Machine learning numpy, school of AI Kuala Lumpur

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Bayes theorem text classification

Likelihood probability, probability of vector X when class C

Prior probability, probability of class C going to occur

$$P(C \mid X) = \frac{P(X|C)\,P(C)}{P(X)}$$

Posterior probability, probability of class C going to happen when vector is X

Marginal probability, probability of vector X, most of the case, its unobserve

Rebranding bayes theorem

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$$1 = k\, P(X \mid C)\, P(C) + k\, P(X \mid C')\, P(C')$$

Rebranding bayes theorem

$$k = \frac{1}{P(X|C)\,P(C) + P(X|C')\,P(C')}$$

$$k = \frac{1}{P(X)}$$

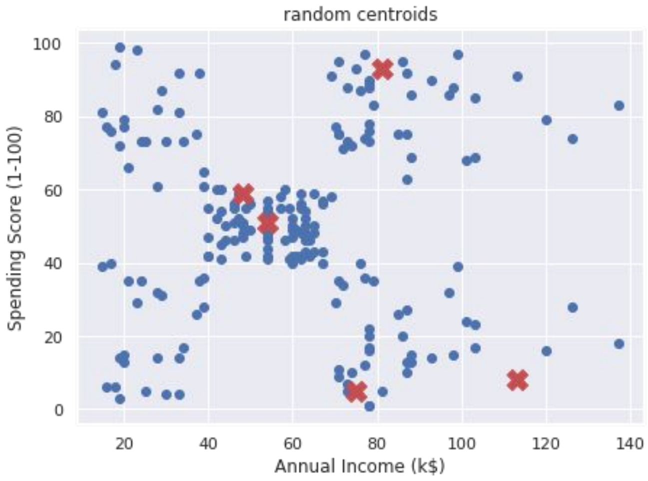
$$P(C \mid X) = \frac{P(X|C)\,P(C)}{P(X|C)\,P(C) + P(X|C')\,P(C')}$$

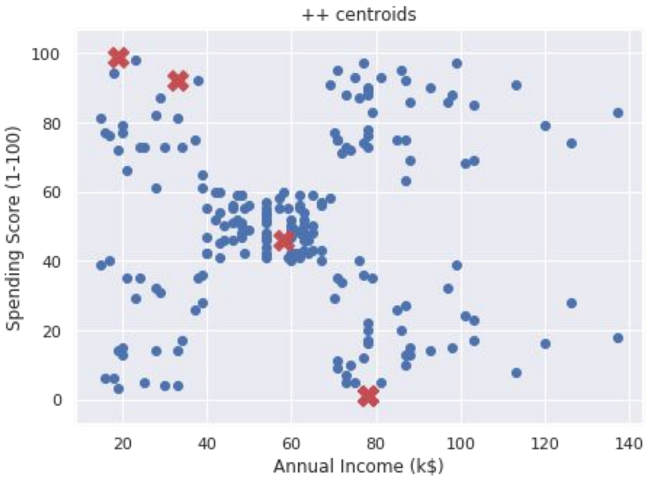
Text classification

index	i	like	chicken	meat	label
1	1	1	1	0	0
2	1	1	0	1	1

$$P(like \mid 0) = \frac{1+count}{\sum count+|V|}$$

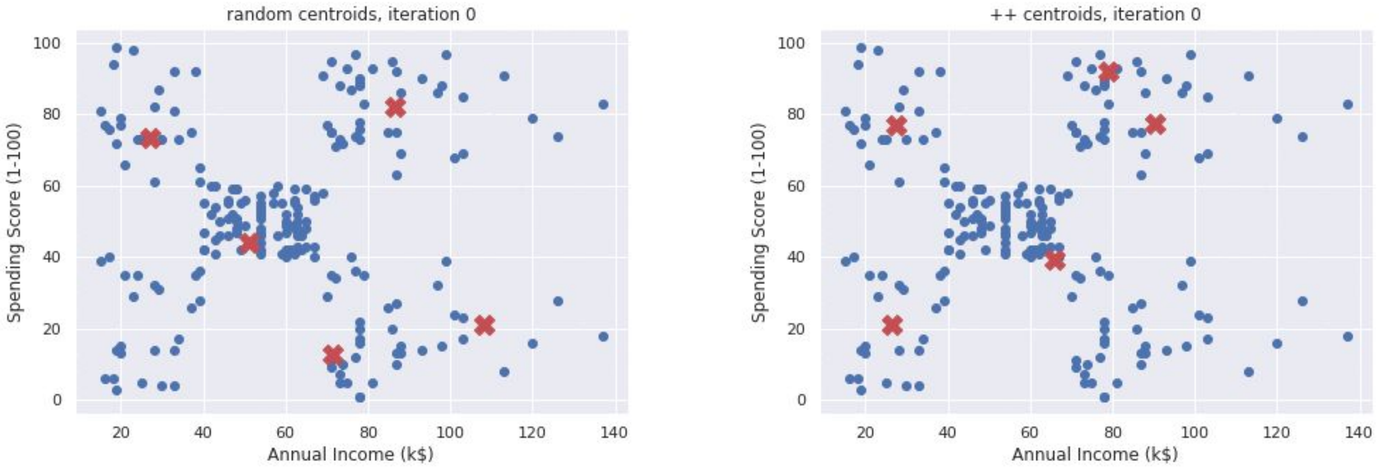
Kmean





1. Initiate random centroids, or use kmeans++.

Kmean



2. Keep iterating to calculate distances between individuals and centroids, and mean clustered individuals.

Kmean

3. To calculate ELBOW,

Iterate N K-means, every iteration, calculate sum of distances between centroids and grouped individuals, and plot.

Principal Component Analysis

Principal Component Analysis

1. Visualization

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Height, x	Weight, y	Bmi, z	Score, a	Hair length, b	Age, c	Steps, d

Principal Component Analysis

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It does not makes sense if you want to plot this table into a vector space, we have 7 dimensions!

Principal Component Analysis

2. Reduce noise

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Principal Component Analysis

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Height, x	Weight, y	Bmi, z	Score, a	Hair length, b	Age, c	Steps, d

Not all these 7 dimensions bring important information! We want to reject some attributes. Maybe 7 does not hurt much. What happen if you have 512 * 512 * 3 (image) dimension?! insane!

