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Fjelltopp
Technology with impact.

session 3: Unsupervised learning

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3rd March 2020

Centre for Ecological Sciences
Indian Institute of Science
Bengaluru, India



Unsupervised learning

What can you do when you have no answers?



Uses of unsupervised learning

- pre-processing (sparse features clustering)
- simplifying data for supervised algorithms
- clustering for data exploration:
 - sparse data
 - big data
 - data for which we lack intuition to choose a statistical model
- label-free segmentation

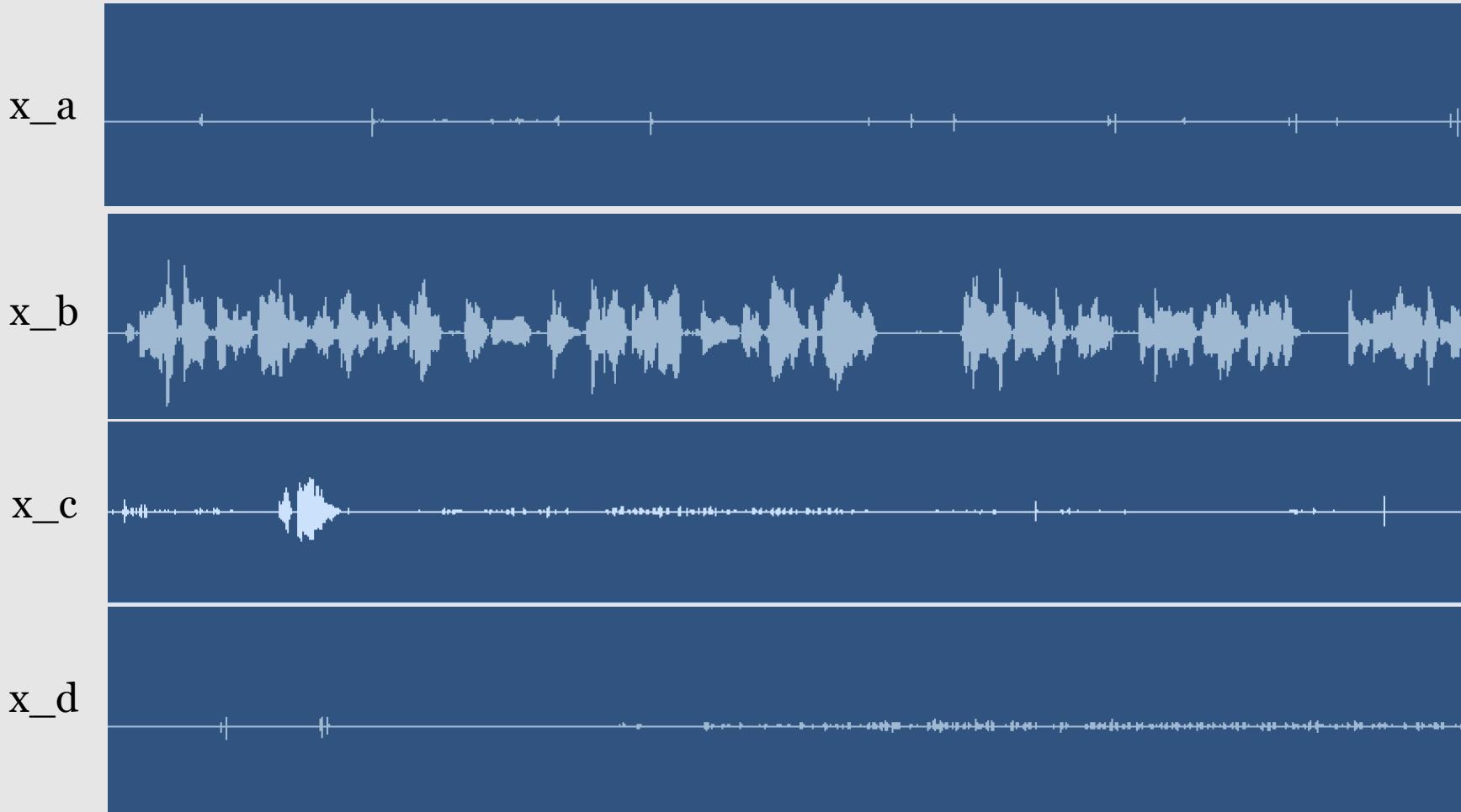


Principles

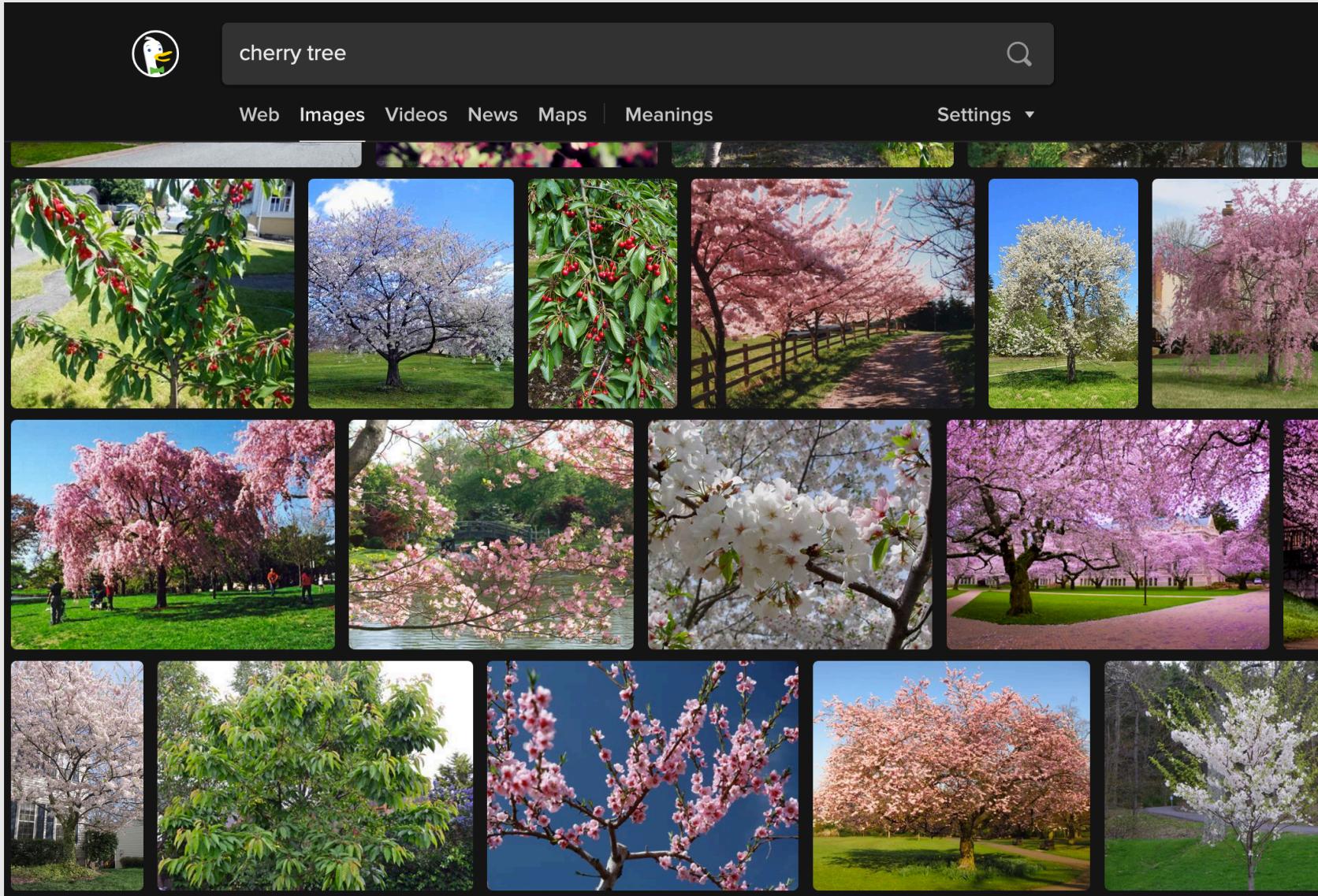
- exploration of variable space in looking for emerging patterns of similarity
- there is no provided ground truth, and in fact often it is not available at all.
- often used with huge amounts of data
- provided: knowledge of the feature space - for instance a definition of distance in feature space - that allows to draw some outcomes from provided data.



