

EMBEDDED VISION DESIGN 3

# UNSUPERVISED ML

JEROEN VEEN



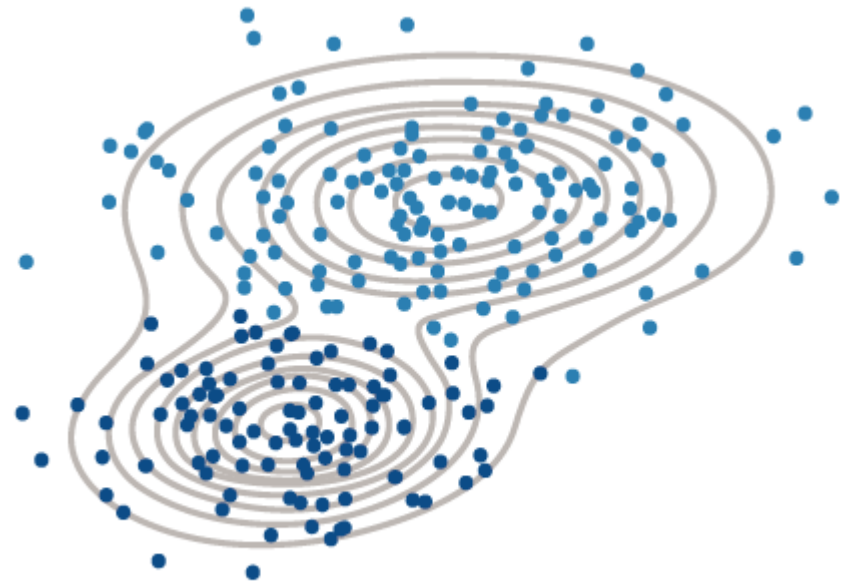
**HAN\_**UNIVERSITY  
OF APPLIED SCIENCES

# CONTENTS

- Clustering
  - K-means
  - Expectation maximization
- Dimensionality reduction
  - Principal component analysis

# CLUSTER ANALYSIS

- Data is partitioned into groups based on some measure of similarity
- The notion of a "cluster" cannot be precisely defined, which is one of the reasons why there are so many clustering algorithms.

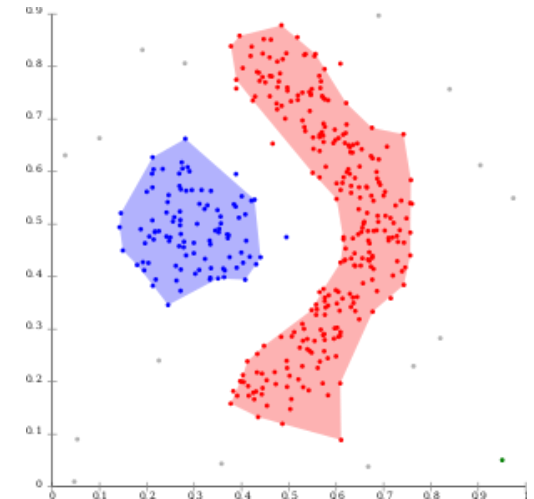
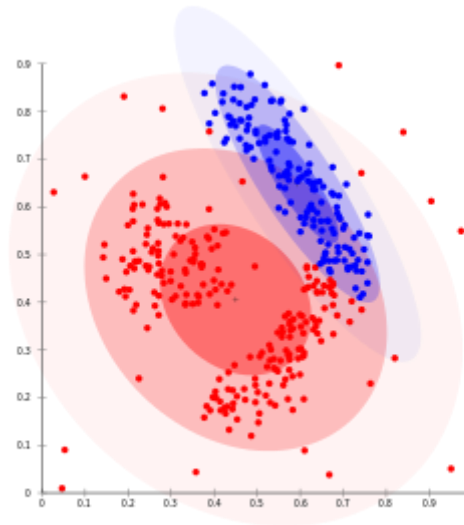
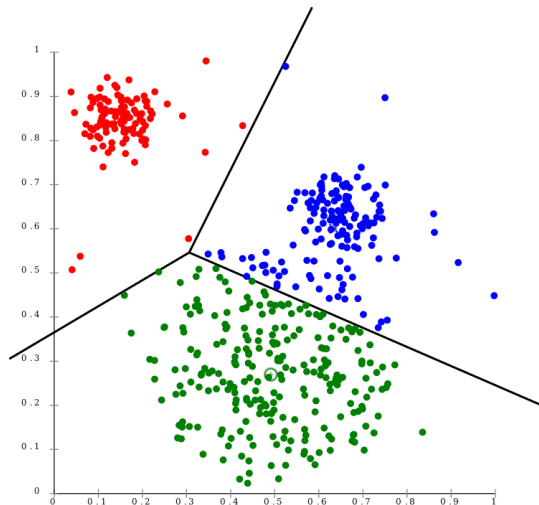


*Gaussian mixture model used to separate data into two clusters.*

Source: Mathworks, Applying Unsupervised Learning

# CLUSTERING ALGORITHMS

- Connectivity
- Centroids
- Distribution
- Density
- ...



# HARD VS SOFT CLUSTERING

- Hard clustering, where each data point belongs to only one cluster
- Soft clustering, where each data point can belong to more than one cluster

If you don't yet know how the data might be grouped:

- Use self-organizing feature maps or hierarchical clustering to look for possible structures in the data.
- Use cluster evaluation to look for the "best" number of groups for a given clustering algorithm.

# K-MEANS

- Partitions data into k number of mutually exclusive clusters.
- How well a point fits into a cluster is determined by the distance from that point to the cluster's center (*inertia*)



Source: Mathworks, Applying Unsupervised Learning

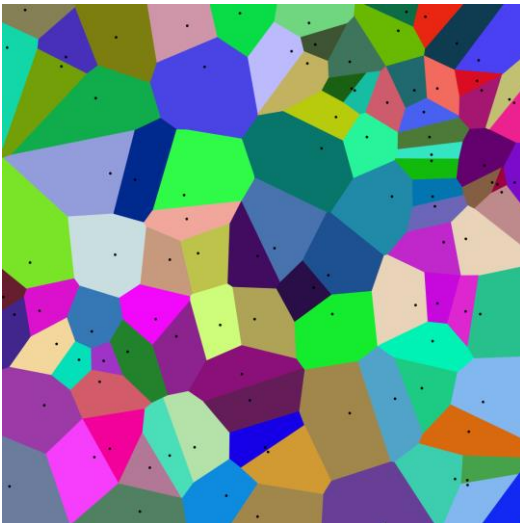
- Best used when the number of clusters is known
- For fast clustering of large data sets