Principal Component Analysis

3. Reduce memory (computer science)

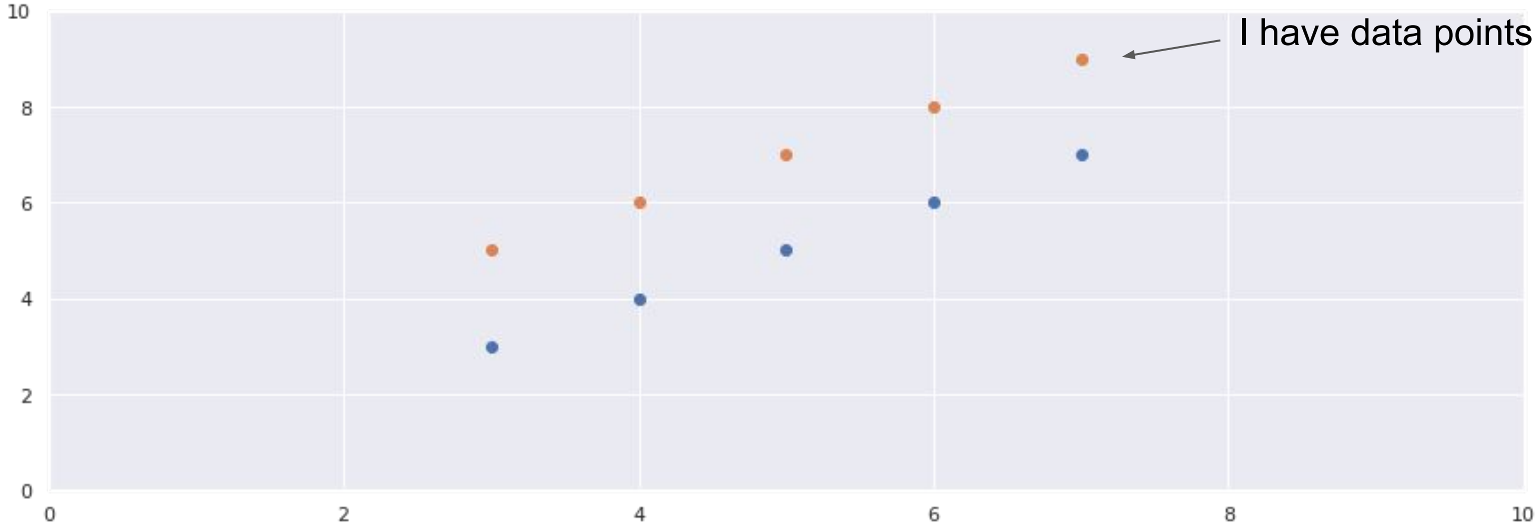
Height, x	Weight, y	Bmi, z	Score, a	Hair length, b	Age, c	Steps, d

Let say a float took 1 bytes, we have 7 columns and 1 billion of rows.

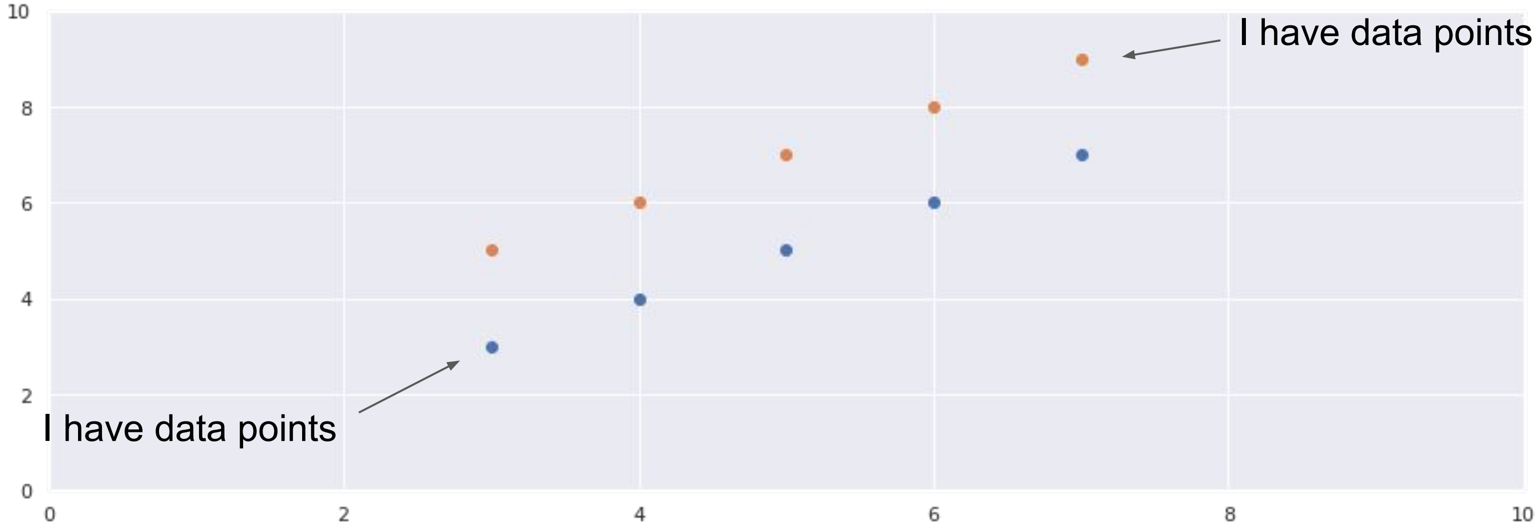
7 * 1,000,000,000 * 1 = 7,000,000,000 bytes == 70 GB!

Drop a column will save us 10 GB of memory!