Variable selection



Unstructured data

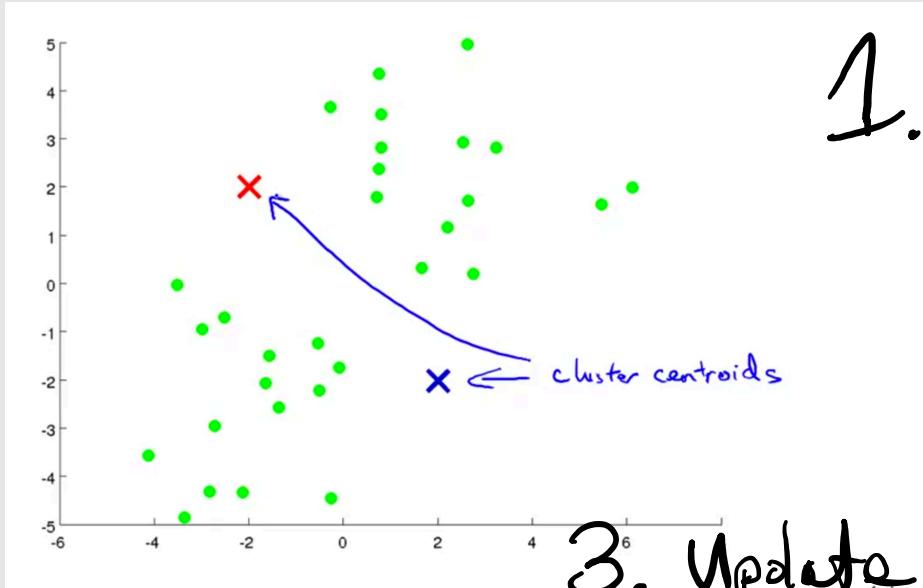


Clustering: finding data similarity

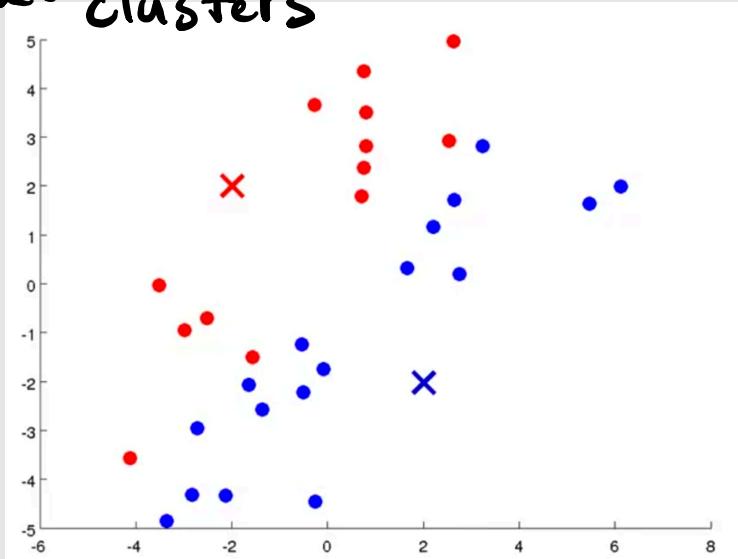


k-means

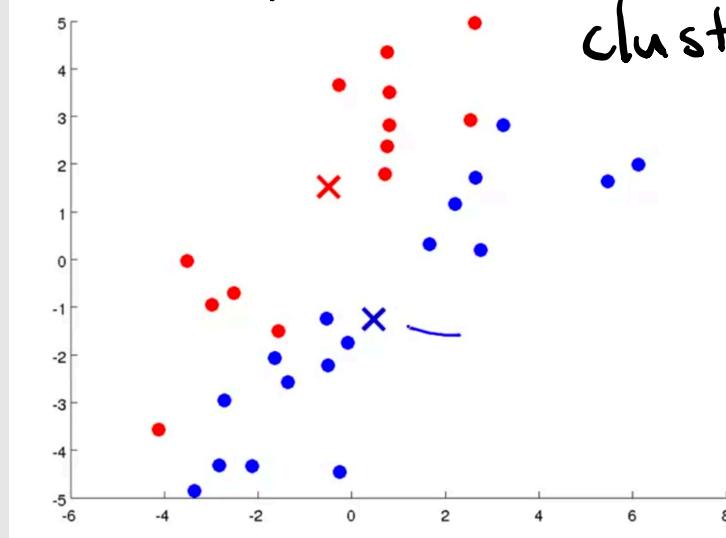
$k = 2$



2. find clusters



3. Update mean of
clusters

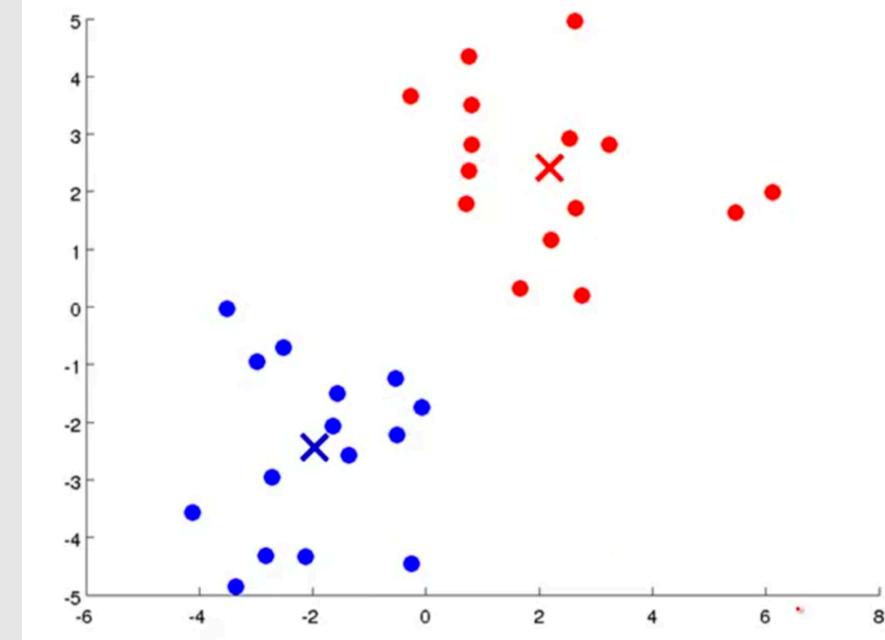
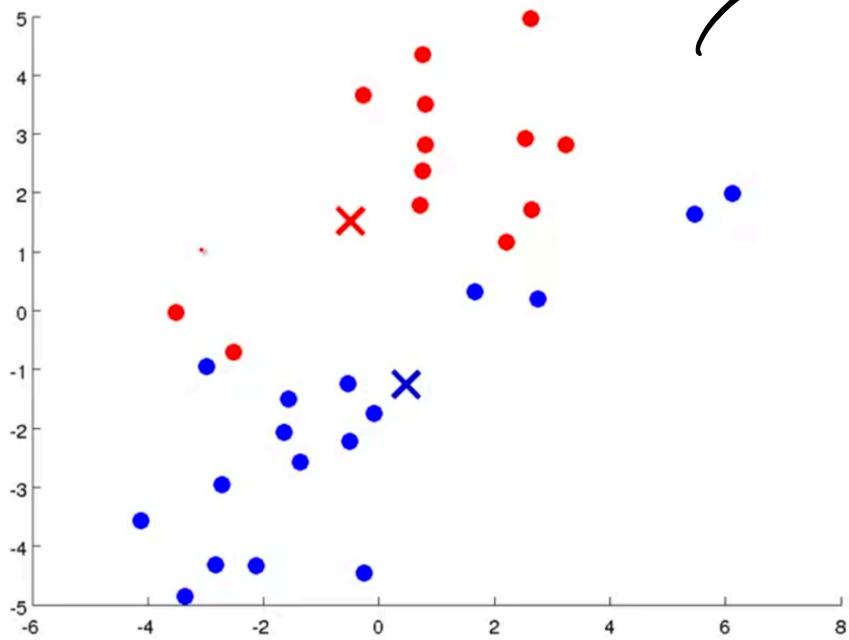


random
initialisation



k means

convergence

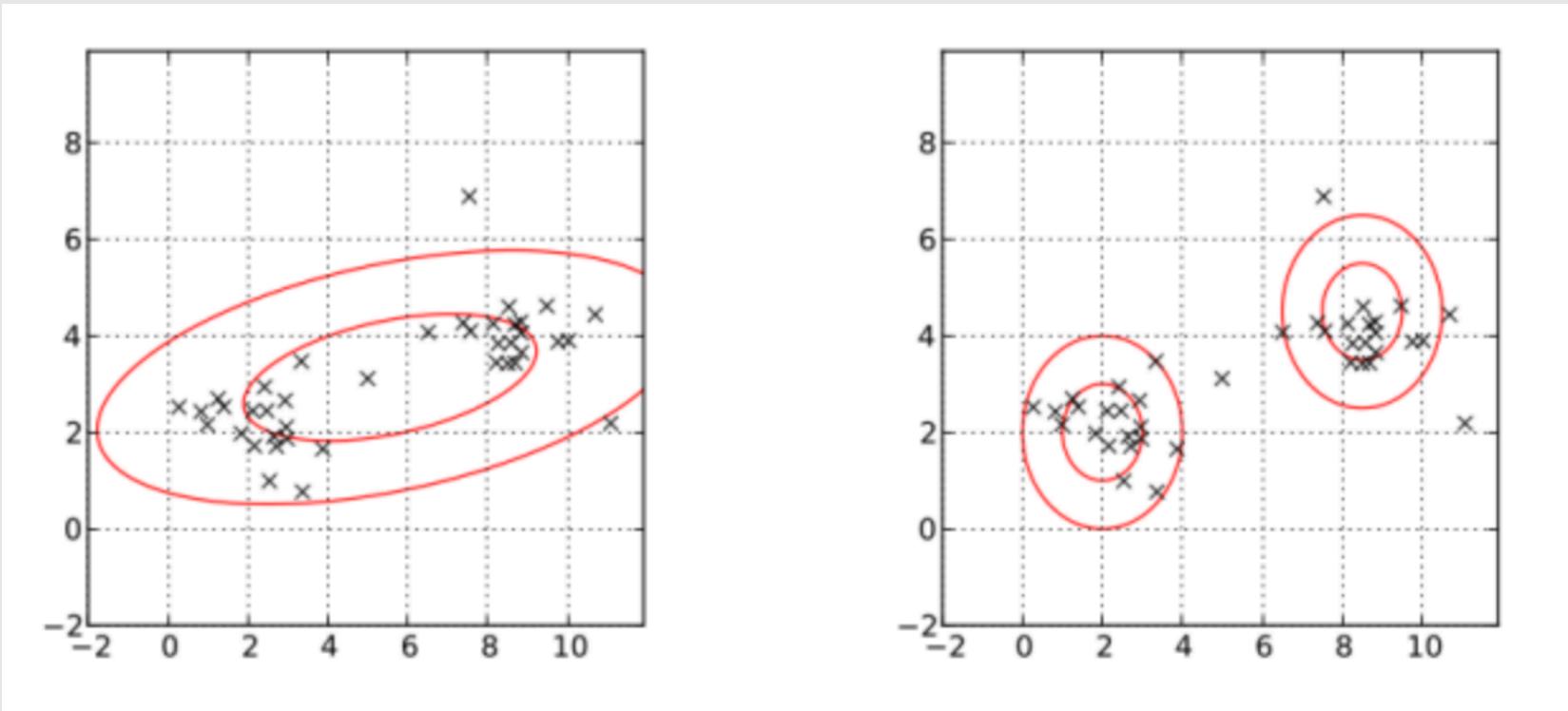


k-medoids

- Just like k-means but choosing median data point as centre

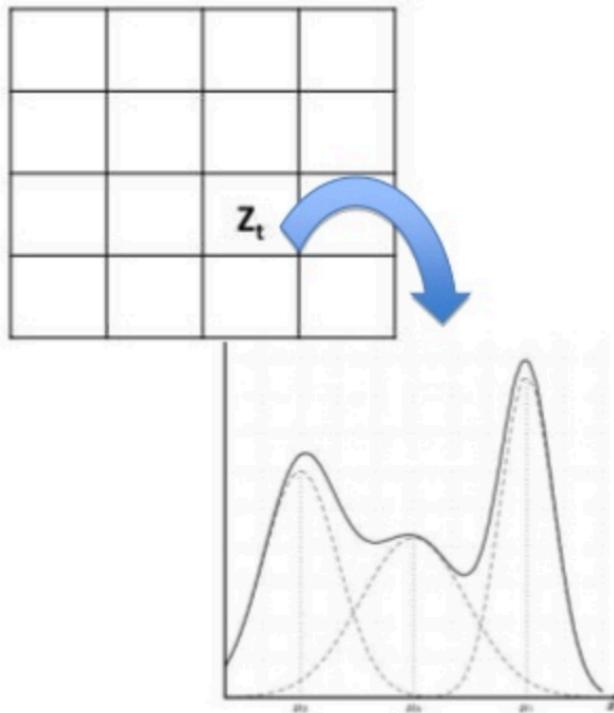


Gaussian Mixture Model



Background subtraction

Gaussian Mixture Model (GMM)



- A GMM is a mixture pdf which is a linear combination of K Gaussian pdfs.
- $\sum w_i = 1$
- each pixel is given one GMM