# K-MEANS

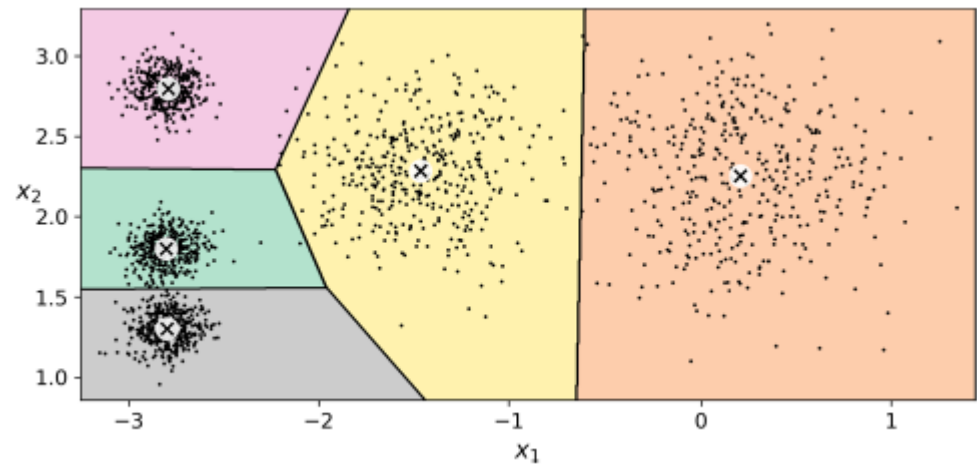
- [https://www.youtube.com/watch?v=\\_aWzGGNrcic](https://www.youtube.com/watch?v=_aWzGGNrcic)
- Do not mistake K-means, which is an unsupervised machine learning, with K-NN which is supervised machine learning.

# VORONOI TESSELLATION

- Decision boundaries for hard clustering



Source: <https://nl.wikipedia.org/wiki/Voronoi-diagram>

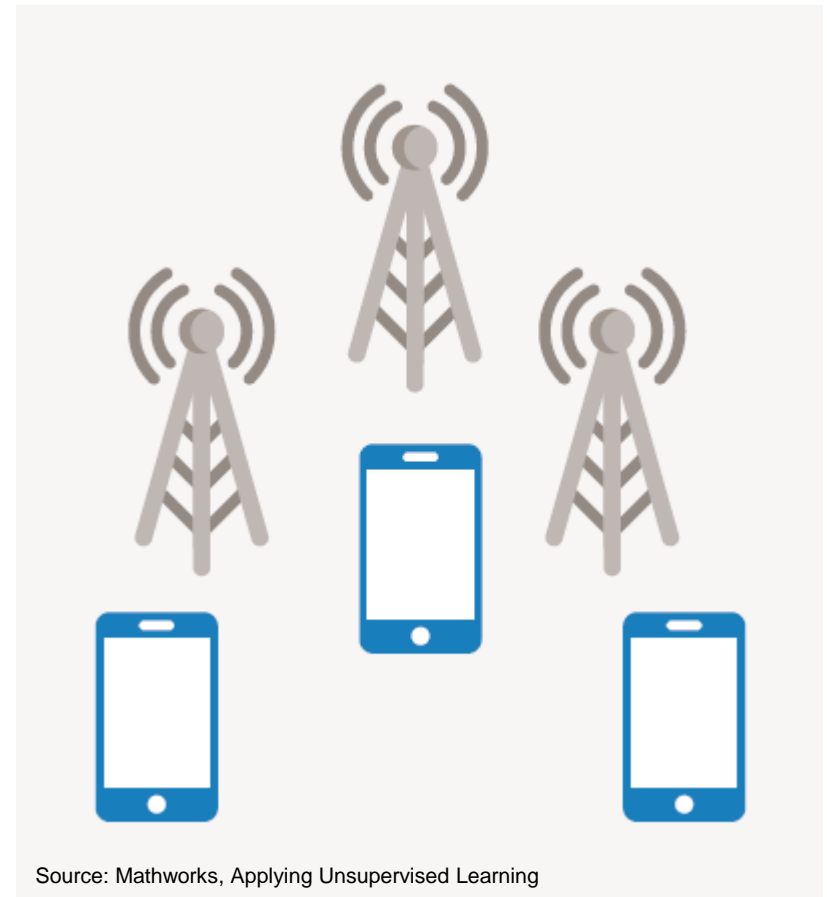


Source: Géron, ISBN: 9781492032632

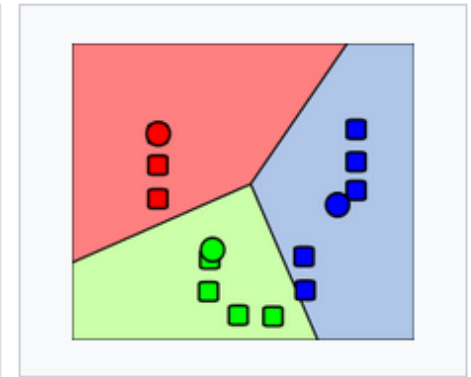
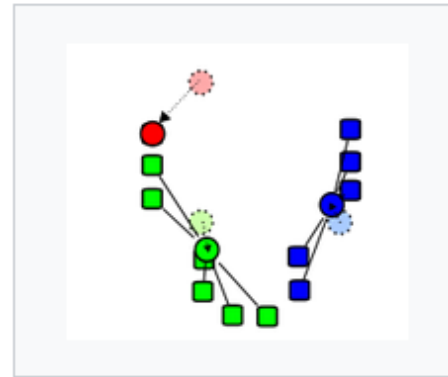
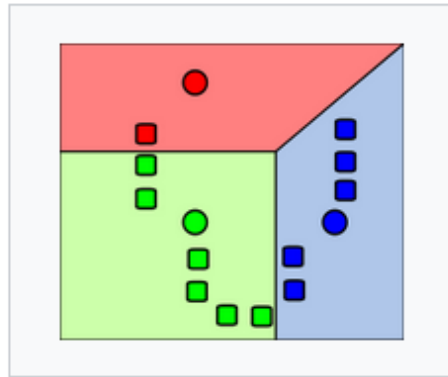
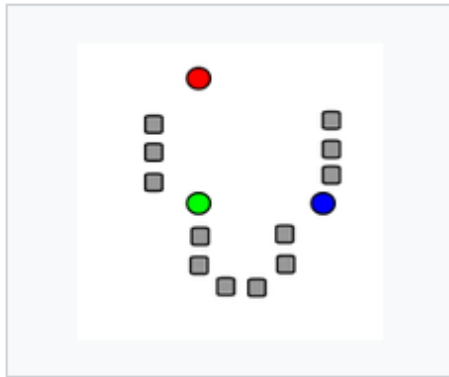


# EXAMPLE: SITE CELL PHONE TOWERS

- Locate cell-phone towers within clusters of people
- Hard clustering: a phone can only talk to one tower at a time



# K-MEANS ALGORITHM



1.  $k$  initial "means" (in this case  $k=3$ ) are randomly generated within the data domain (shown in color).