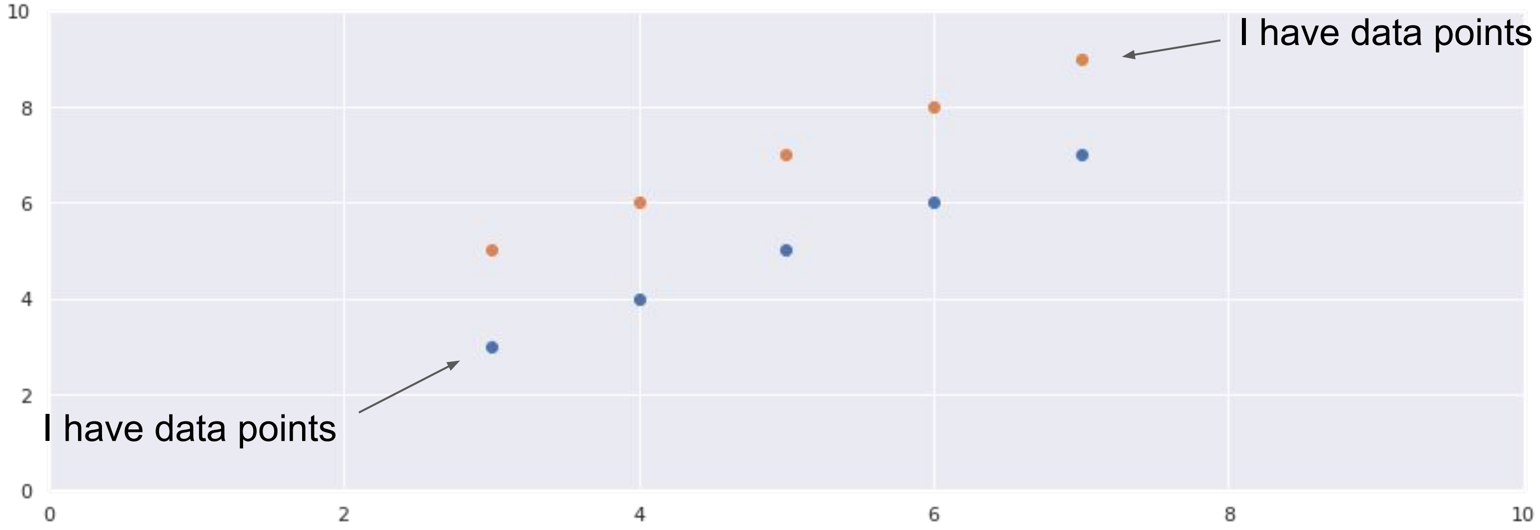
Principal Component Analysis



Principal Component Analysis

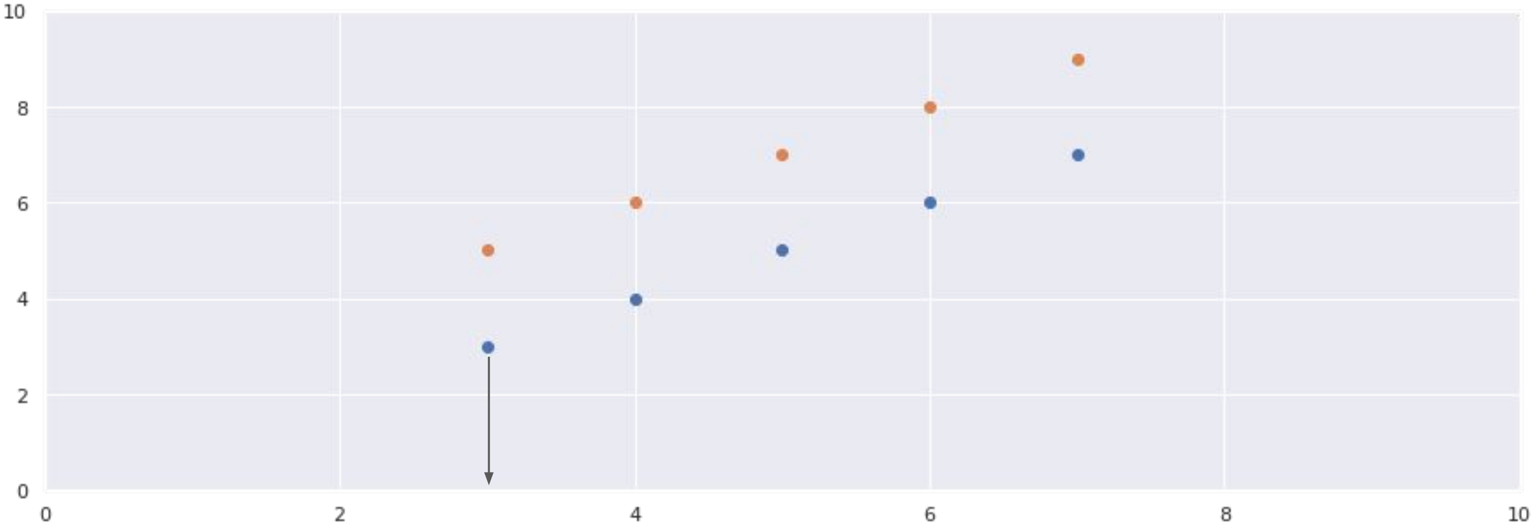


Principal Component Analysis



Let say, this plane is R^n , we only visualize it on R^2 , I want to visualize the data points at axis-0, which is x-axis.

Principal Component Analysis



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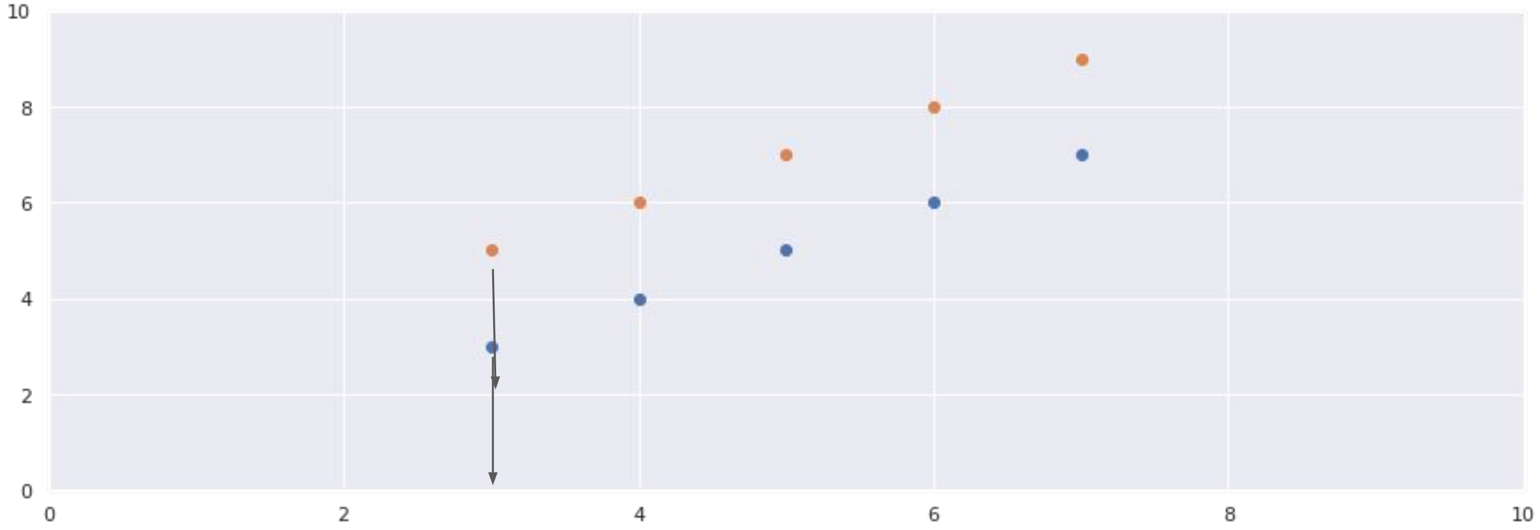

