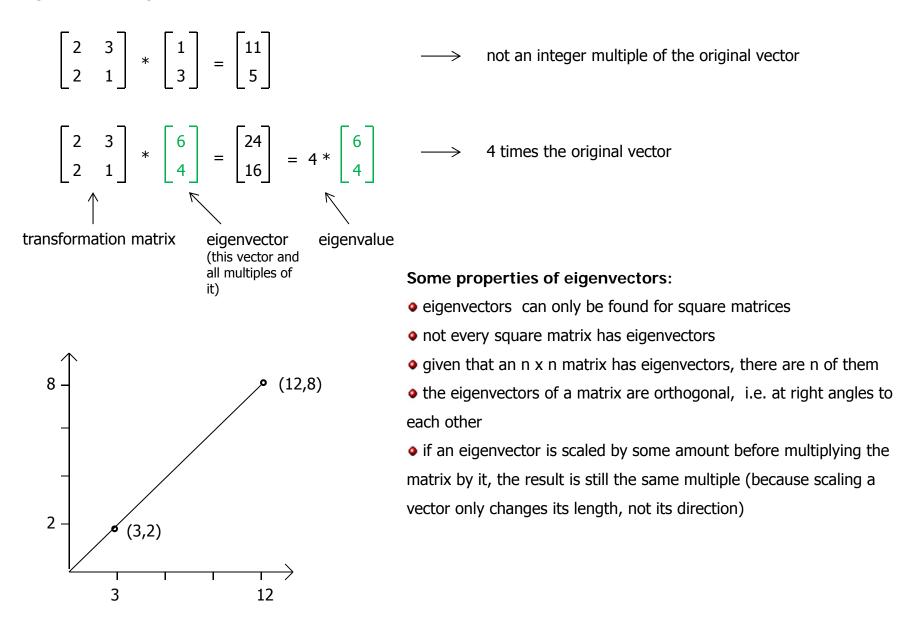


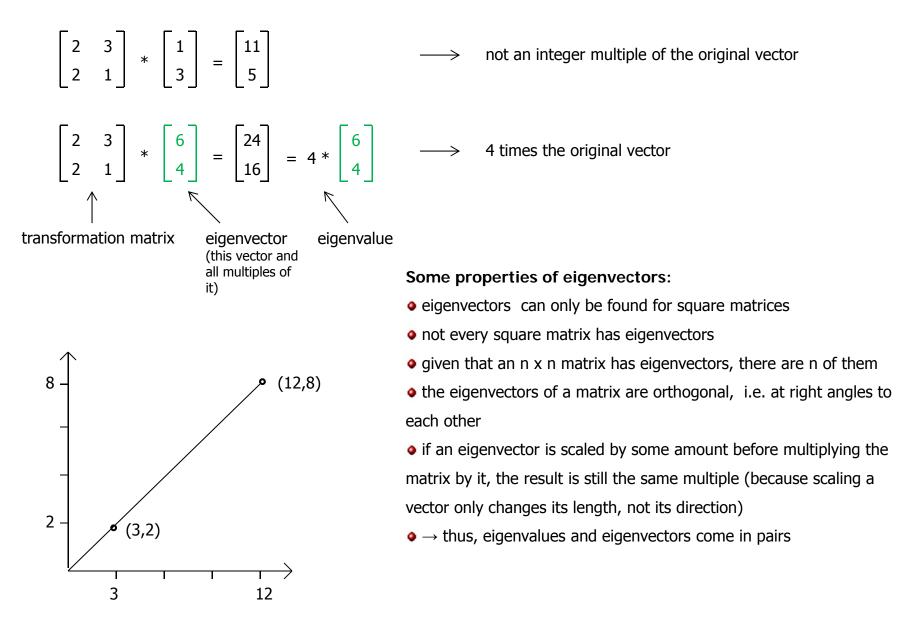












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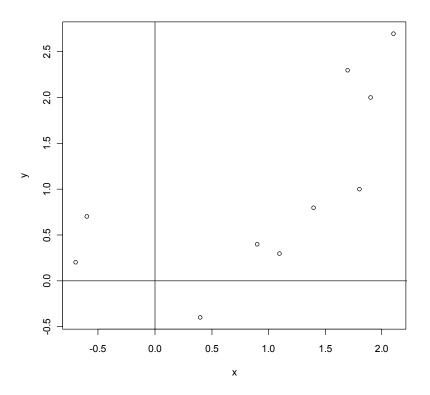
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- a technique for identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences
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- example: data of 2 dimensions:

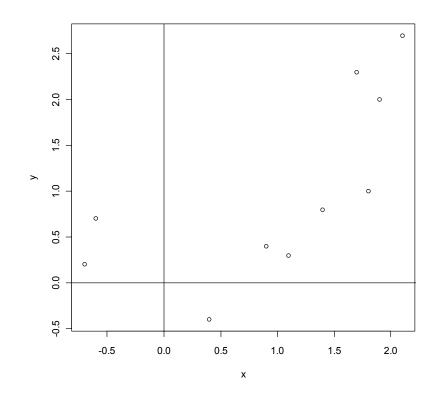
original data:

Х	у		
-0.7	0.2		
2.1	2.7 2.3		
1.7			
1.4	0.8		
1.9	2		
1.8	1		
0.4	-0.4 0.3		
1.1			
0.9	0.4		
-0.6	0.7		



- a technique for identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences
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- example: data of 2 dimensions:

original data:		cent	centered data:		
x	У	X		у	
-0.7	0.2	-1.	7	-0.8	
2.1	2.7	1.	1	1.7	
1.7	2.3	0.2	7	1.3	
1.4	0.8	0.4	4	-0.2	
1.9	2	0.9	9	1	
1.8	1	0.8	8	0	
0.4	-0.4	-0.	6	-1.4	
1.1	0.3	0.1	1	-0.7	
0.9	0.4	-0.	1	-0.6	
-0.6	0.7	-1.	6	-0.3	



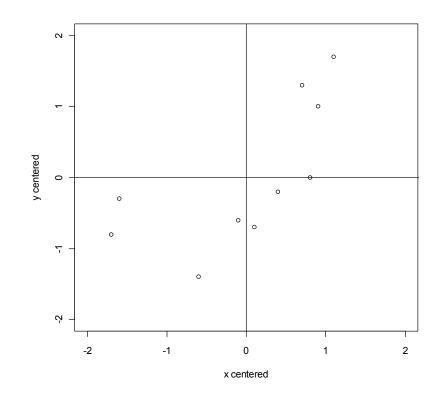
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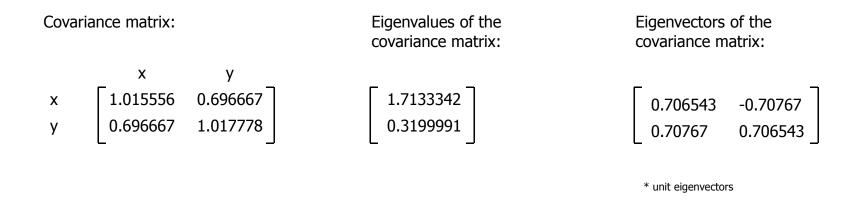
centered data.

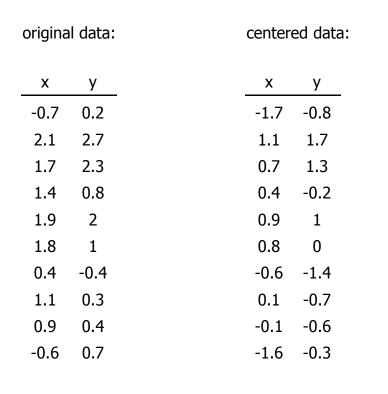
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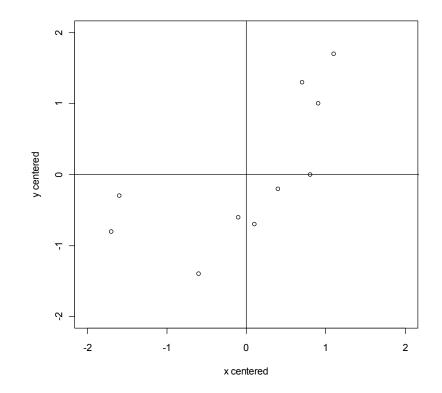
original data.