2.  $k$  clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3. The centroid of each of the  $k$  clusters becomes the new mean.

4. Steps 2 and 3 are repeated until convergence has been reached.

Source: [https://en.wikipedia.org/wiki/K-means\\_clustering](https://en.wikipedia.org/wiki/K-means_clustering)

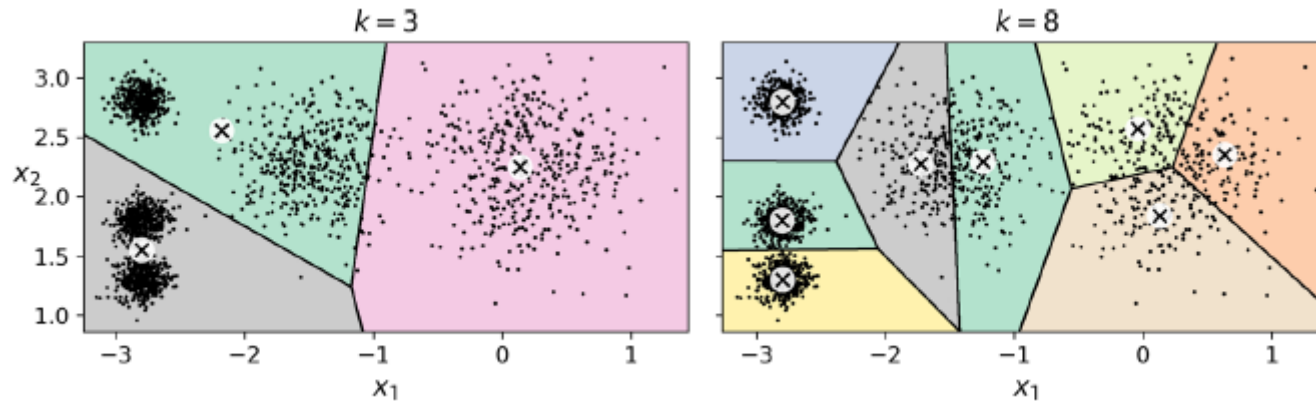
# IMPROVING THE CENTROID INITIALIZATION

- Problem: Convergence to a local optimum (suboptimal solution)
- Possible solutions:
  1. Supply approximate centroids (initial guesses)
  2. Run the algorithm multiple times with different random initialization and keep the 'best' solution
  3. Select centroids within the dataset that are distant from one another (*K-Means++*)

# FURTHER IMPROVEMENTS

- Accelerated K-Means
  - avoiding many unnecessary distance calculations by exploiting the triangle inequality
- Mini-batch K-Means
  - Keeping smaller data sets in memory

# OPTIMAL NUMBER OF CLUSTERS

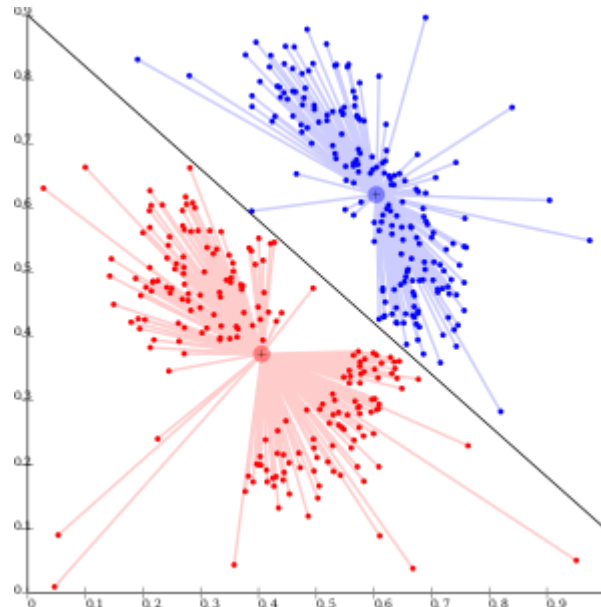


Source: Géron, ISBN: 9781492032632

- Inertia is not a proper metric
- Silhouette: measure how similar an object is to its own cluster (cohesion) compared to other clusters (separation)

# LIMITATIONS OF K-MEANS

- does not behave very well when the clusters have varying sizes.
- cannot represent density-based clusters



Source: [https://en.wikipedia.org/wiki/Cluster\\_analysis#/media/File:KMeans-density-data.svg](https://en.wikipedia.org/wiki/Cluster_analysis#/media/File:KMeans-density-data.svg)

# CLUSTERING APPLICATIONS

- Image segmentation
- Preprocessing
  - Dimensionality reduction
  - Semi-supervised learning

# APPLICATION: COLOR SEGMENTATION

Original image



10 colors



8 colors



6 colors



4 colors



2 colors



Source: Geron, ISBN: 9781492032632



# APPLICATION: SEMI-SUPERVISED LEARNING

- Dimensionality reduction
- Label propagation
- Active learning, e.g. uncertainty sampling

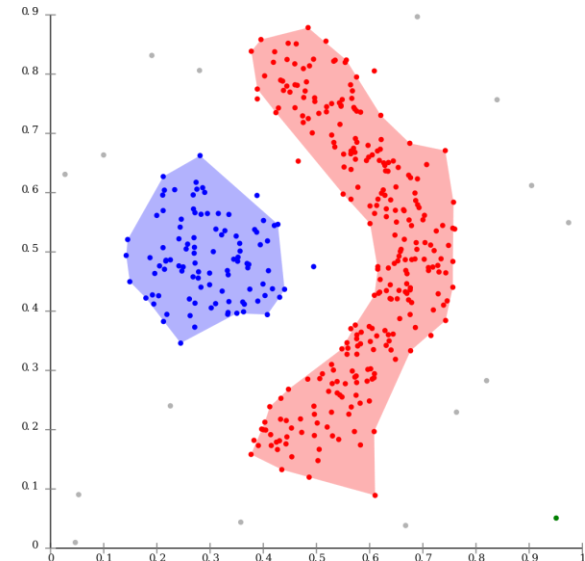


Clustered MNIST representatives

# DENSITY-BASED SPATIAL CLUSTERING OF APPLICATIONS WITH NOISE

- Aka DBSCAN
- $\epsilon$ -neighborhood
- core instance
- if all the clusters are dense enough and if well separated
- Finds non-linearly separable clusters on which k-means or Gaussian Mixture EM clustering fails

Special (efficient) variant of spectral clustering: Connected components



Source:  
<https://en.wikipedia.org/wiki/DBSCAN#/media/File:DBSCAN-density-data.svg>

# POPULAR CLUSTERING ALGORITHMS

- Agglomerative clustering
- Mean-Shift
- Affinity propagation
- OPTICS
- Etc.