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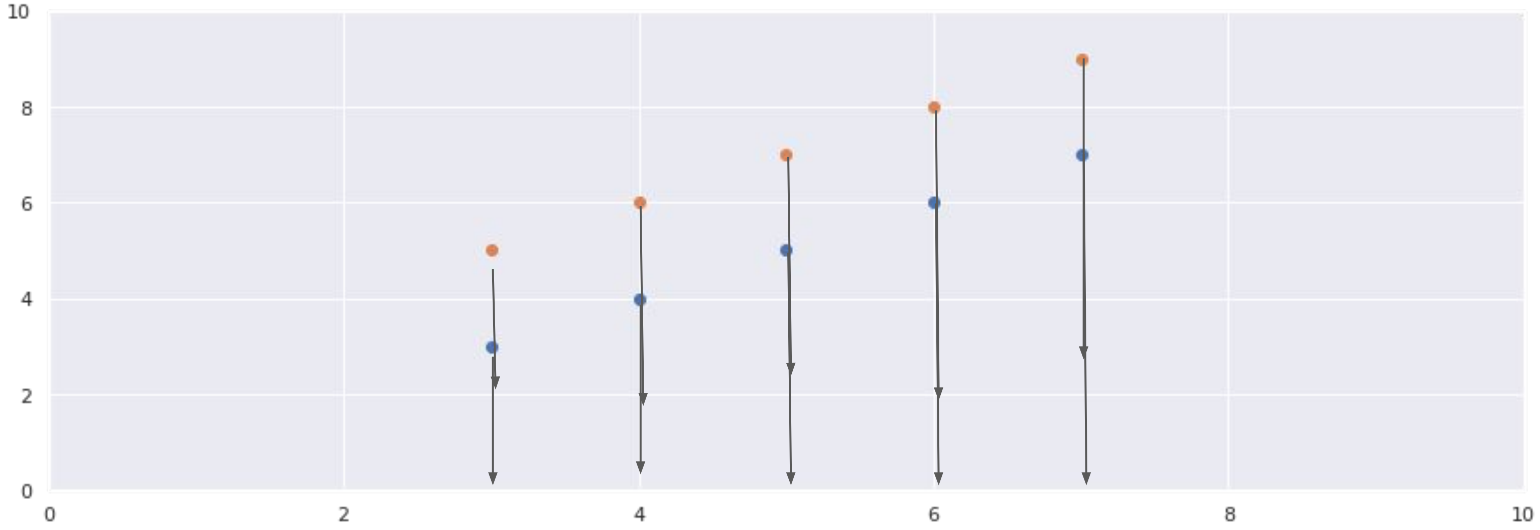
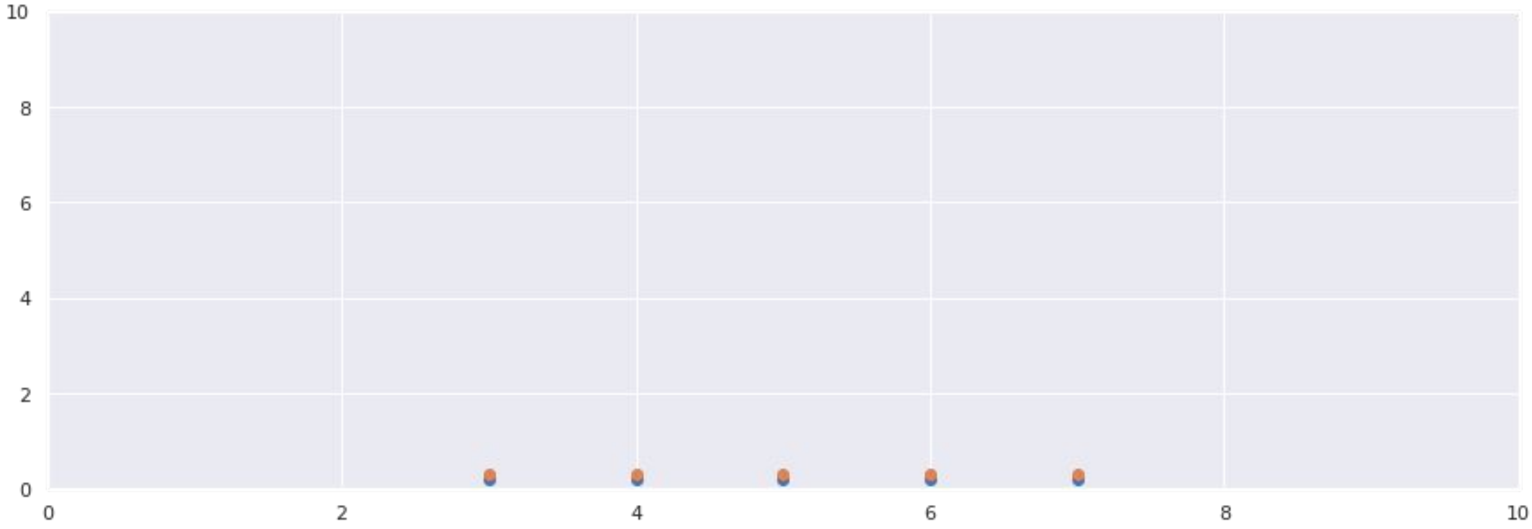
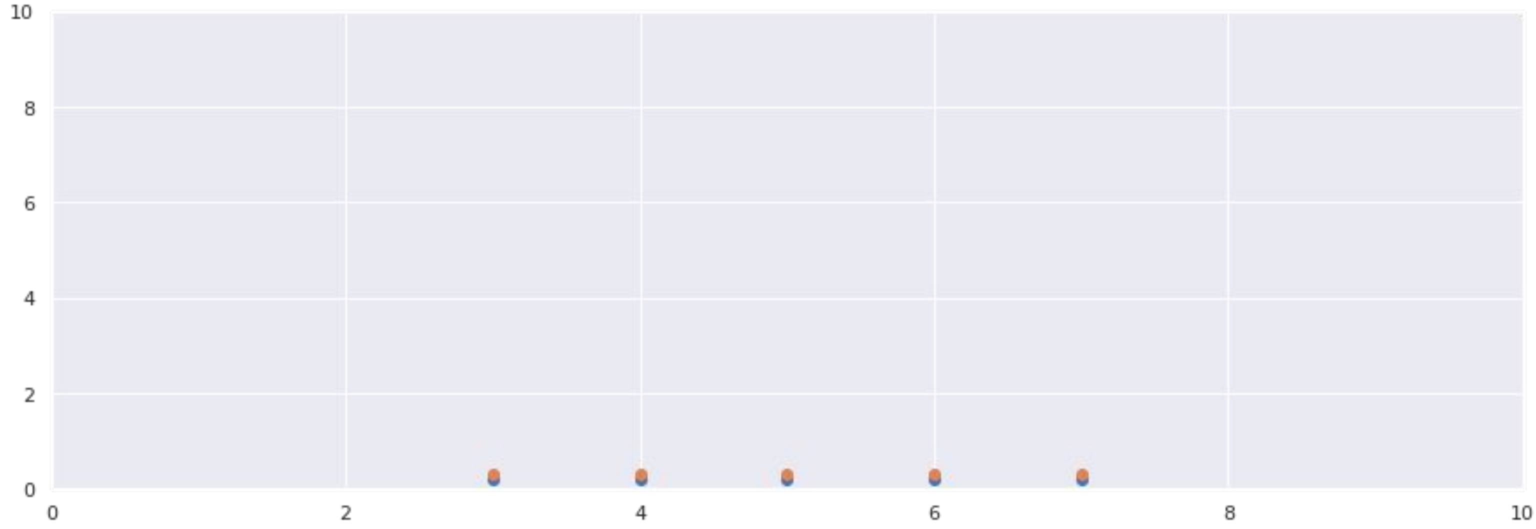