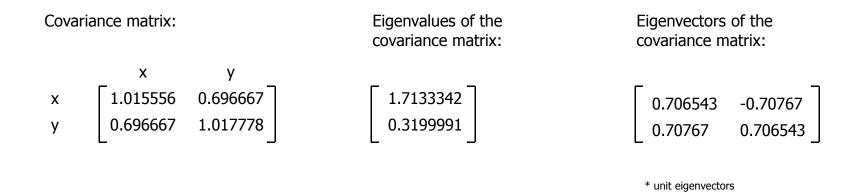
onginal data:		center		
х	У		х	у
-0.7	0.2		-1.7	-0.8
2.1	2.7		1.1	1.7
1.7	2.3		0.7	1.3
1.4	0.8		0.4	-0.2
1.9	2		0.9	1
1.8	1		0.8	0
0.4	-0.4		-0.6	-1.4
1.1	0.3		0.1	-0.7
0.9	0.4		-0.1	-0.6
-0.6	0.7		-1.6	-0.3











Х

-0.7

2.1

1.7

1.4

1.9

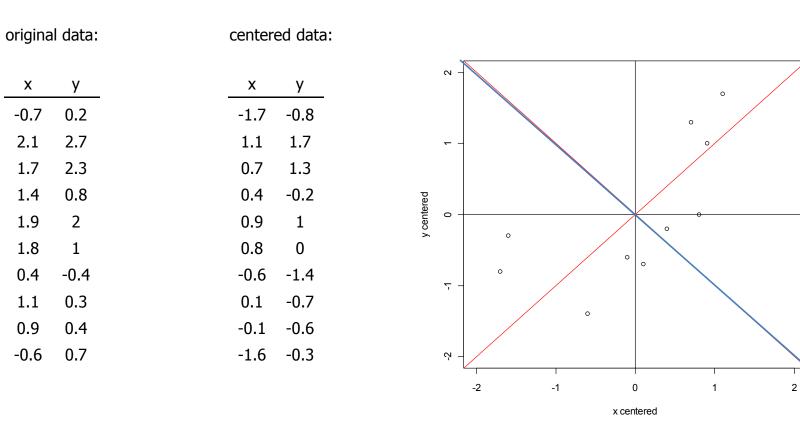
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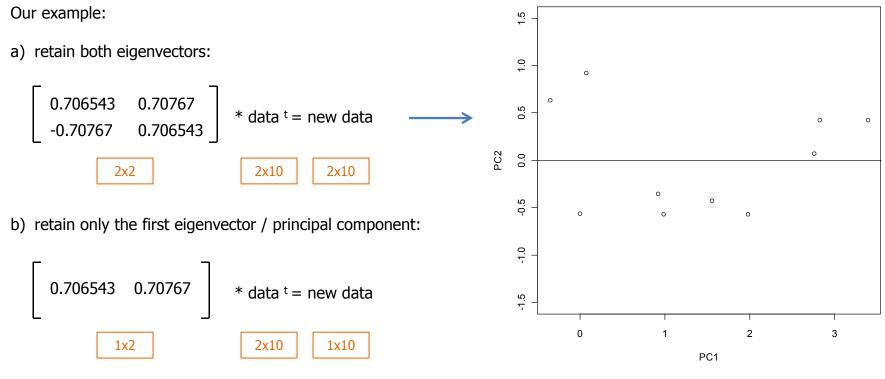