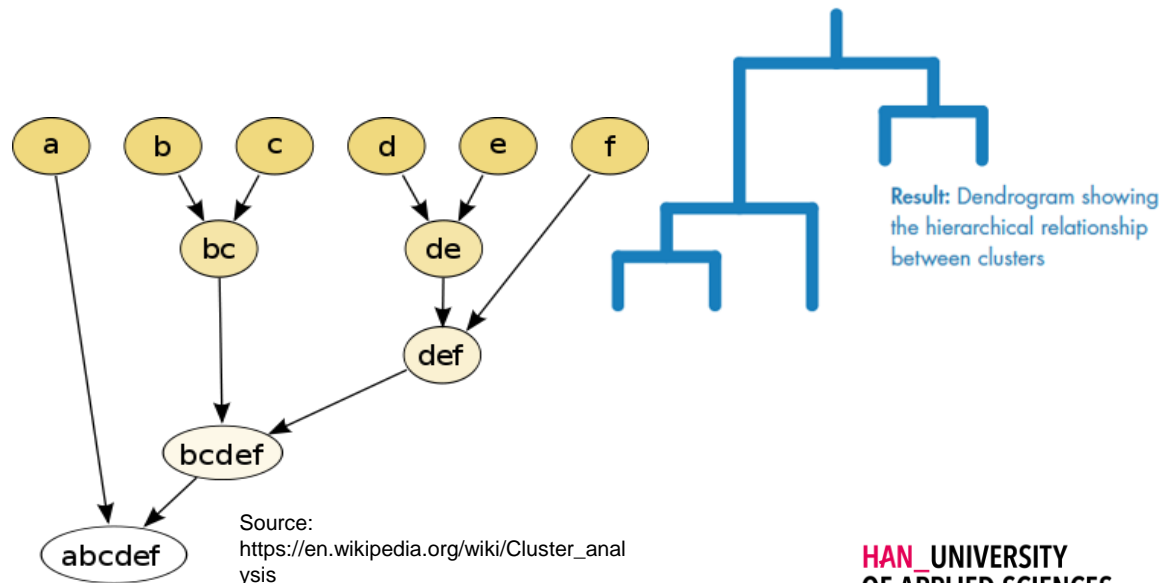
## Hierarchical Clustering

### How it Works

Produces nested sets of clusters by analyzing similarities between pairs of points and grouping objects into a binary, hierarchical tree.

### Best Used...

- When you don't know in advance how many clusters are in your data
- You want visualization to guide your selection



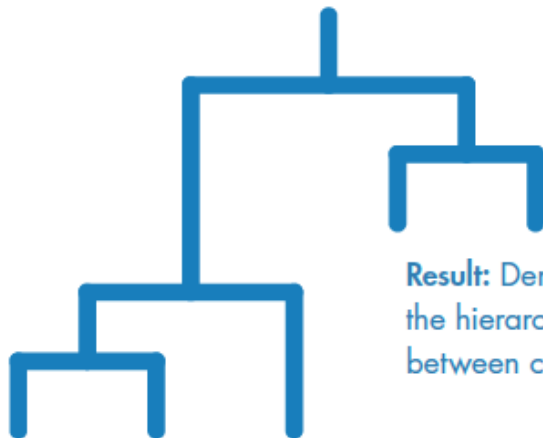
## Hierarchical Clustering

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Result: Dendrogram showing the hierarchical relationship between clusters

## Self-Organizing Map

### How It Works

Neural-network based clustering that transforms a dataset into a topology-preserving 2D map.

### Best Used...

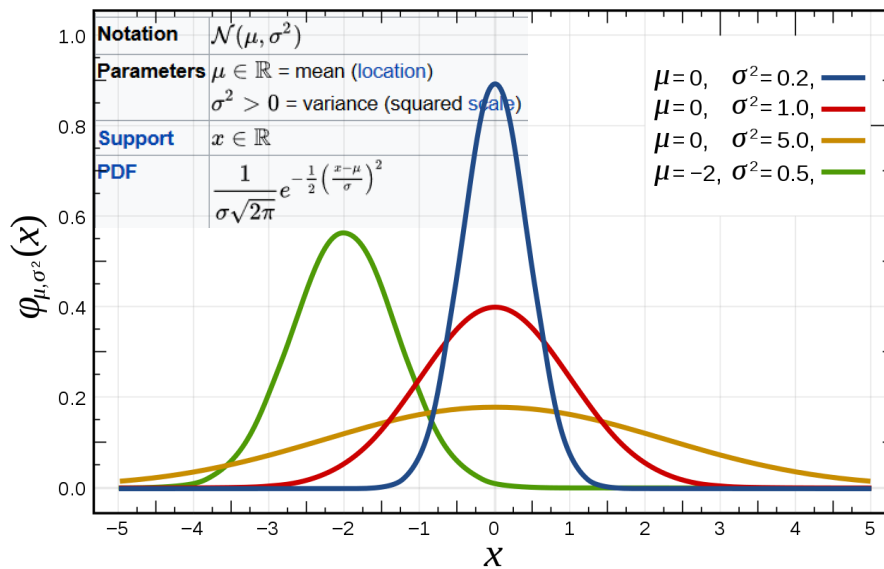
- To visualize high-dimensional data in 2D or 3D
- To deduce the dimensionality of data by preserving topology (shape)



Result:  
Lower-dimension  
(typically 2D)  
representation

# GAUSSIAN MIXTURE MODELS (GMM)

- Probabilistic model, assuming normally distributed subpopulations



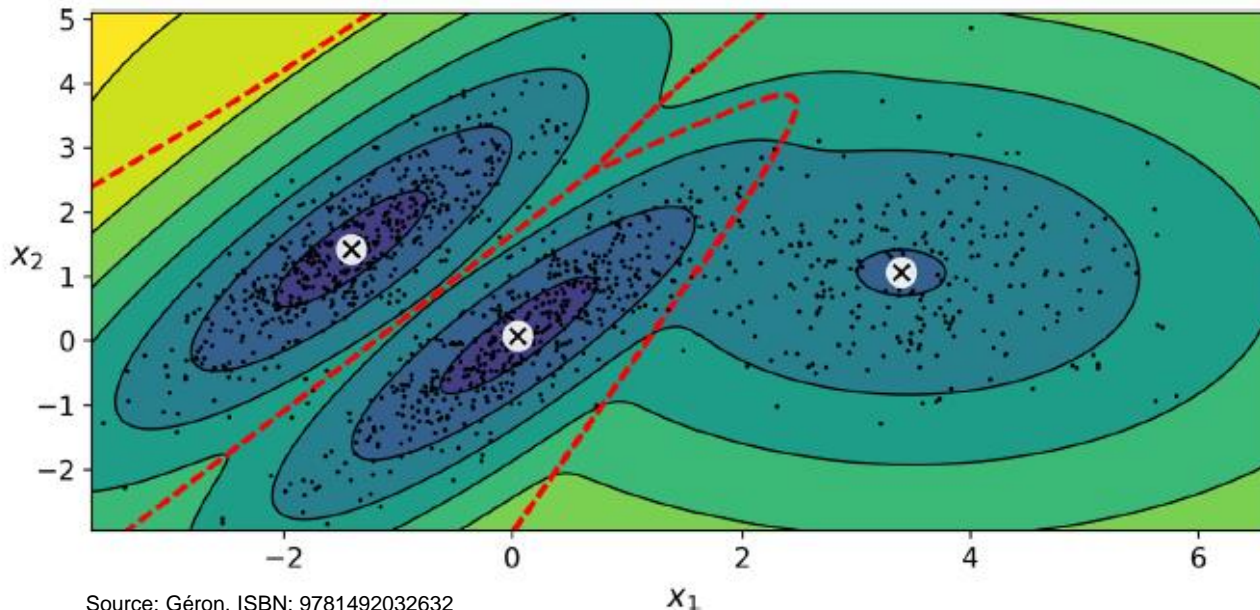
Source: [https://en.wikipedia.org/wiki/Normal\\_distribution](https://en.wikipedia.org/wiki/Normal_distribution)