Principal Component Analysis



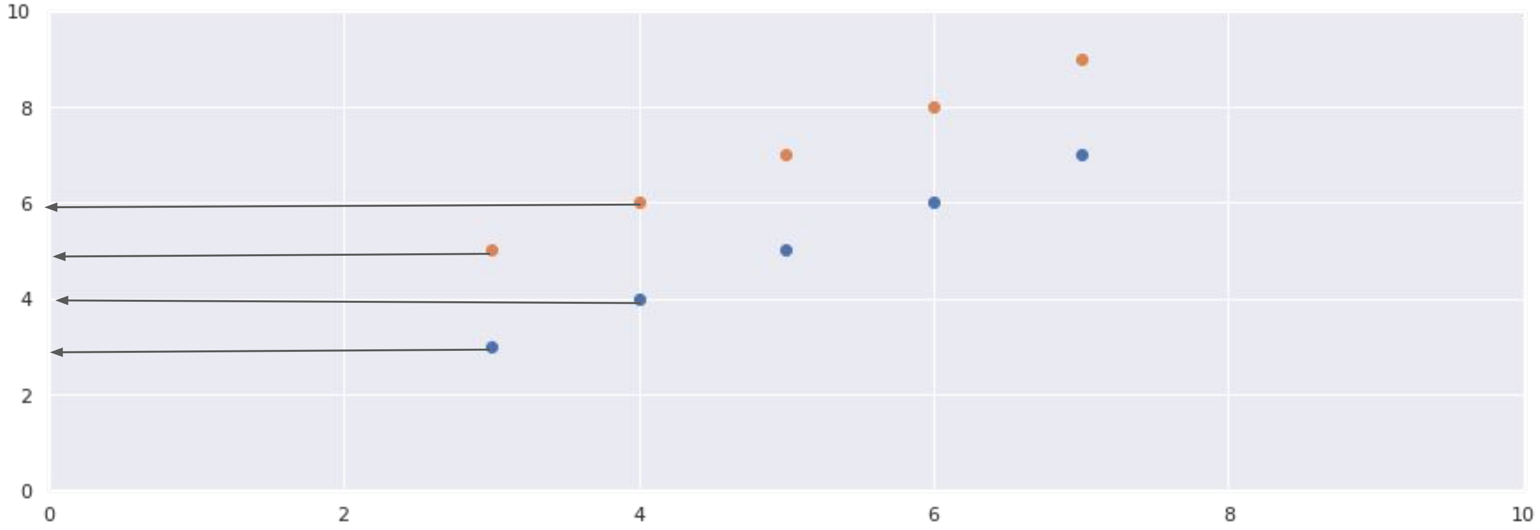
We cannot distinguish between oranges and blues!

Principal Component Analysis

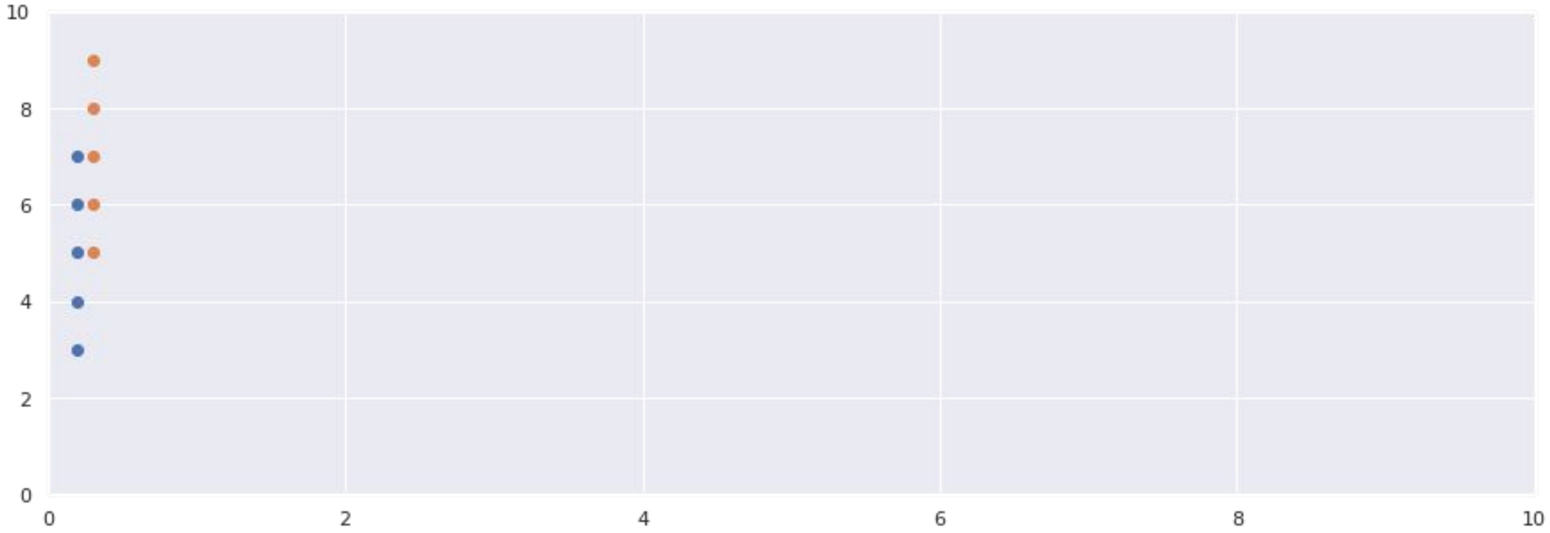


We cannot distinguish between oranges and blues! How about axis-2, which is, axis-y?