Compression and reduced dimensionality:

- the eigenvector associated with the highest eigenvalue is the principal component of the dataset; it captures the most significant relationship between the data dimensions
- ordering eigenvalues from highest to lowest gives the components in order of significance
- if we want, we can ignore the components of lesser significance this results in a loss of information, but if the eigenvalues are small, the loss will not be great
- thus, in a dataset with *n* dimensions/variables, one may obtain the *n* eigenvectors & eigenvalues and decide to retain *p* of them \rightarrow this results in a final dataset with only *p* dimensions

- feature vector – a vector containing only the eigenvectors representing the dimensions we want to keep – in our example data, 2 choices:

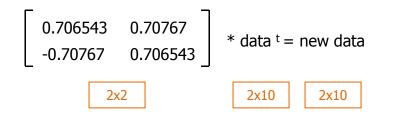
- the final dataset is obtained by multiplying the transpose of the feature vector (on the left) with the transposed original dataset
- this will give us the original data solely in terms of the vectors we chose



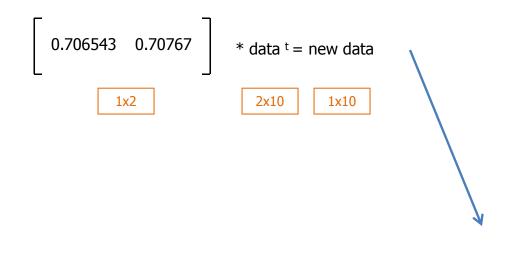
Original data, rotated so that the eigenvectors are the axes - no loss of information.

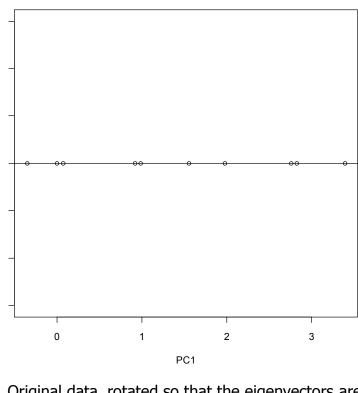
Our example:

a) retain both eigenvectors:



b) retain only the first eigenvector / principal component:





Original data, rotated so that the eigenvectors are the axes - no loss of information.

Only 1 dimension left – we threw away the other axis.

Thus: we transformed the data so that is expressed in terms of the patterns, where the patterns are the lines that most closely describe the relationships between the data.

Now, the values of the data points tell us exactly where (i.e., above/below) the trend lines the data point sits.

- similar to Cholesky decomposition as one can use both to fully decompose the original covariance matrix

V₁₁

\V₂₂

- in addition, both produce uncorrelated factors

Eigenvalue decomposition:

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$$\begin{bmatrix} c_{11} & c_{21} \\ c_{21} & c_{22} \end{bmatrix} * \begin{bmatrix} e_{11} \\ e_{21} \end{bmatrix} = v1 * \begin{bmatrix} e_{11} \\ e_{21} \end{bmatrix}$$

$$v_{11} \qquad v_{11} \qquad v_$$

Cholesky decomposition:

$$\begin{bmatrix} c_{11} & c_{21} \\ c_{21} & c_{22} \end{bmatrix} = \begin{bmatrix} I_{11} \\ I_{21} & I_{22} \end{bmatrix} \begin{bmatrix} va_{11} \\ va_{22} \end{bmatrix} \begin{bmatrix} I_{11} & I_{21} \\ I_{22} \end{bmatrix} \xrightarrow{va_1} \xrightarrow{va_1} \xrightarrow{(ch_1)} \xrightarrow{(ch_2)} \xrightarrow{(ch_2)} \xrightarrow{va_2}$$
Eigenvalue: decomposition
$$C = E V E^{-1}$$
Cholesky decomposition:

 $\mathsf{C}=\Lambda\,\Psi\,\Lambda^{\mathrm{t}}$

Thank you for your attention.