Source: Mathworks, Applying Unsupervised Learning

# EXPECTATION MAXIMIZATION (EM)

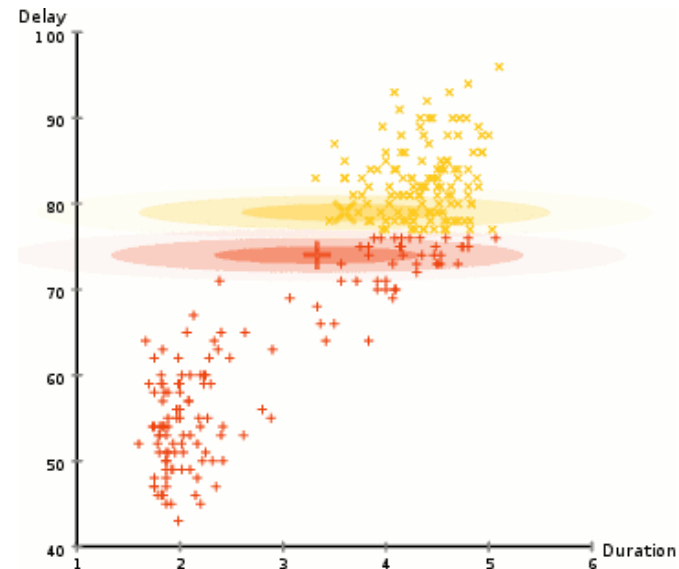
- *a priori* given number of components
- Generalization of K-Means
- Soft cluster assignments



Source: Géron, ISBN: 9781492032632

# EXAMPLE: EM CLUSTERING OF GEYSER ERUPTION DATA

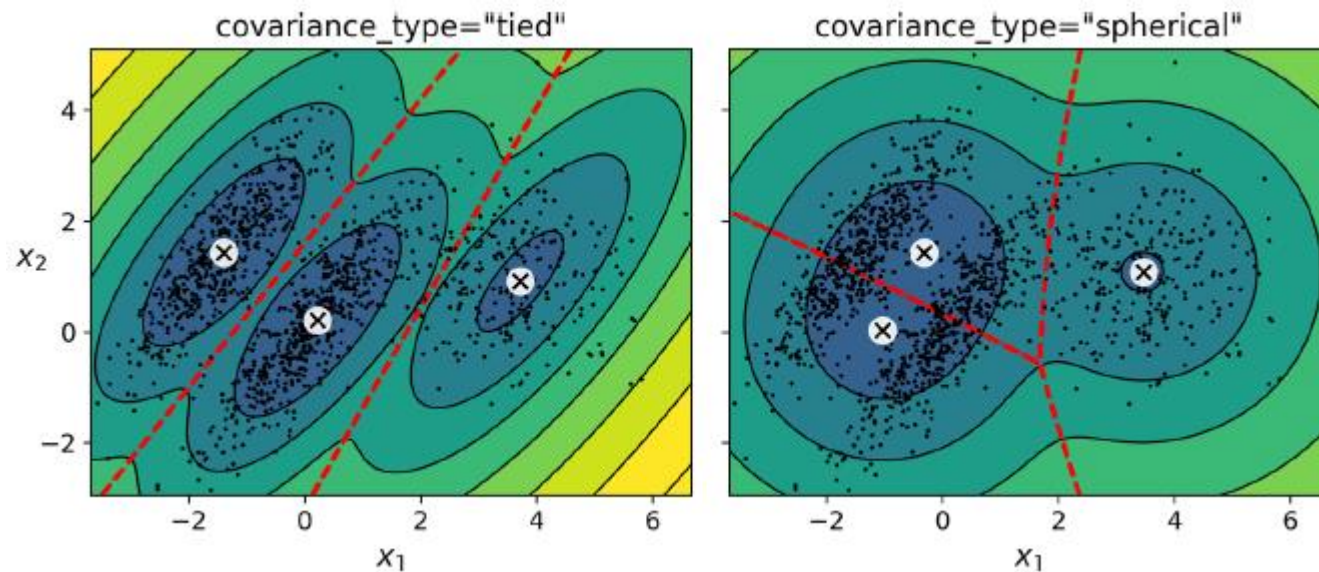
- Highly predictable geothermal feature
- Erupted every 44 minutes to two hours since 2000



Source: [https://en.wikipedia.org/wiki/Expectation%E2%80%93maximization\\_algorithm](https://en.wikipedia.org/wiki/Expectation%E2%80%93maximization_algorithm)