Principal Component Analysis

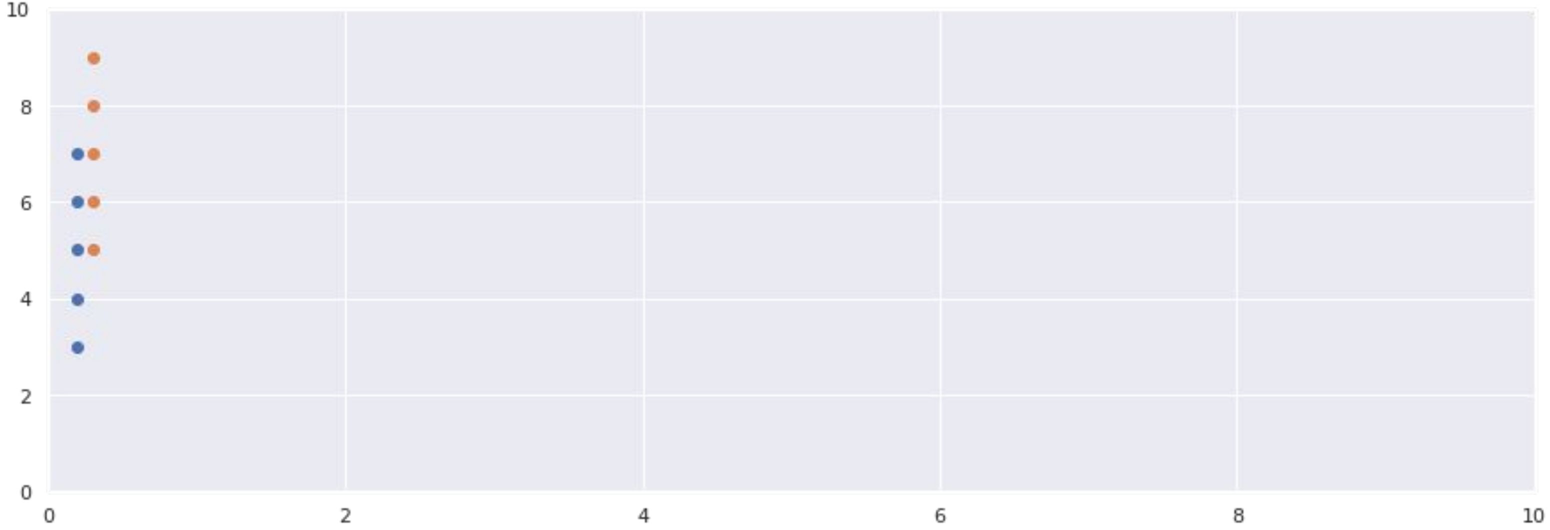


Principal Component Analysis



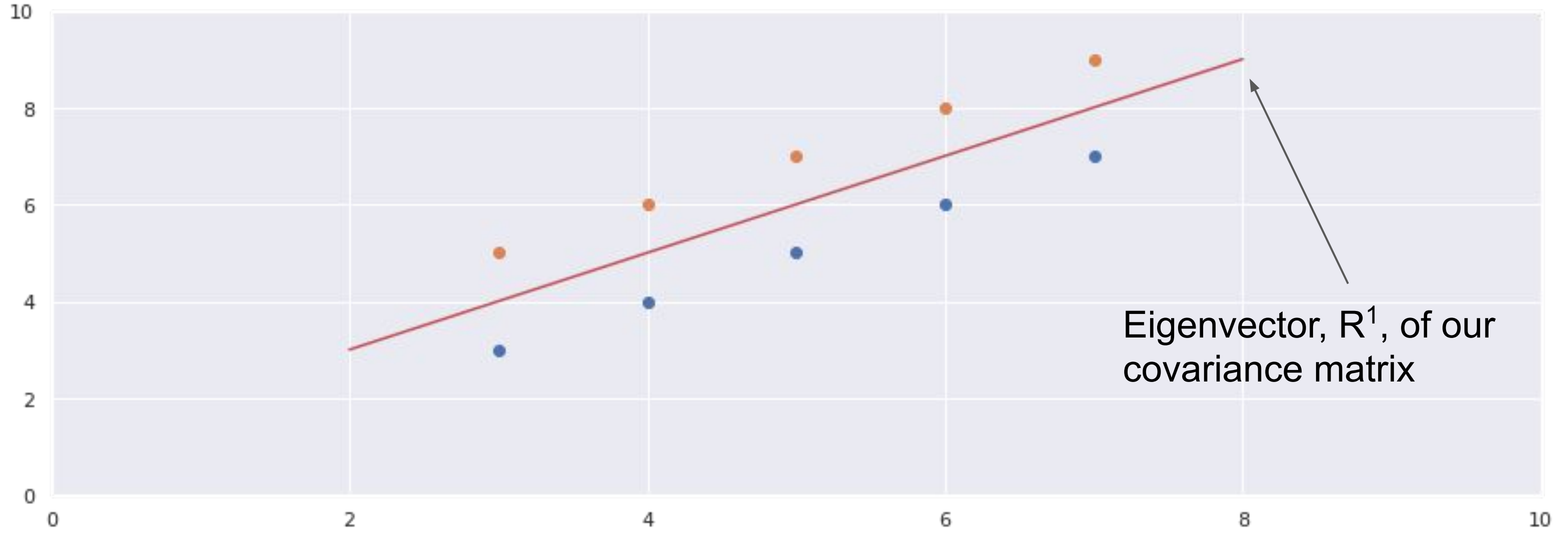
It is quite okay, just a few data points overlapped each others.

Principal Component Analysis



It is quite okay, just a few data points overlapped each others. **But we don't overlapping right?!**

Principal component analysis



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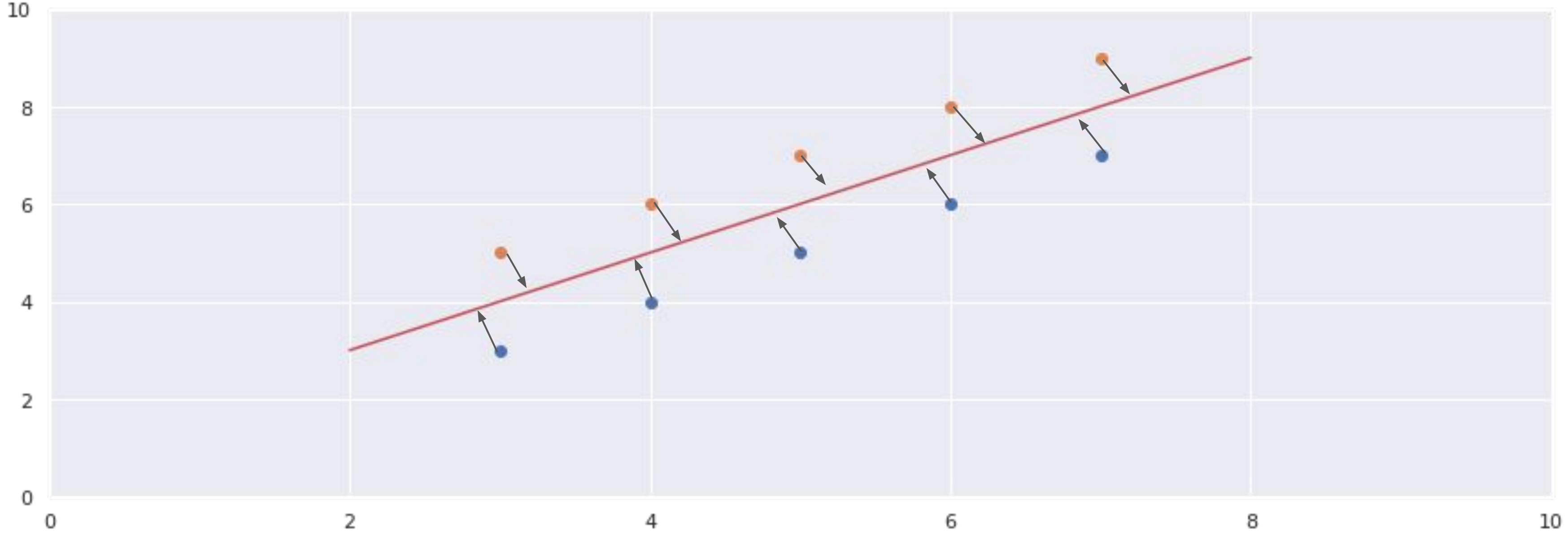