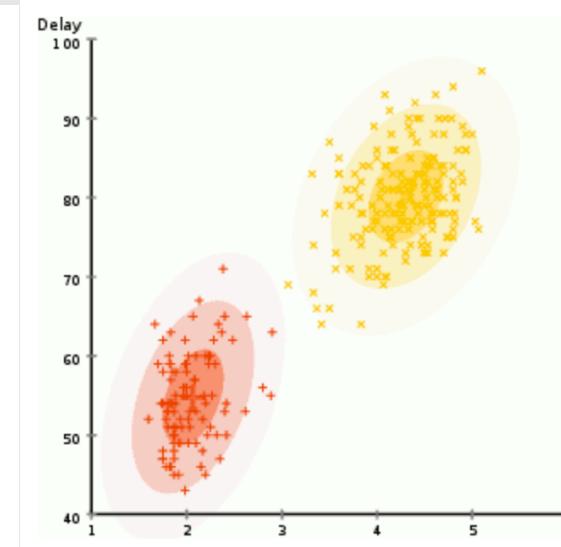
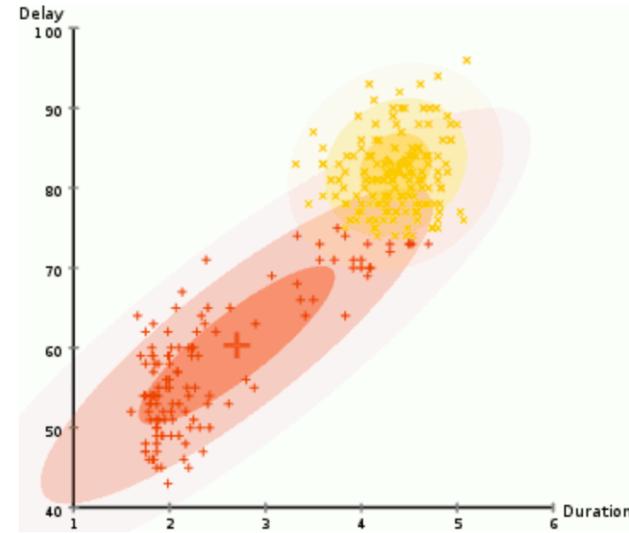
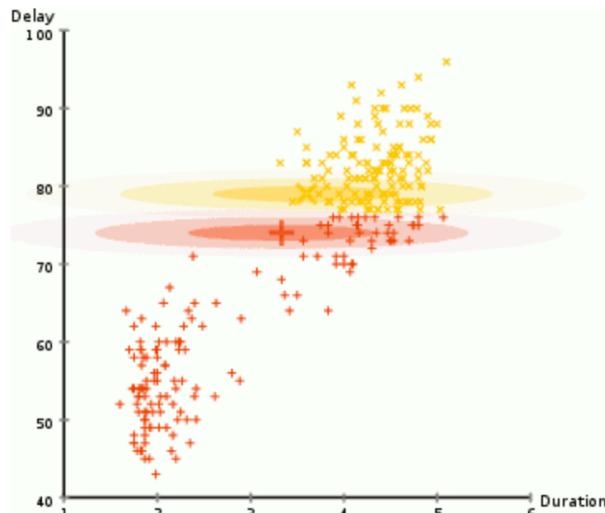
source: Zivkovic , 2004. Improved adaptive gaussian mixture model for background subtraction. Figure by Raviraj singh shekhawat



Example:



Algorithm for GMM: Expectation-Maximisation



https://commons.wikimedia.org/wiki/File:EM_Clustering_of_Old_Faithful_data.gif



Mean-shift segmentation

790

IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 17, NO. 8, AUGUST 1995

- KDE + gradient ascent

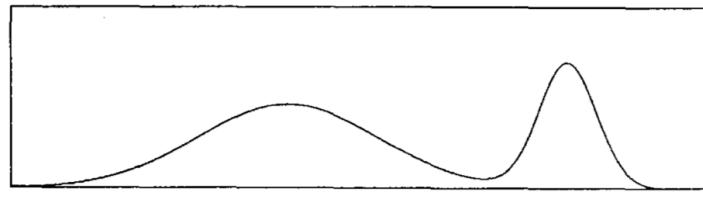
Mean Shift, Mode Seeking, and Clustering

Yizong Cheng

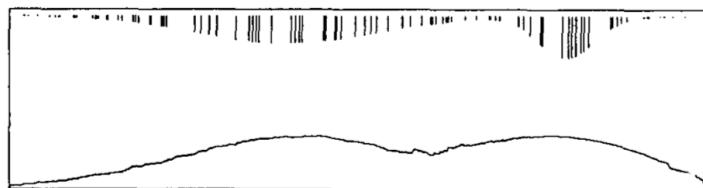
Abstract—Mean shift, a simple iterative procedure that shifts each data point to the average of data points in its neighborhood, is generalized and analyzed in this paper. This generalization makes some k -means like clustering algorithms its special cases. It is shown that mean shift is a mode-seeking process on a surface “shadow mapping analysis.”

A relation among kernels called “shadow” will be defined in Section III. It will be proved that mean shift on any kernel is equivalent to gradient ascent on the density estimated with a shadow of its. Convergence and its rate is the subject of Section IV. In Section V, we show that mean shift can be used to find local maxima of a function f . We call it “multistart global optimization by mean transform.”

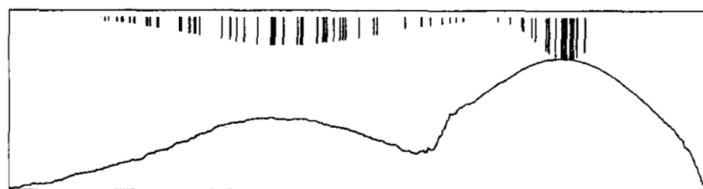
In the last section, we apply mean shift to clustering, the



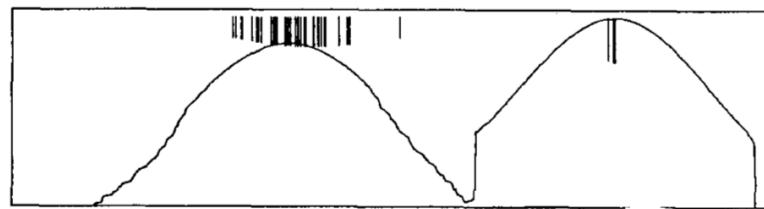
(a)



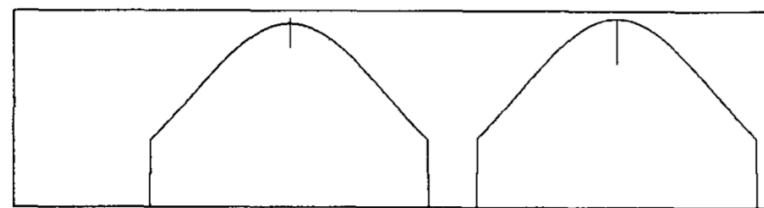
(b)



(c)



(d)

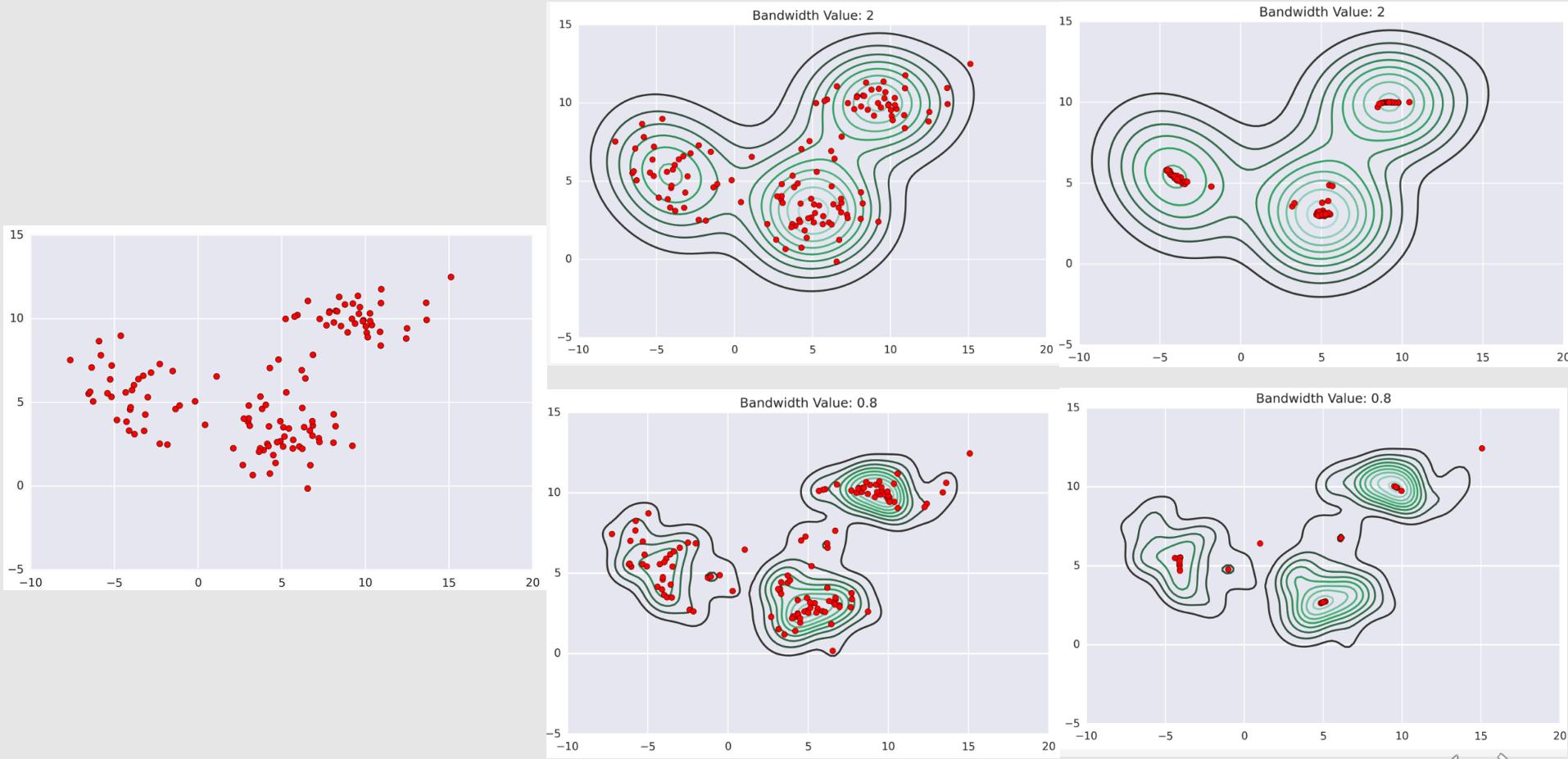


(e)

Fig. 8. Multistart global optimization using blurring. (a) shows the function f , whose global maximum is to be found. The next four figures show the mean shift of S , at the (b) initial, (c) first, (d) third, and (e) fifth iterations of a blurring process when f is used as the weight function. In each of these four figures, the vertical bars show the positions and f values of the S points, and the curve shows the q function, whose local maxima locations approximate those of f .



Mean-shift segmentation



EM vs mean-shift?

Gaussian mean shift is an EM algorithm

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August 23, 2006

Abstract

The mean-shift algorithm, based on ideas proposed by Fukunaga and Hostetler (1975), is a hill-climbing algorithm on the density defined by a finite mixture or a kernel density estimate. Mean-shift can be used as a nonparametric clustering method and has attracted recent attention in computer vision applications such as image segmentation or tracking. We show that, when the kernel is Gaussian, mean-shift is an expectation-maximisation (EM) algorithm, and when the kernel is non-gaussian, mean-shift is a generalised EM algorithm. This implies that mean-shift converges from almost any starting point and that, in general, its convergence is of linear order. For Gaussian mean-shift we show: (1) the rate of linear convergence approaches 0 (superlinear convergence) for very narrow or very wide kernels, but is often close to 1 (thus extremely slow) for intermediate widths, and exactly 1 (sublinear convergence) for widths at which modes merge; (2) the iterates approach the mode along the local principal component of the data points from the inside of the convex hull of the data points; (3) the convergence domains are nonconvex and can be disconnected and show fractal behaviour. We suggest ways of accelerating mean-shift based on the EM interpretation.