# APPLYING CONSTRAINTS

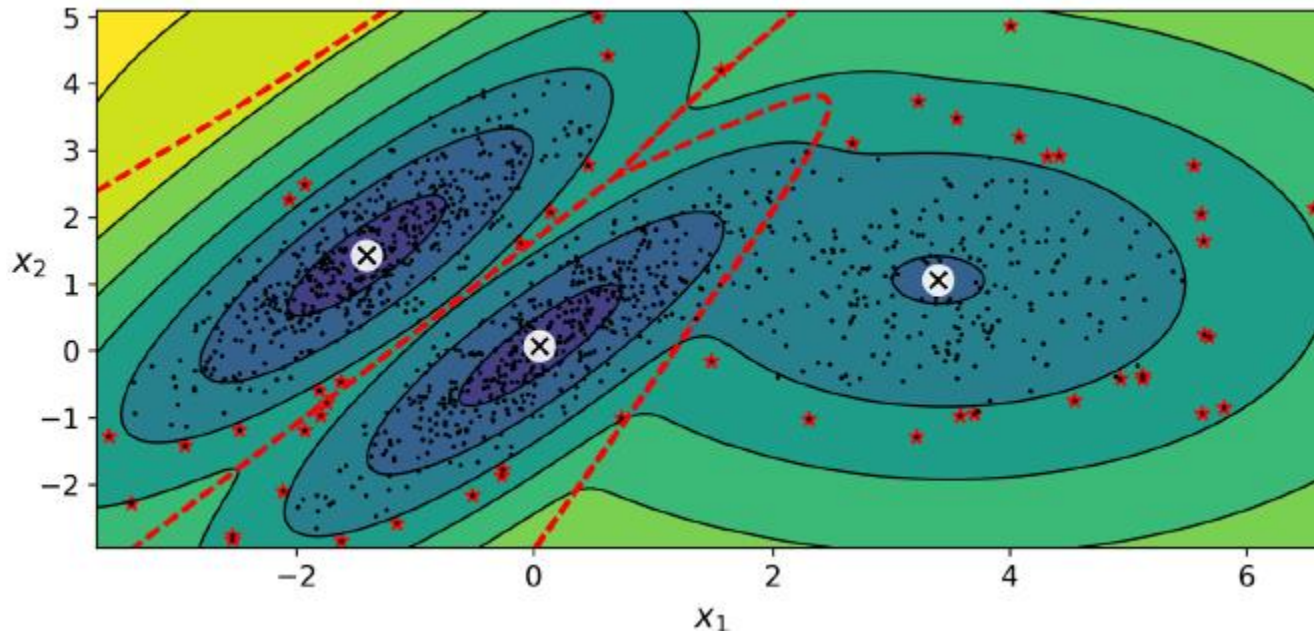
- When there are many dimensions, or many clusters, or few instances, EM can struggle to converge to the optimal solution.
- You might need to reduce the difficulty of the task by limiting the number of parameters that the algorithm has to learn.





# APPLICATION: ANOMALY DETECTION

- Aka outlier detection



- -> Dbscan (Density Based Spatial Clustering of Applications with Noise)

# SELECTING THE NUMBER OF CLUSTERS

- Inertia and silhouette are not proper metrics
- Model selection criteria from statistics, e.g.
  - Bayesian information criterion (BIC)
  - Akaike information criterion (AIC)

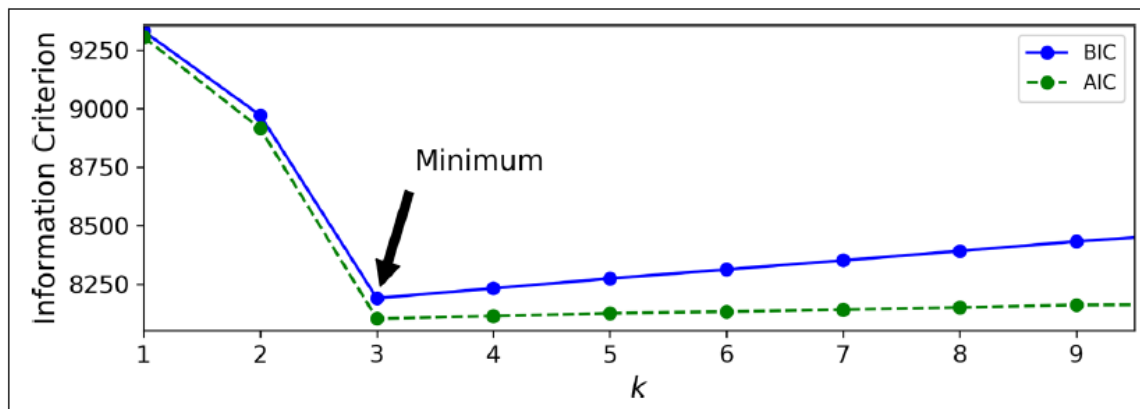
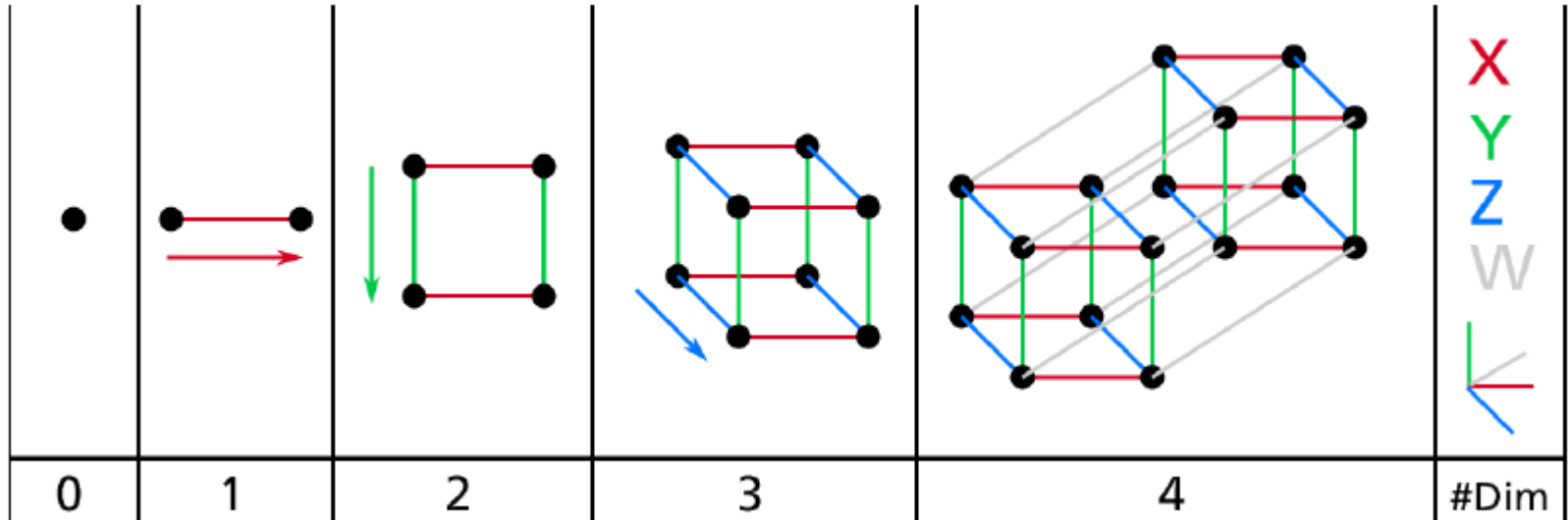