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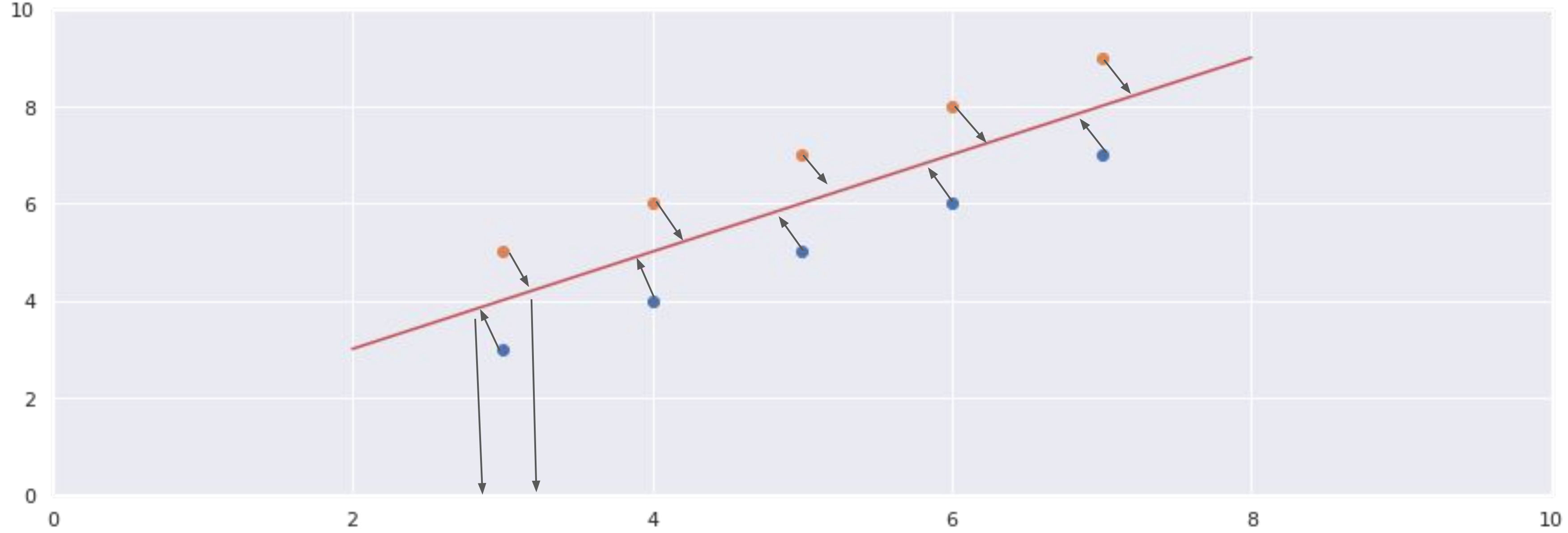

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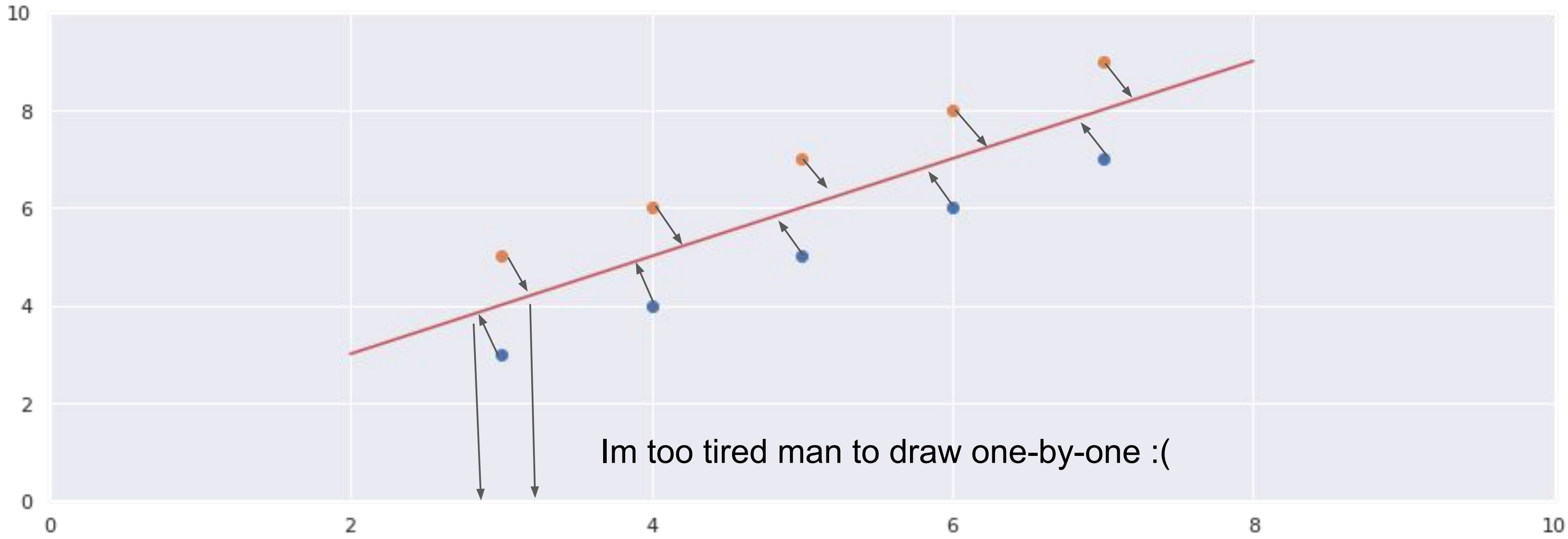
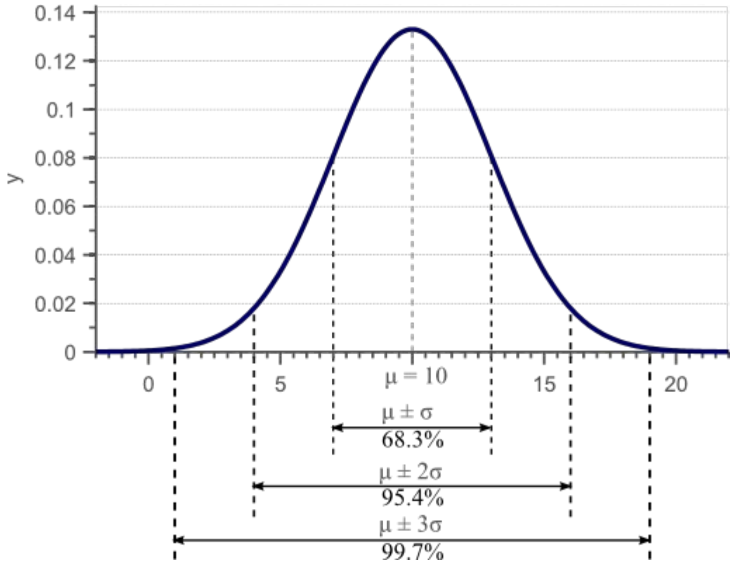