Keywords: mean-shift algorithm, Gaussian mixtures, kernel density estimators, EM algorithm, clustering



DBSCAN – industry standard

Published in Proceedings of 2nd International Conference on Knowledge Discovery and Data Mining (KDD-96)

A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise

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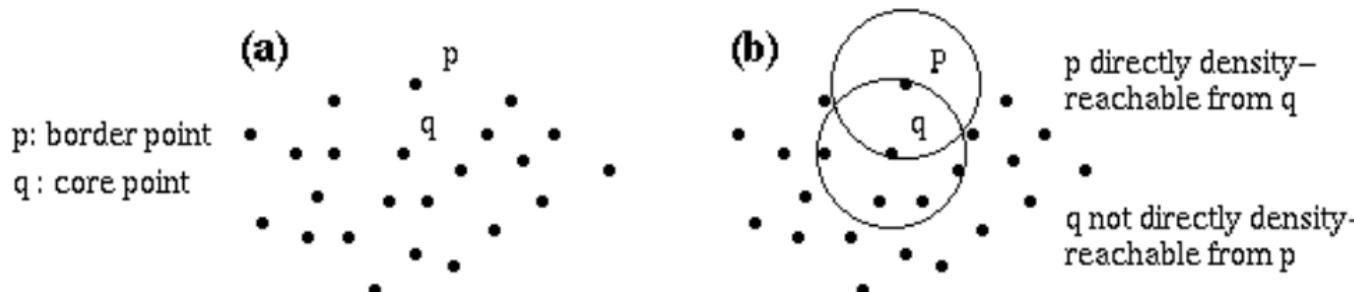


figure 2: core points and border points

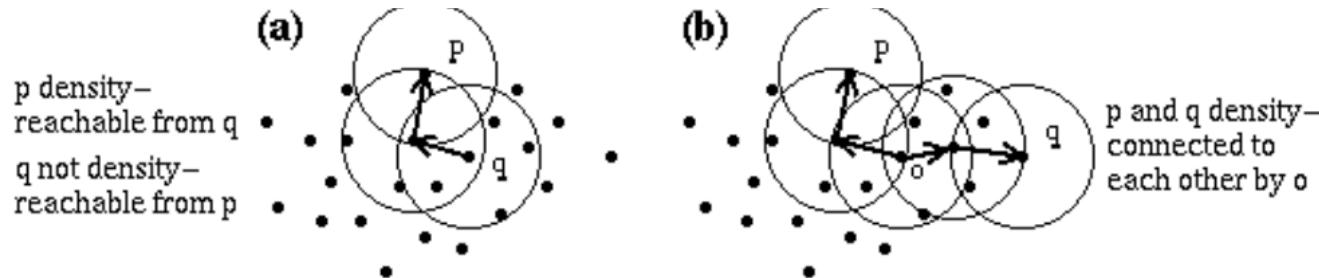


figure 3: density-reachability and density-connectivity

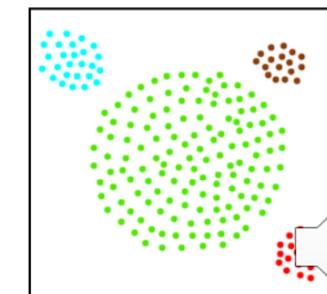
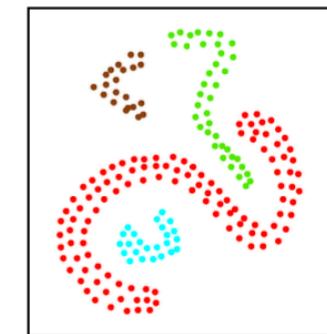
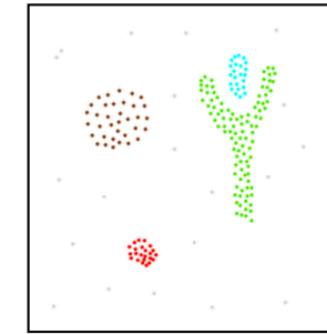
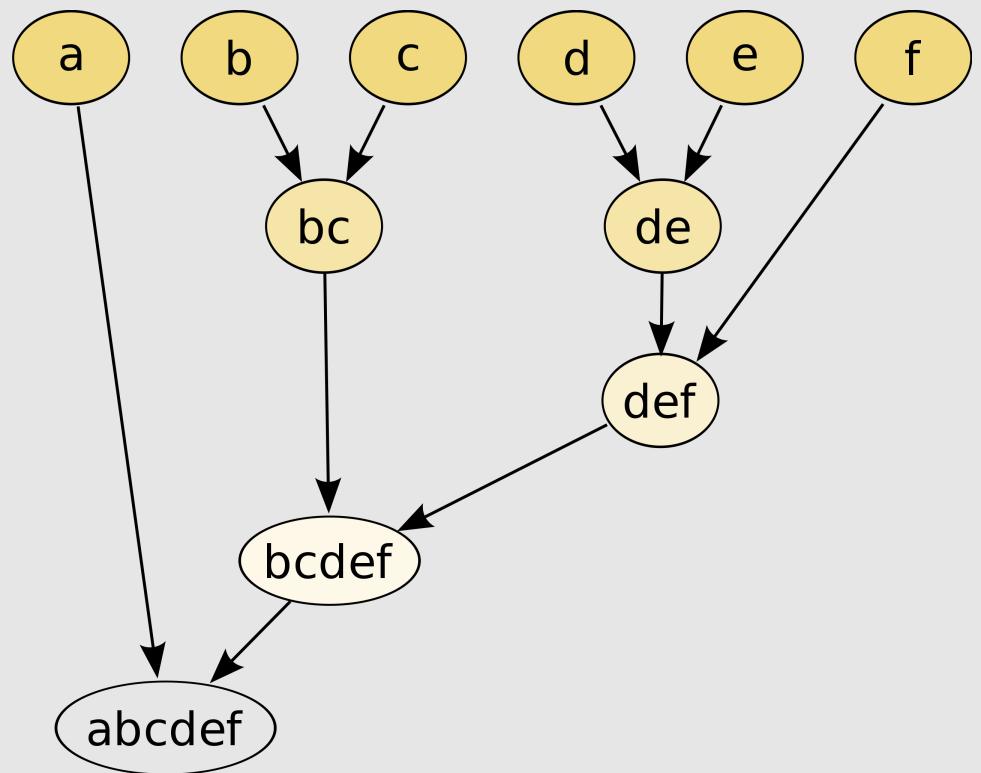
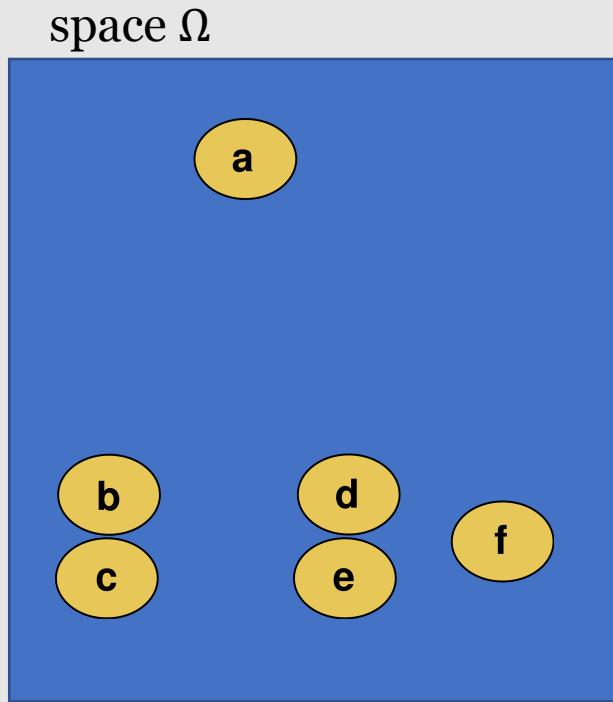