Figure 9-21. AIC and BIC for different numbers of clusters  $k$

# DIMENSIONALITY REDUCTION

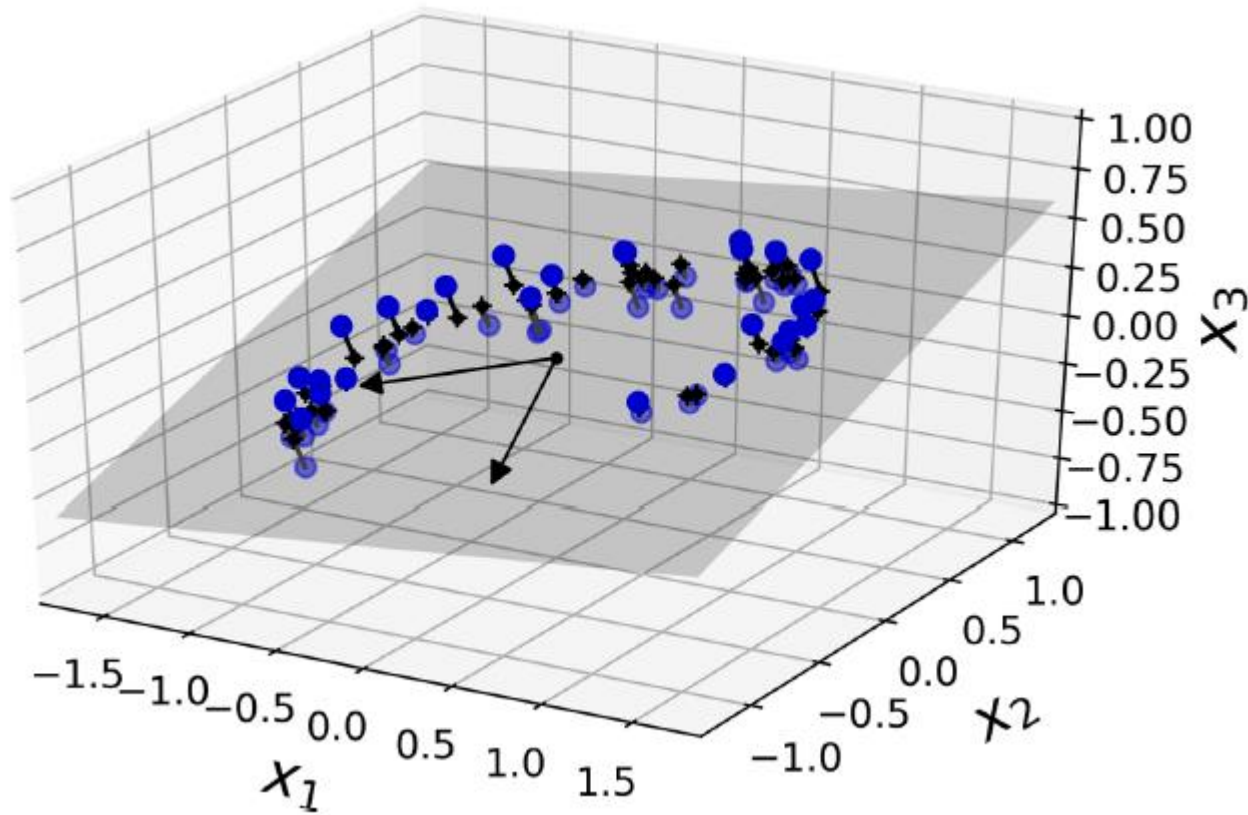
- curse of dimensionality



Source: Géron, ISBN: 9781492032632

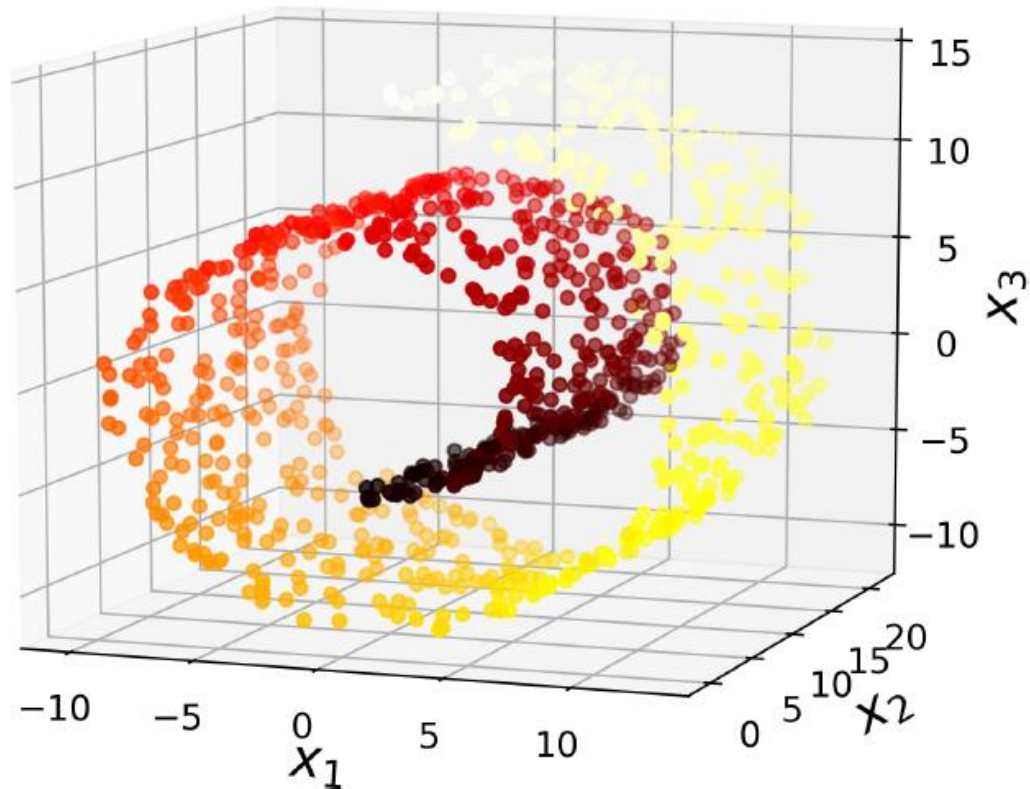
- high-dimensional datasets are at risk of being very sparse

# PROJECTION



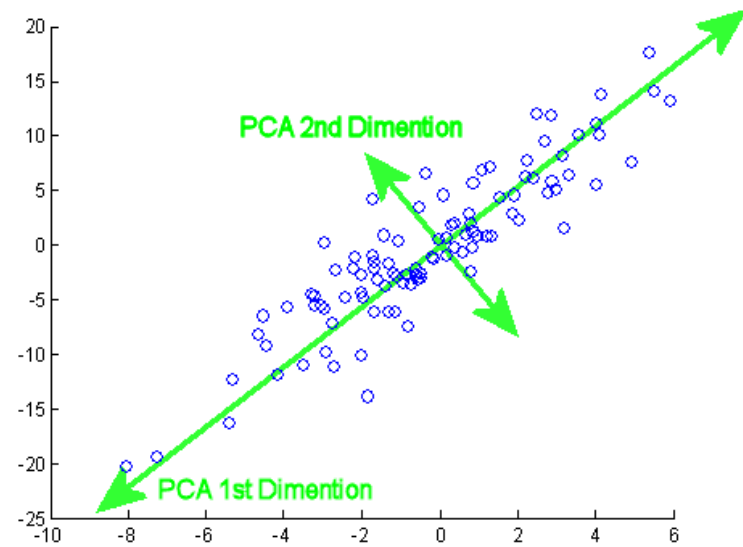
# MANIFOLD LEARNING

- Assumption: most real-world high-dimensional datasets lie close to a much lower-dimensional manifold.