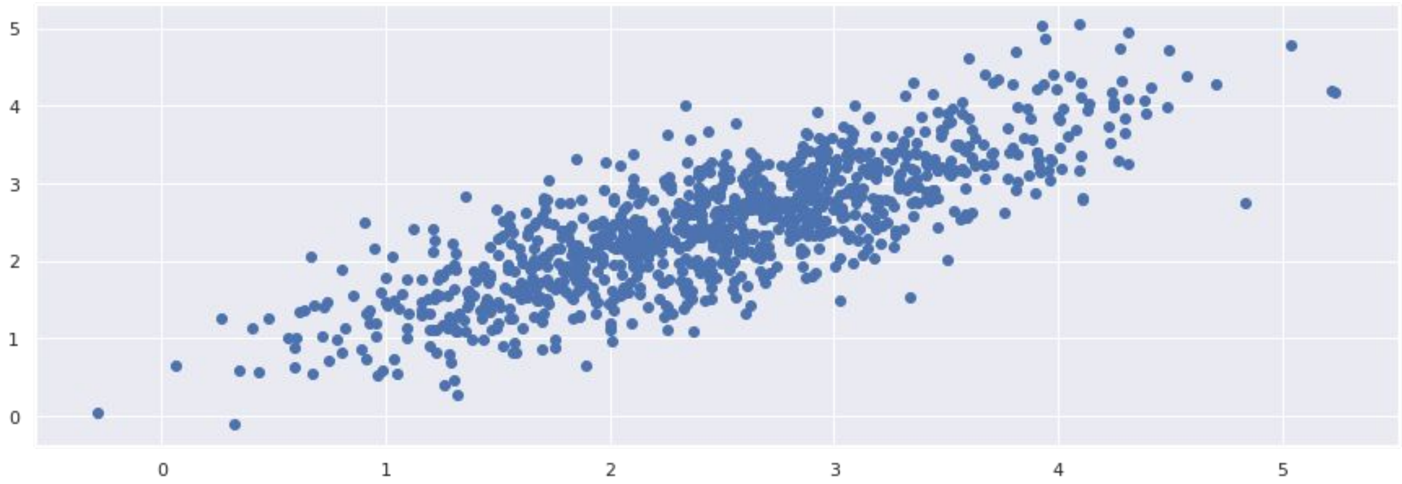
Principal component analysis

How to make sense of it?



$$s^2 = \frac{\Sigma X^2 - \frac{(\Sigma X)^2}{N}}{N-1}$$

Principal component analysis



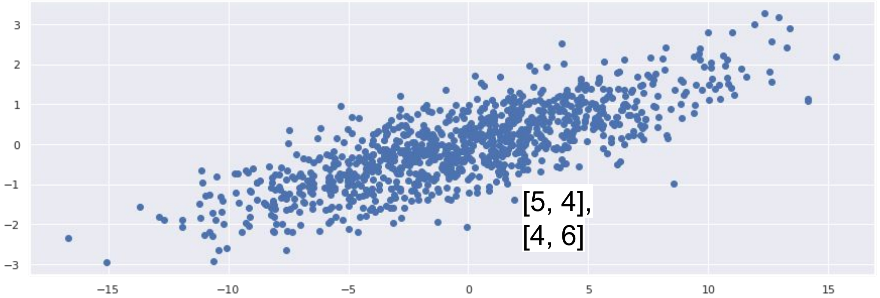
$$\mathrm{conv}(x, y) = \frac{\sum (x - \overline{x})(y - \overline{y})}{n}$$

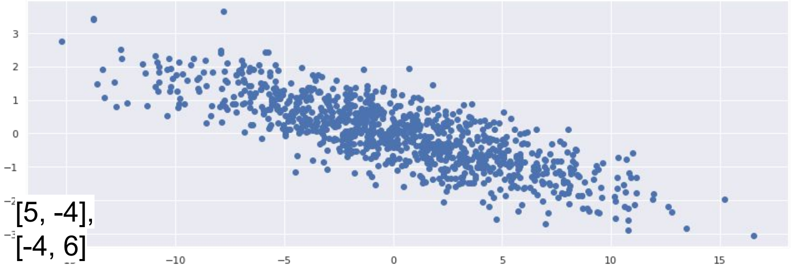
Principal component analysis

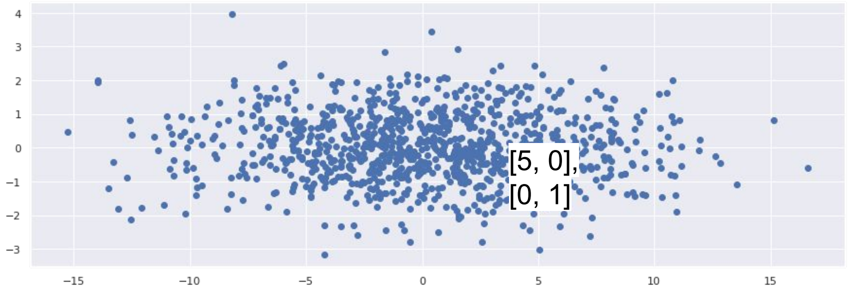
$$\Sigma = \begin{bmatrix} \sigma(x,x) & \sigma(x,y) \\ \sigma(y,x) & \sigma(y,y) \end{bmatrix}$$

$$X.T \cdot X$$

Principal component analysis

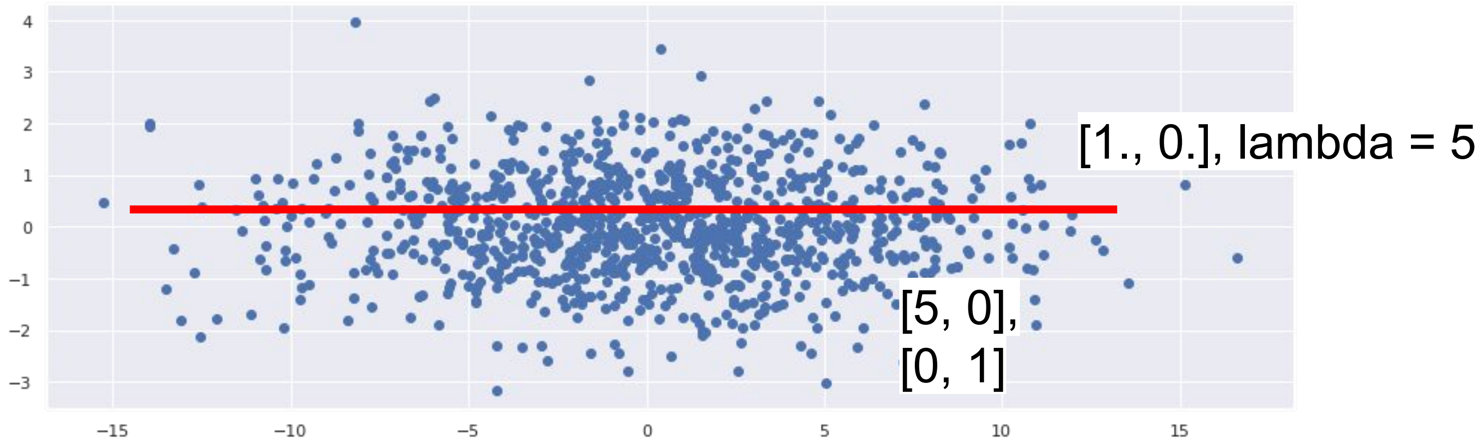






Value 1 is y axis, 0 correlation

Principal component analysis




```
l, v = np.linalg.eig(np.array([[5,0],[0,1]]))
l, v
(array([5., 1.]), array([[1., 0.],
                          [0., 1.]]))
```