figure 6: Clusterings discovered by DBSCAN

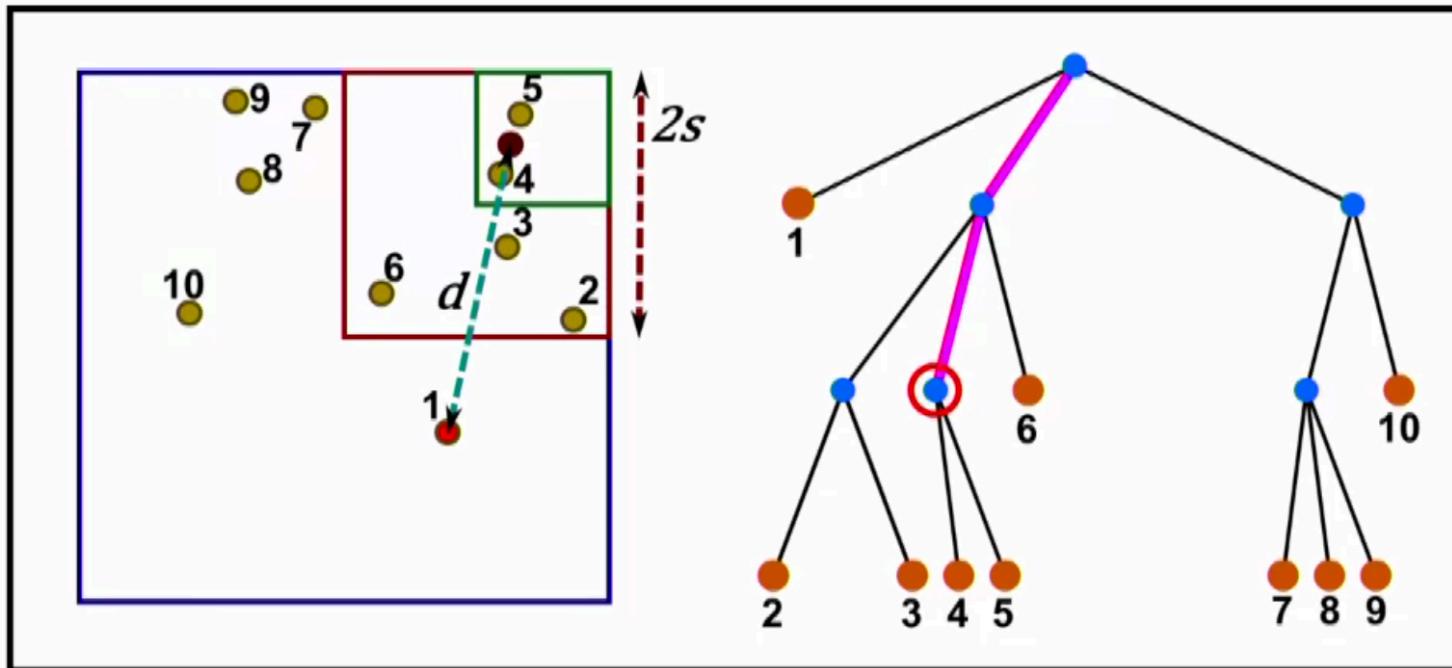
Hierarchical clustering



https://en.wikipedia.org/wiki/Hierarchical_clustering

Barnes-Hut algorithm: using the quadtree

Continue with NE quadrant, level 2



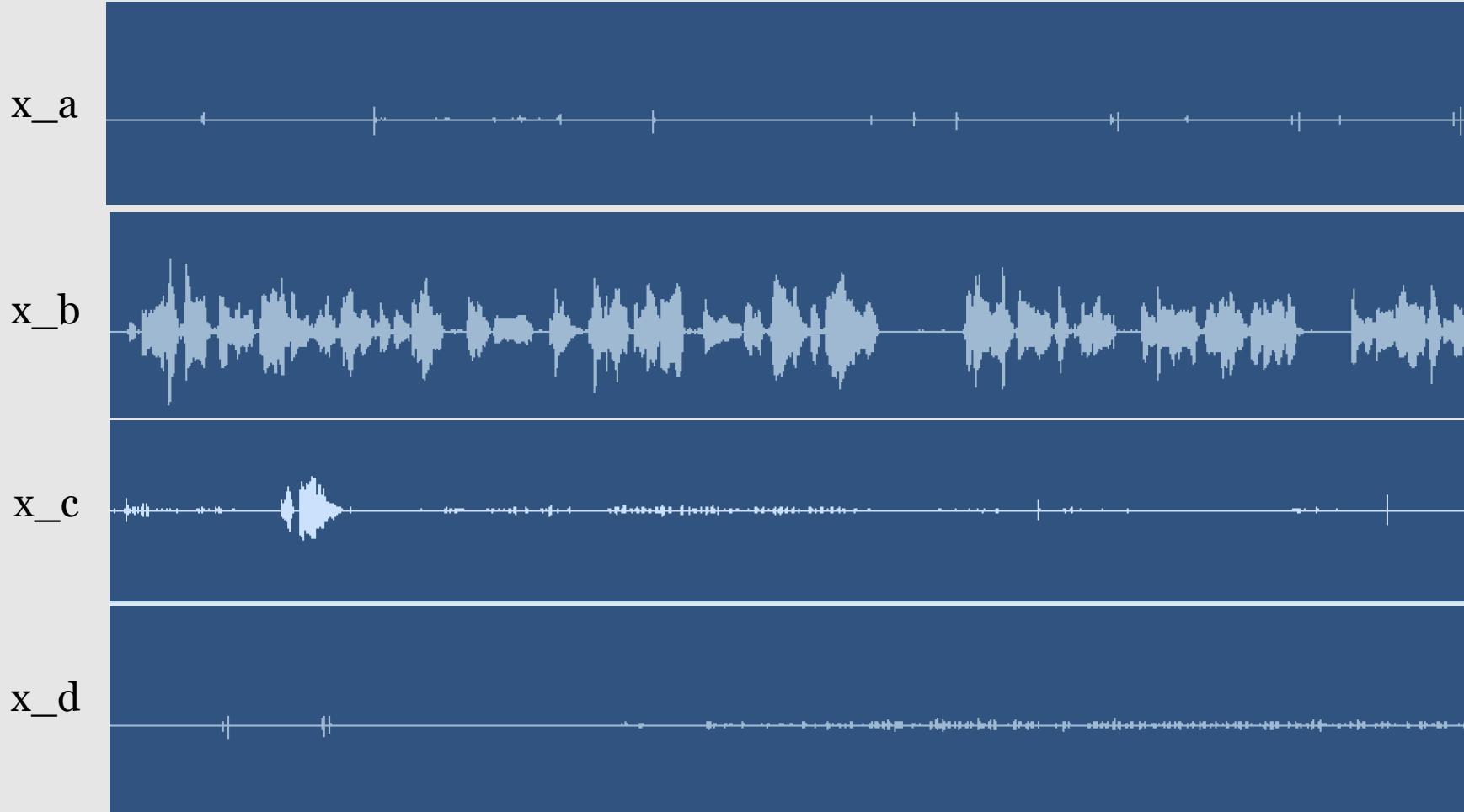
Two bodies in this quadrant. Can we replace them by their center of mass?

source: <https://www.coursera.org/learn/modeling-simulation-natural-processes>

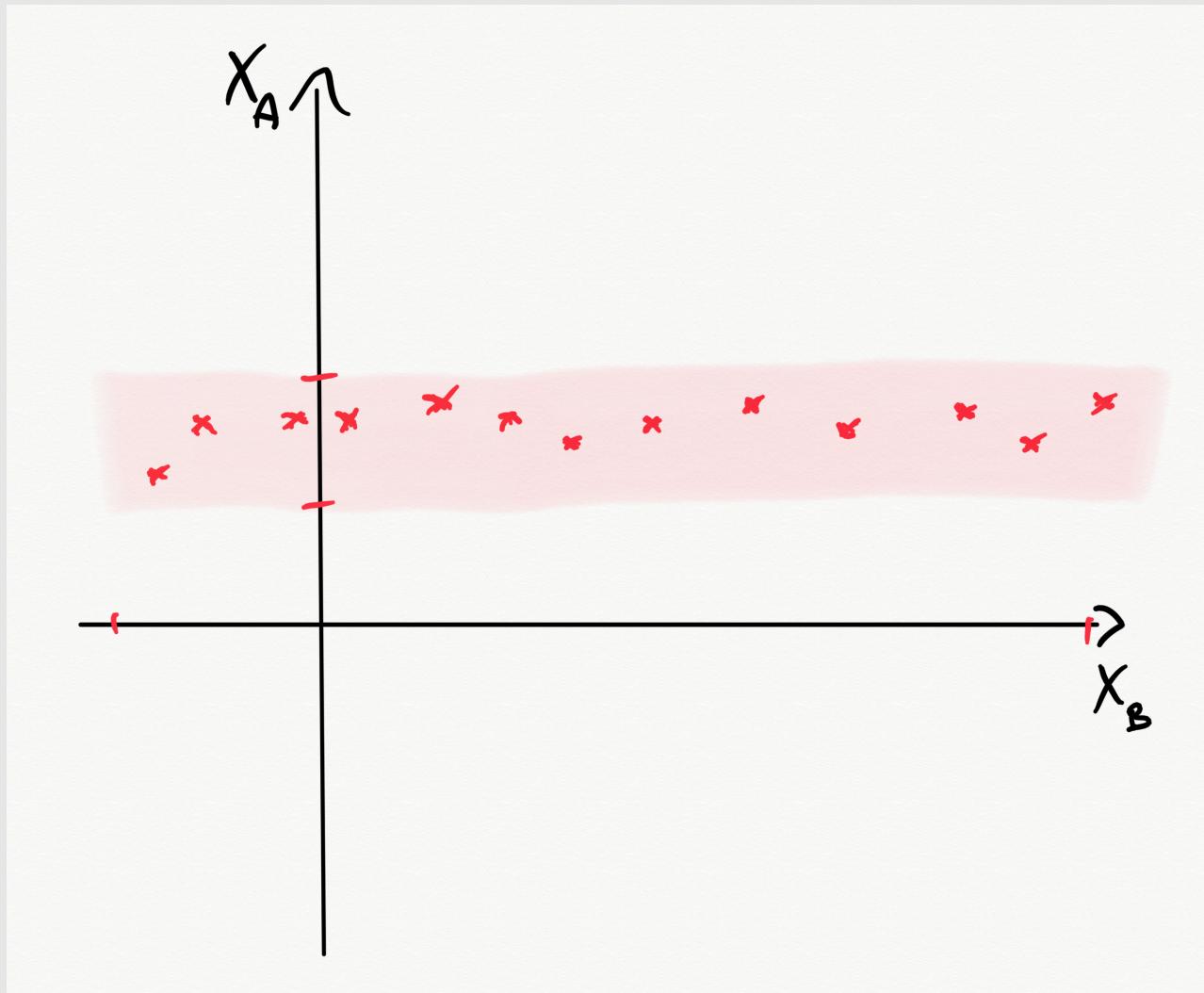
Component Analysis: feature selection, dimensionality reduction, encoding...



Variable selection



Variable selection



Principle Component Analysis

[559]

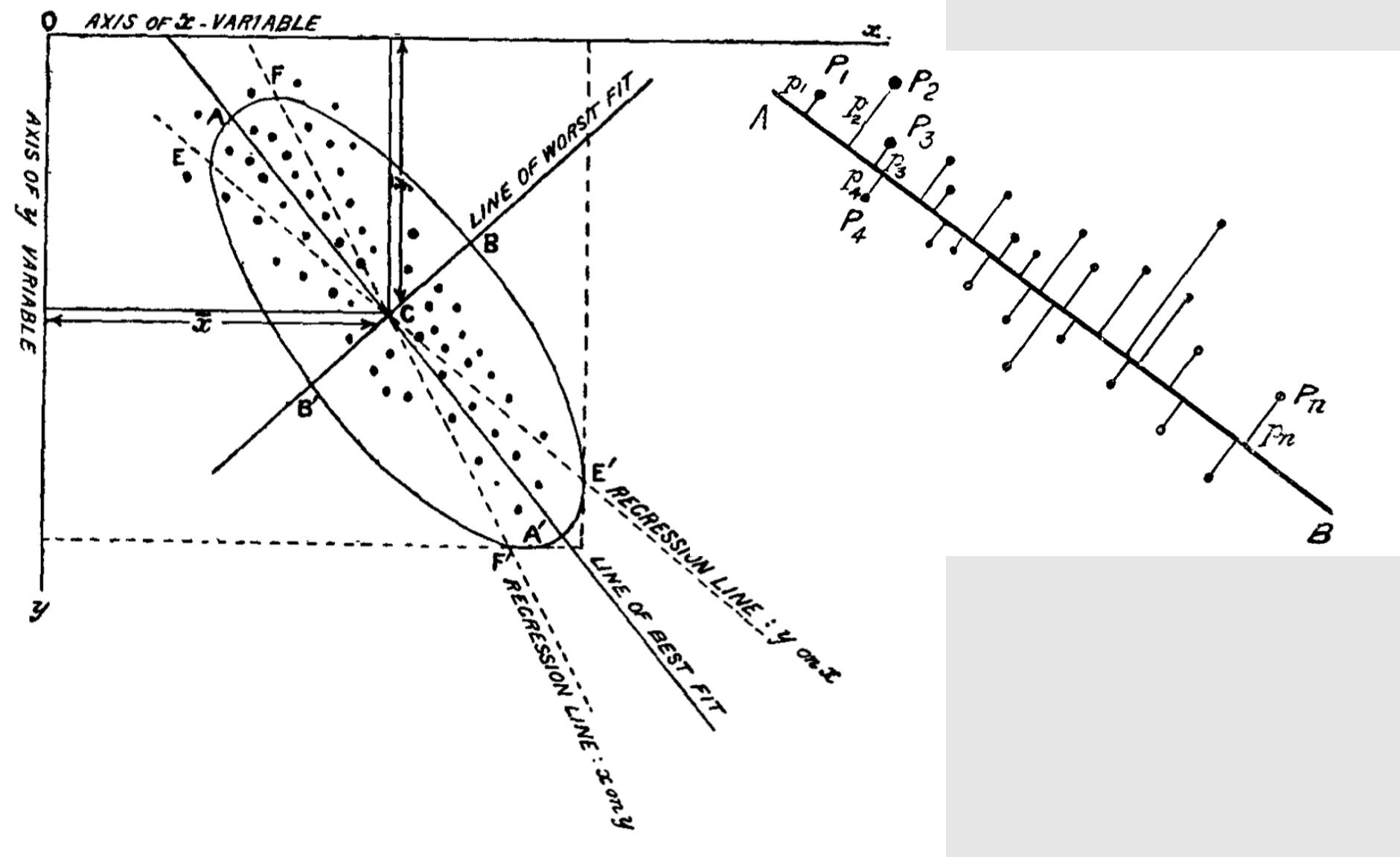
LIII. *On Lines and Planes of Closest Fit to Systems of Points in Space.* By KARL PEARSON, F.R.S., University College, London*.