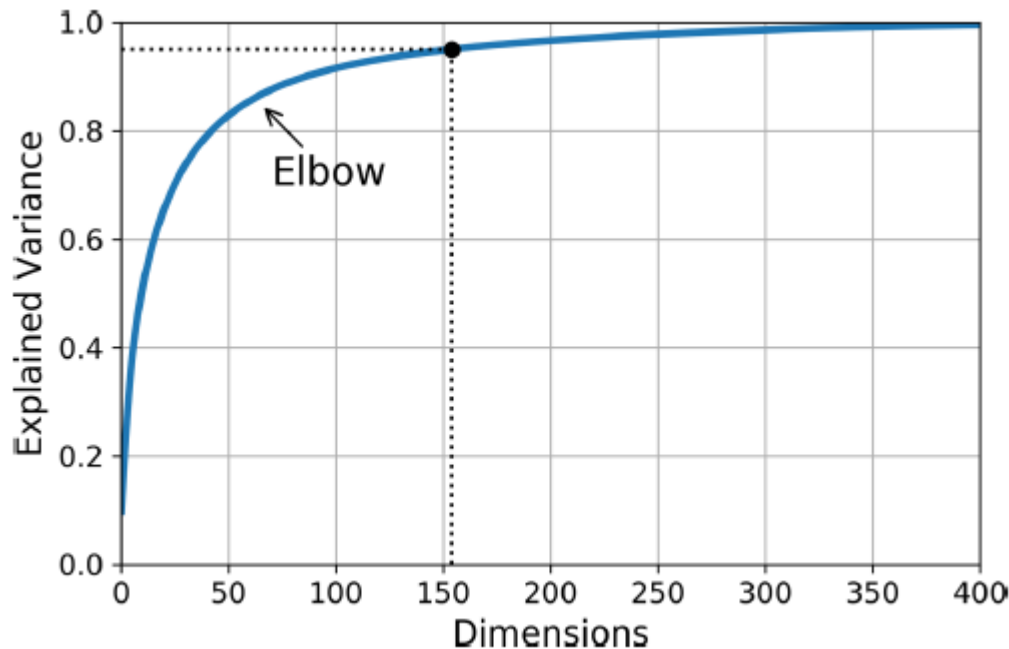
# PRINCIPAL COMPONENT ANALYSIS (PCA)

- Choose the right hyperplane
- Most of the information in high-dimensional dataset is captured by the first few principal components (PCs)
- Maximum variance
- PCA finds a zero-centered unit vector pointing in the direction of the PC



# CHOOSING THE NUMBER OF DIMENSIONS

- Explain sufficiently large portion of the variance (e.g., 95%).
- Or for visualization, reduce to 2 or 3
- Elbow point



## EXAMPLE: MNIST DATASET COMPRESSION

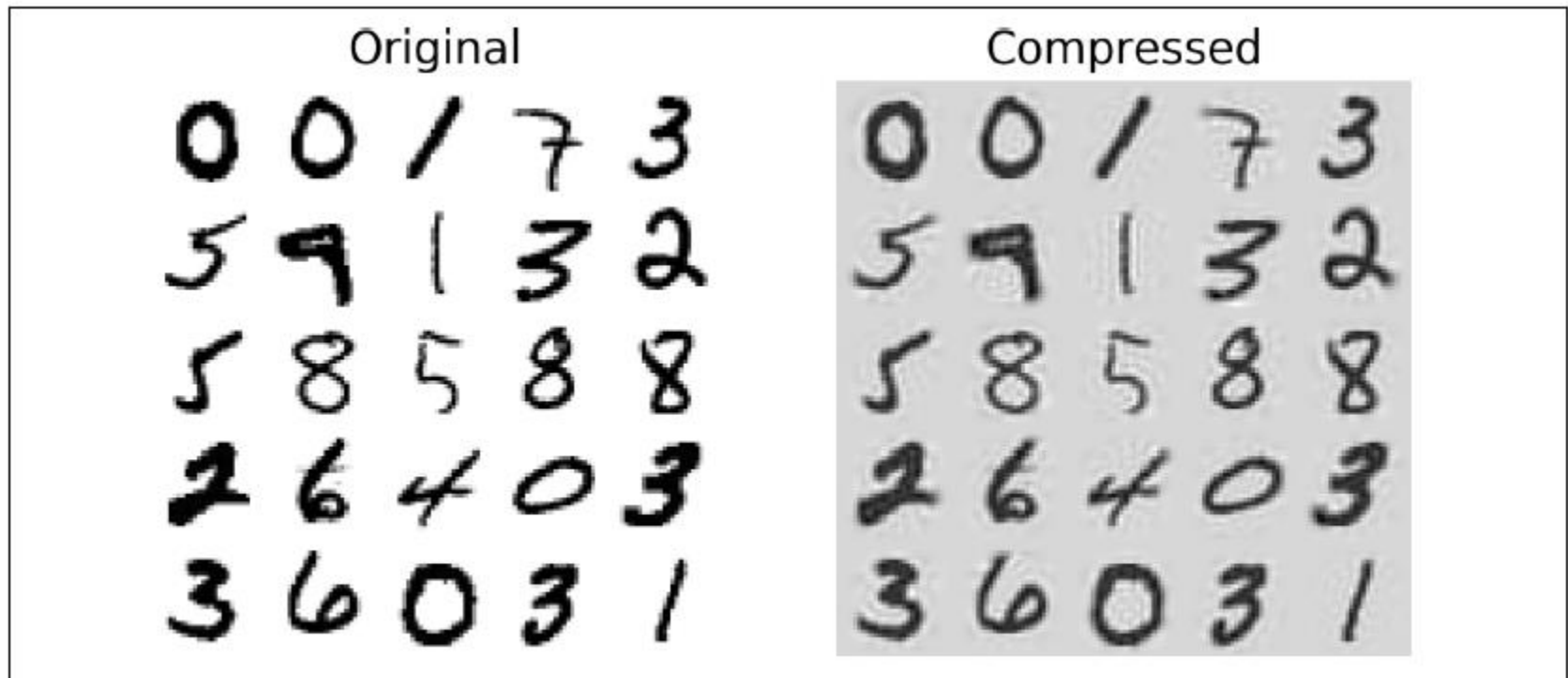


Figure 8-9. MNIST compression that preserves 95% of the variance



# NEXT WEEK

- Hands-on:
  - Work on your EVD3 portfolio
- Theory:
  - Quiz3: ML performance
  - Questions? Other topics?
  - Work on your EVD3 portfolio