(1) In many physical, statistical, and biological investigations it is desirable to represent a system of points in plane, three, or higher dimensioned space by the "best-fitting" straight line or plane. Analytically this consists in taking

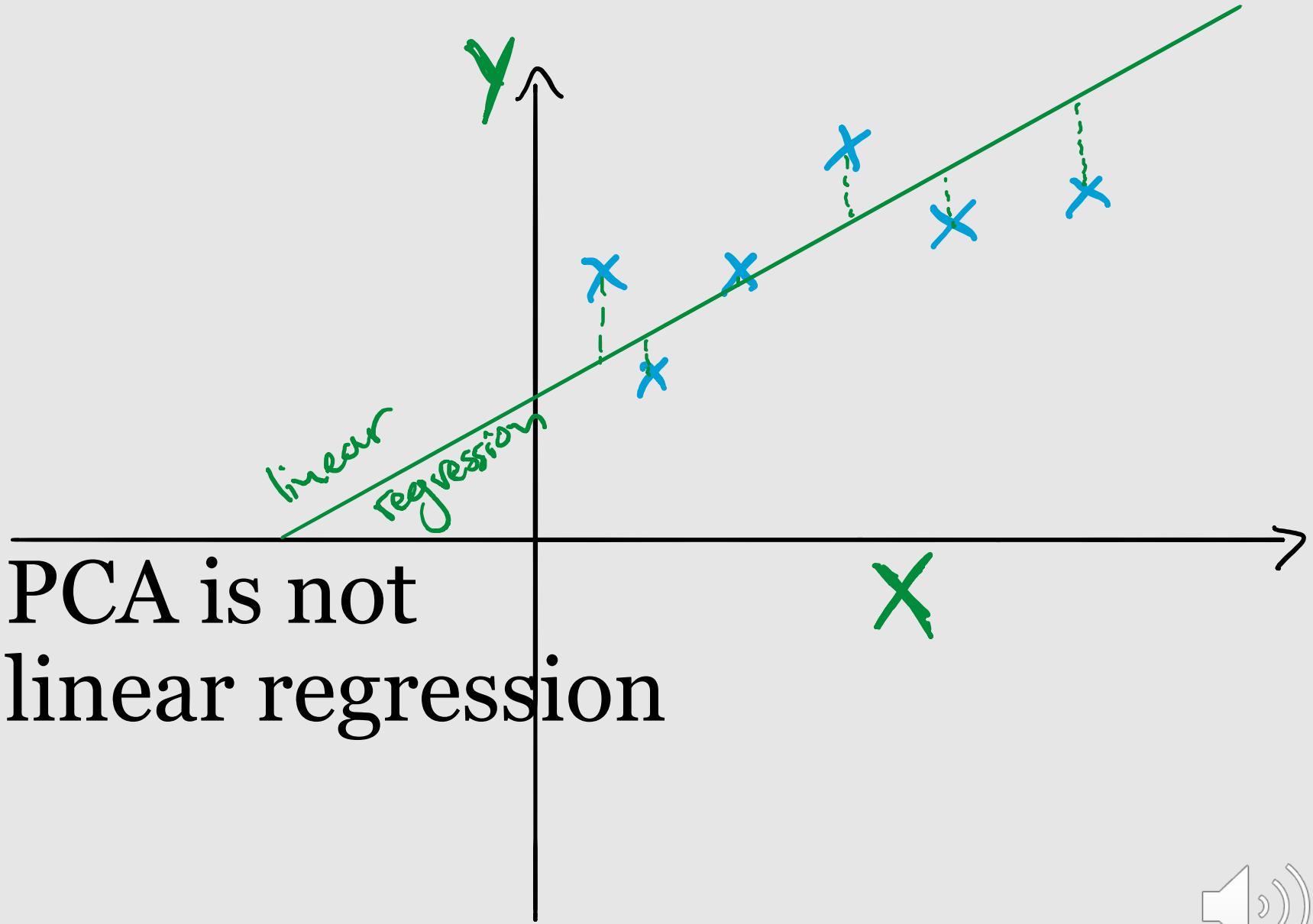
$$y = a_0 + a_1 x, \quad \text{or} \quad z = a_0 + a_1 x + b_1 y,$$
$$\text{or} \quad z = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 + \dots + a_n x_n,$$

where y , x , z , x_1 , x_2 , \dots , x_n are variables, and determining the "best" values for the constants a_0 , a_1 , b_1 , a_0 , a_1 , a_2 , a_3 , \dots , a_n

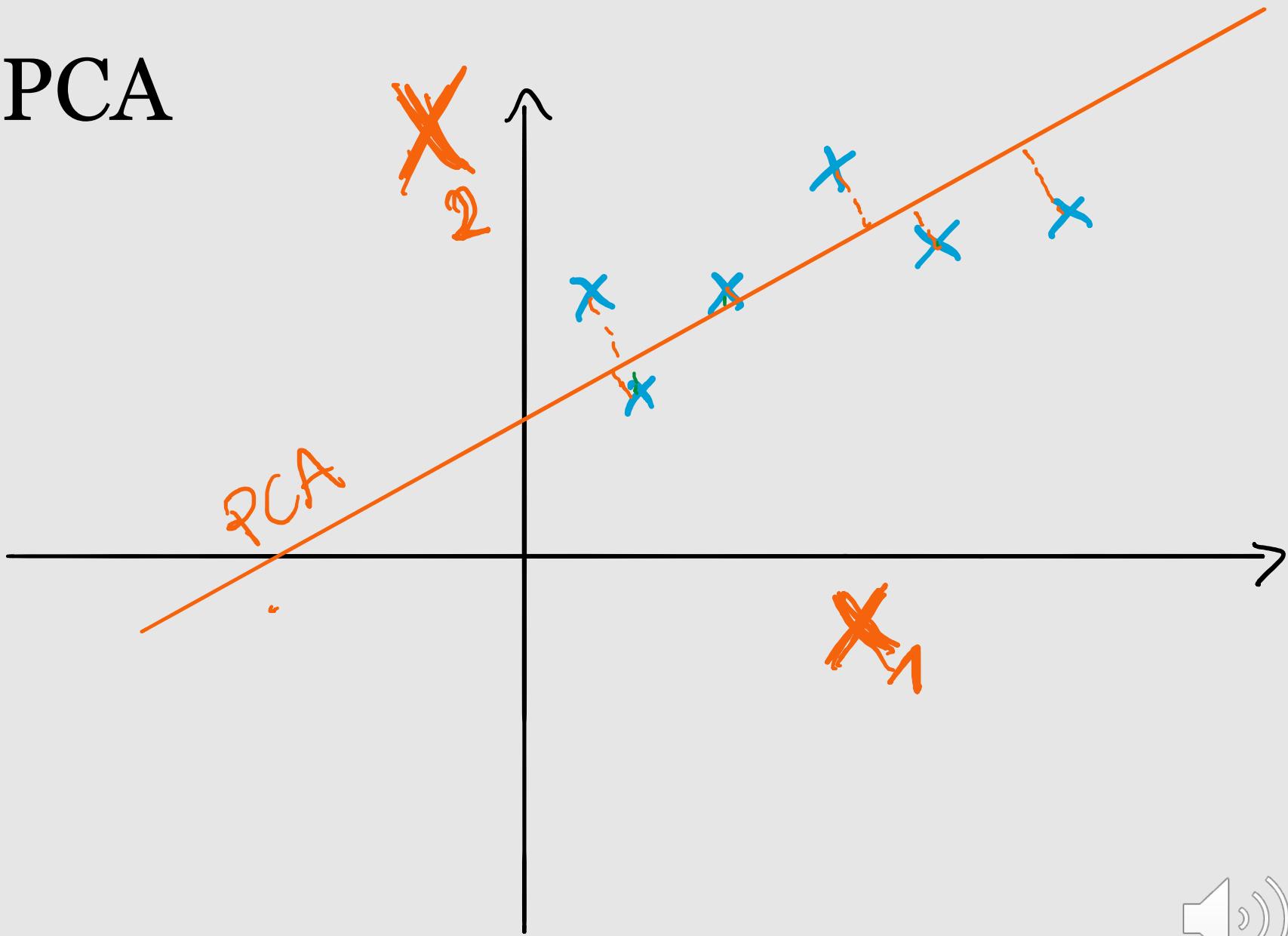




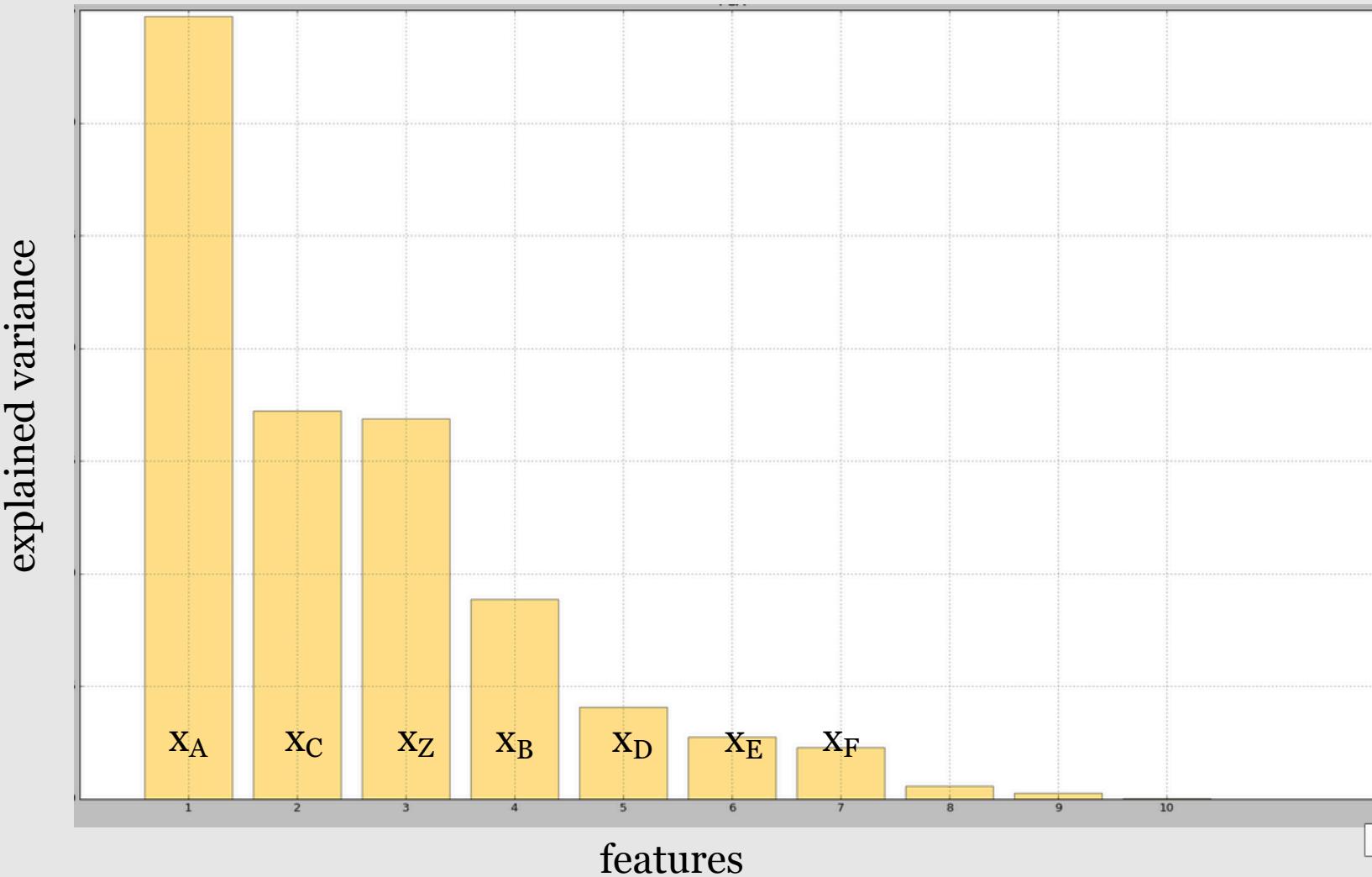
PCA is not
linear regression



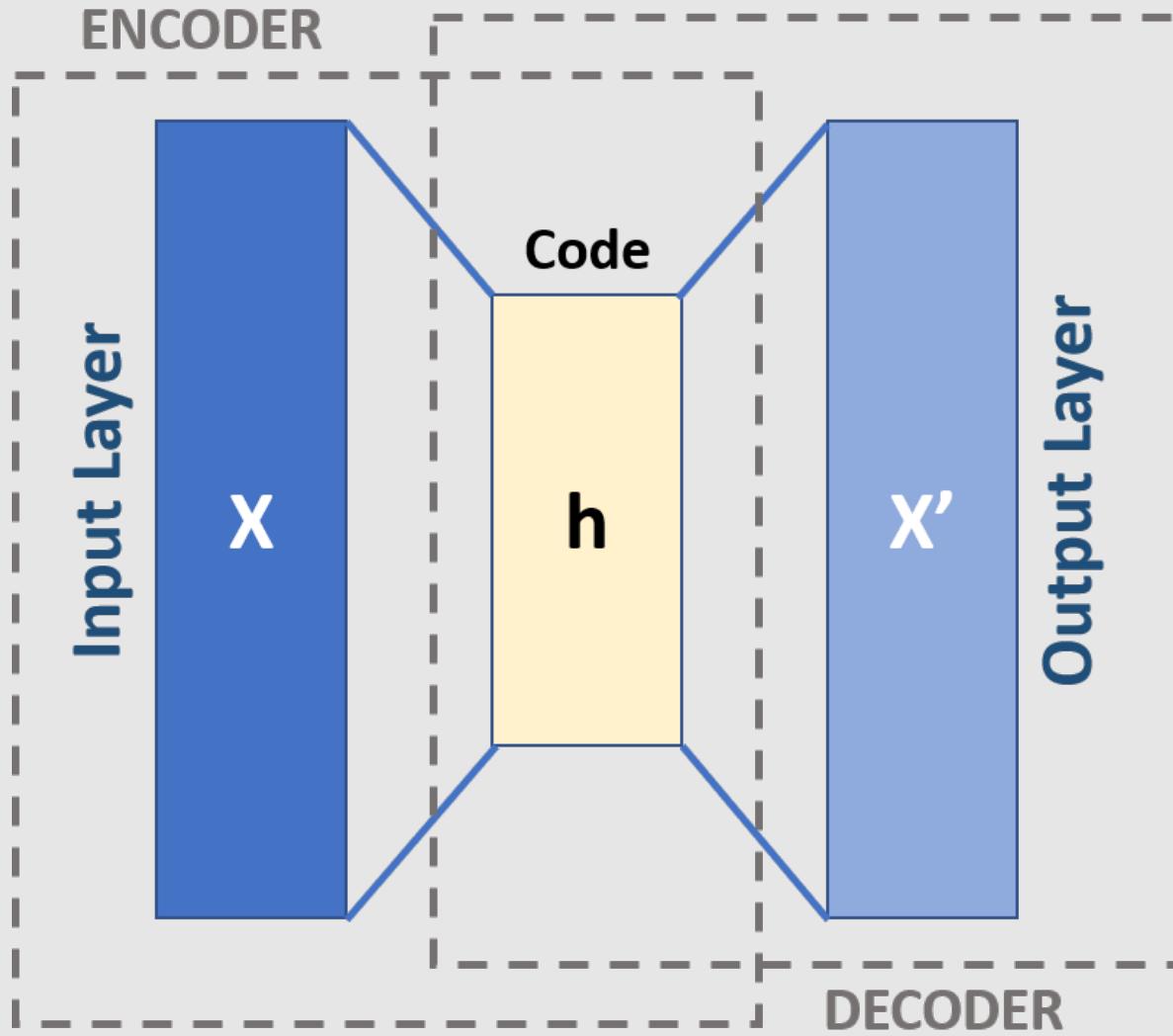
PCA



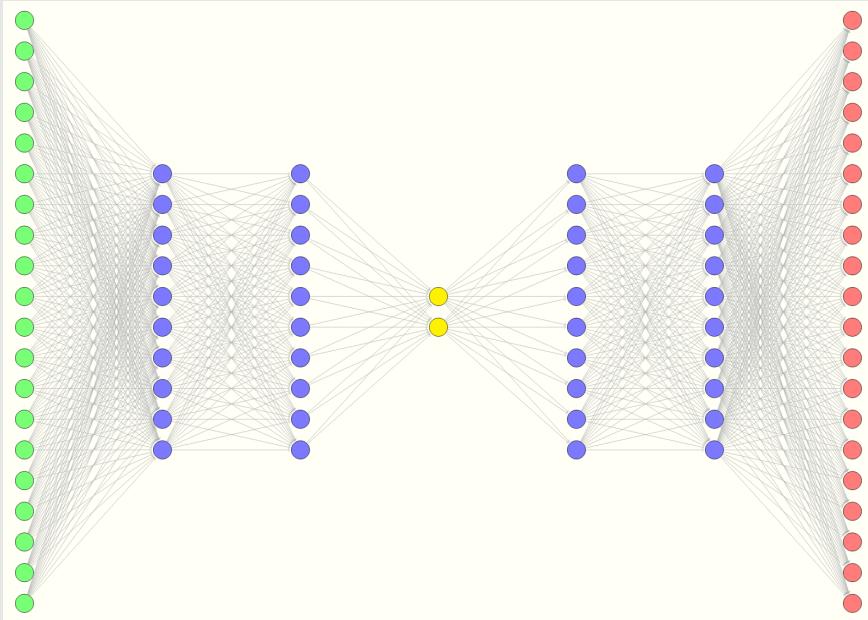
PCA – feature selection



Autoencoder



Autoencoder



source: <https://gertjanvandenburg.com/blog/autoencoder/>

An overfitting
algorithm

Finding the simplest
function allowing
reconstruction of the
data within some
margin of error



Visualizing Data using t-SNE

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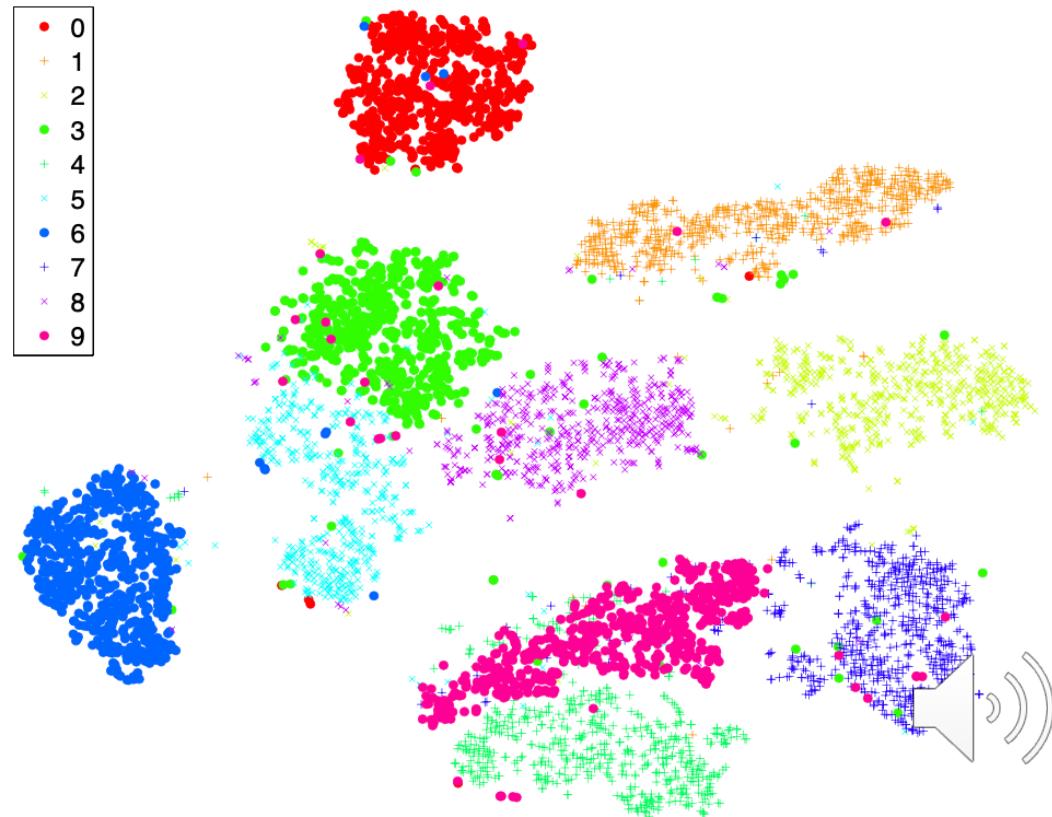
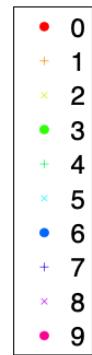
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Example

Phenotypic Profiling of High Throughput Imaging Screens with Generic Deep Convolutional Features

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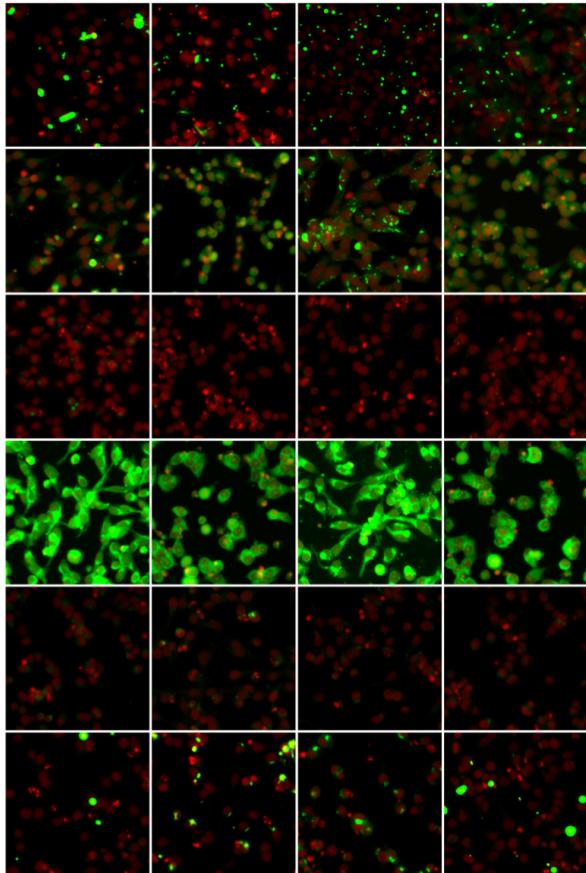


Figure 4. Samples from six of the 70 phenotypic clusters detected by k-means. Each row shows four example images from a single cluster. Rows 2 and 4 show genuine GFP expression.

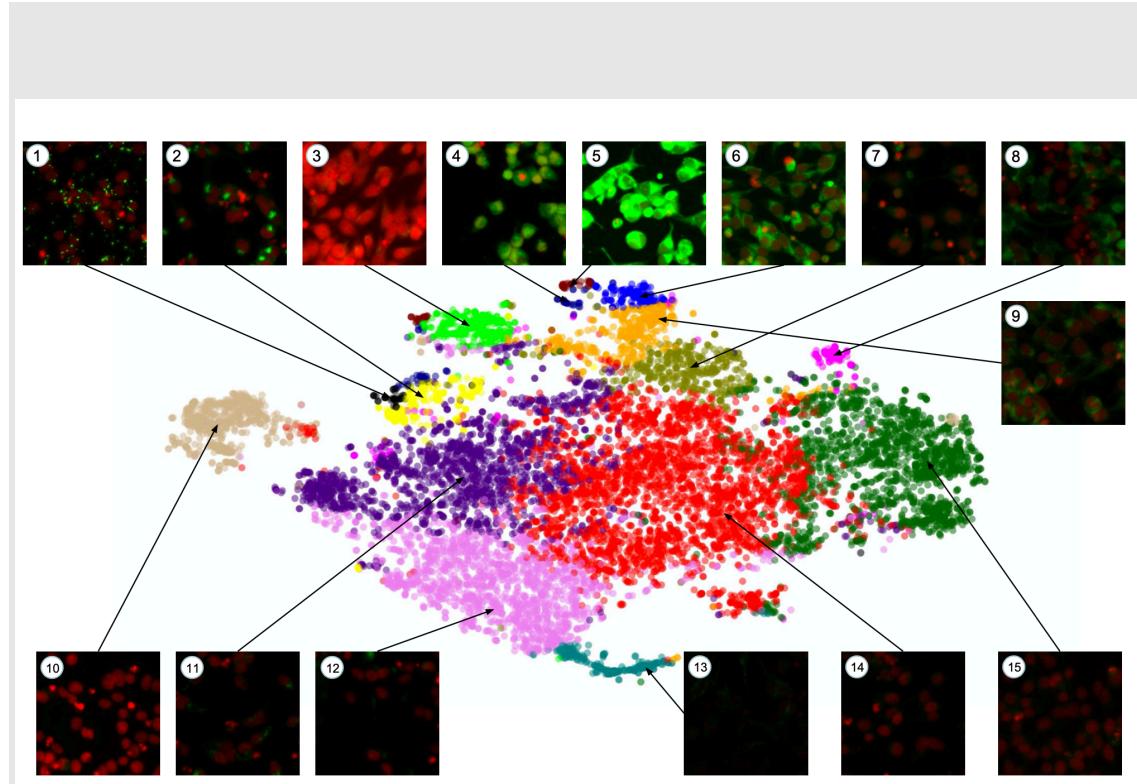


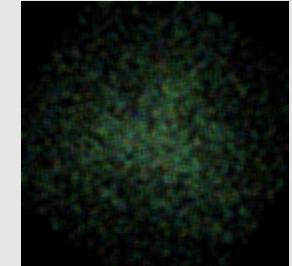
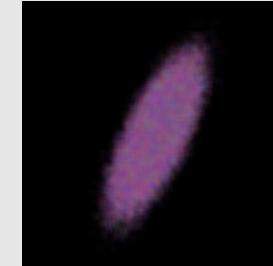
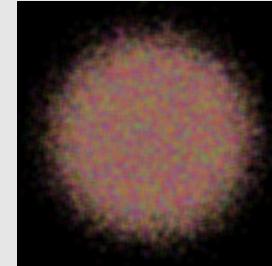
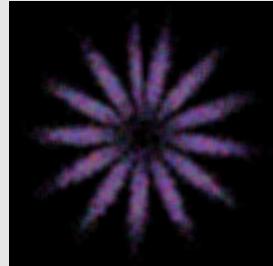
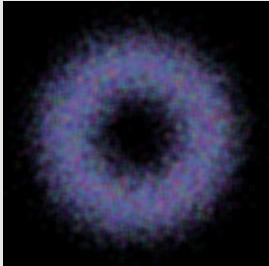
Figure 5. A t-SNE embedding of our dataset, with colours showing phenotypic clusters discovered by k-means. For visualization purposes, we set $k = 15$ here.



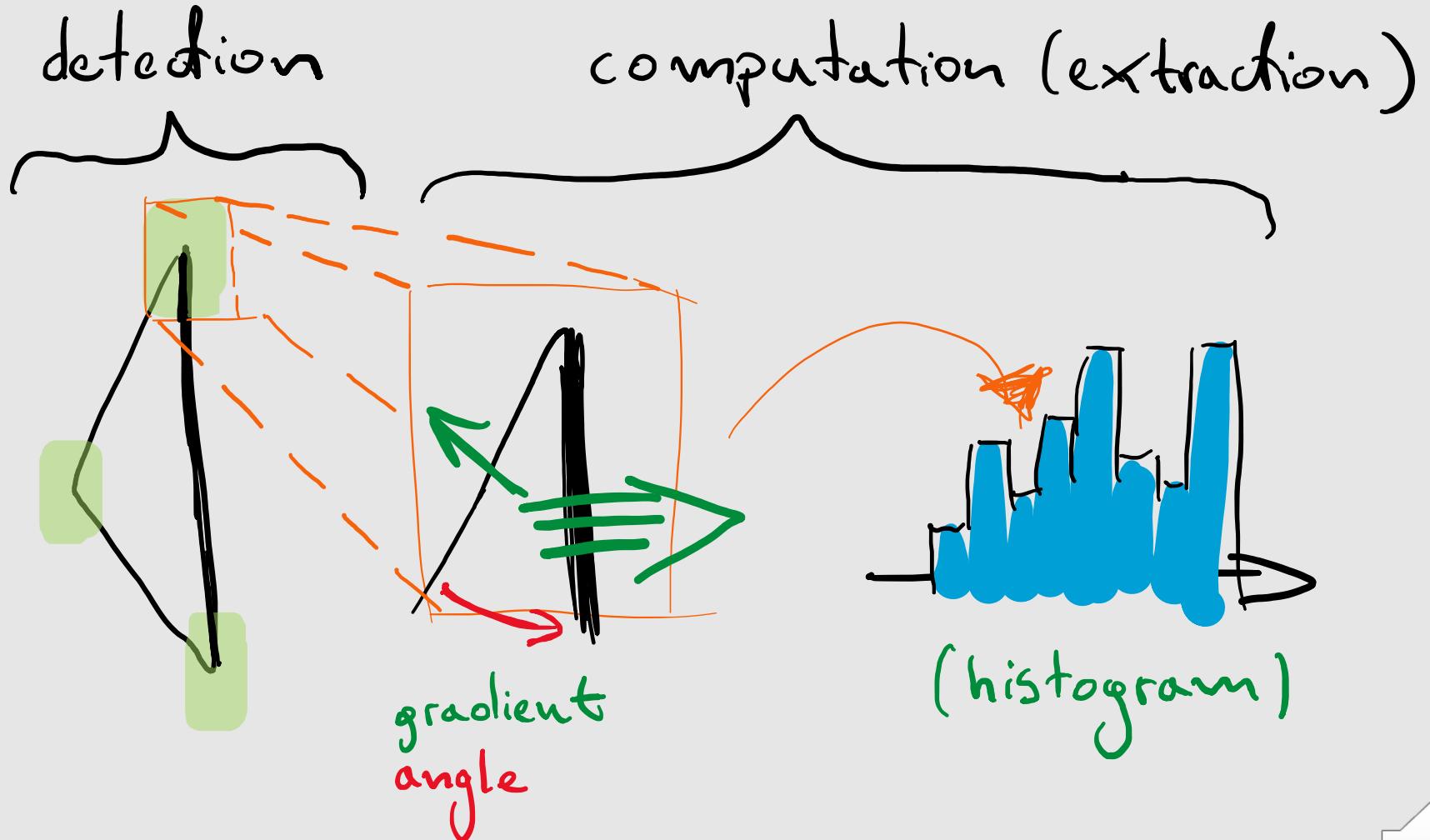
Problem representation

Basic features

- colour statistics (over whole or part of the image)
- edges and gradients
- corners
- shapes (convolution/autocorrelation)



Sparse Features

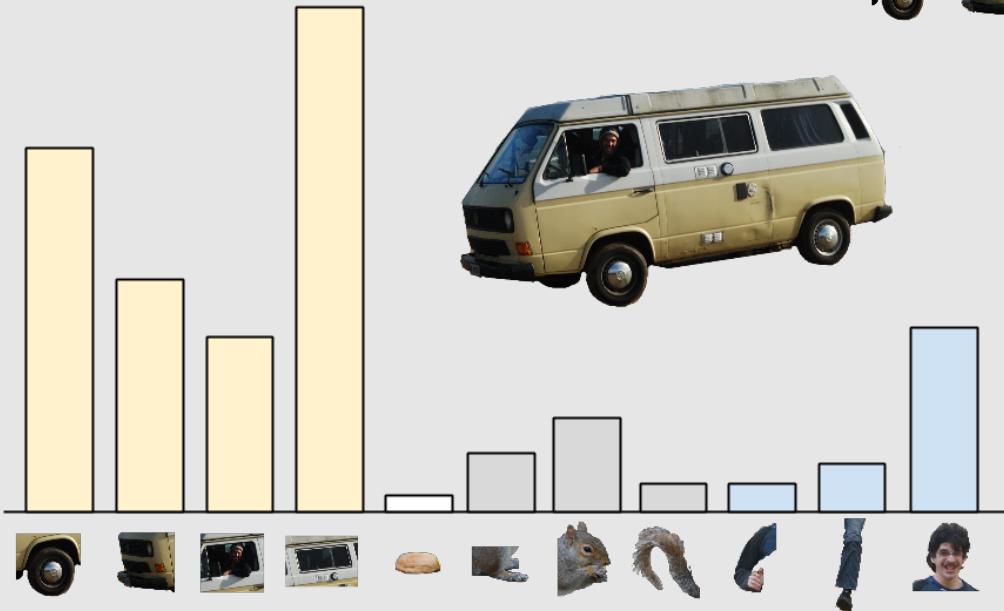
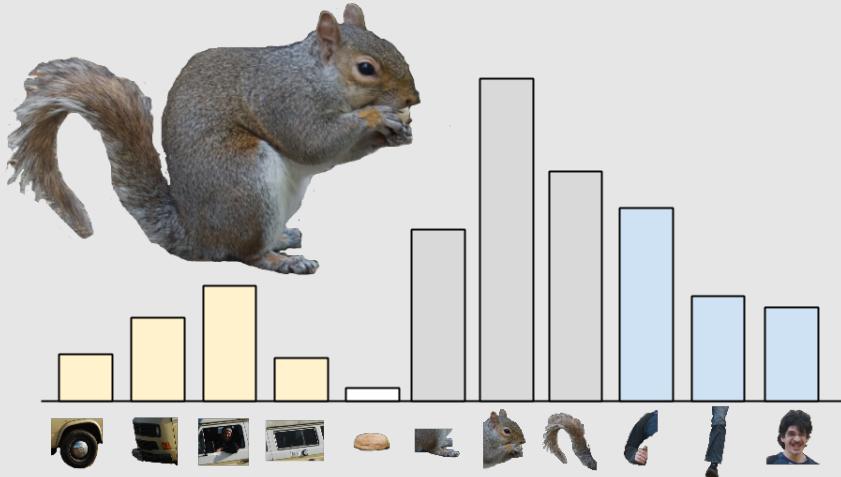


Bag of Visual Words

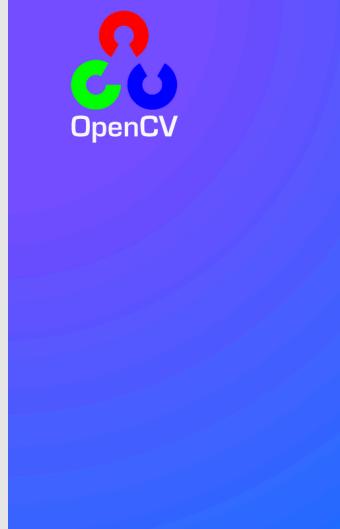


codebook (vocabulary)





OpenCV C++ library



OpenCV 4.1.2

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computer vision
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Python bindings



OpenCV vs Scikit Learn

	OpenCV	Scikit Learn
Use	Industry and academia: from robotics to business analytics	Science and statistics
Language	C++/Java/Python	Python
Current version:	4.1.2	0.17
	Industry proven but at times poorly documented and inconsistent. Many well tested famous algorithms.	Excellent tutorials and examples, much easier to use and pythonesque.

