

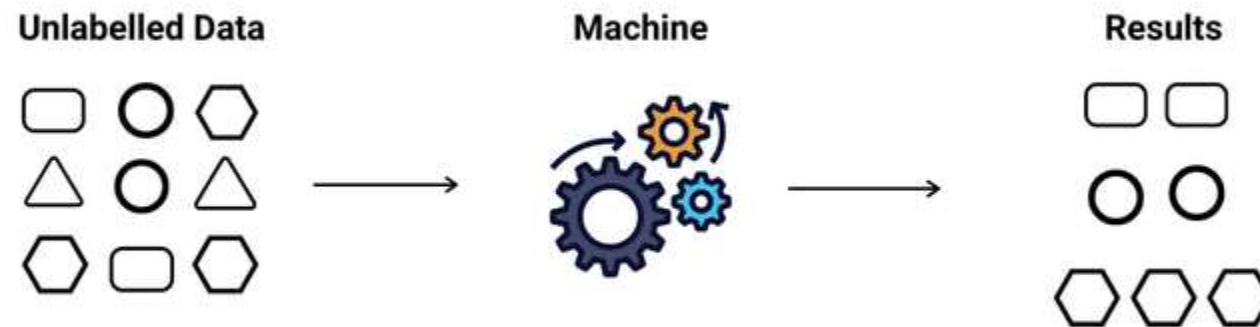
ML Fundamentals: Session 3

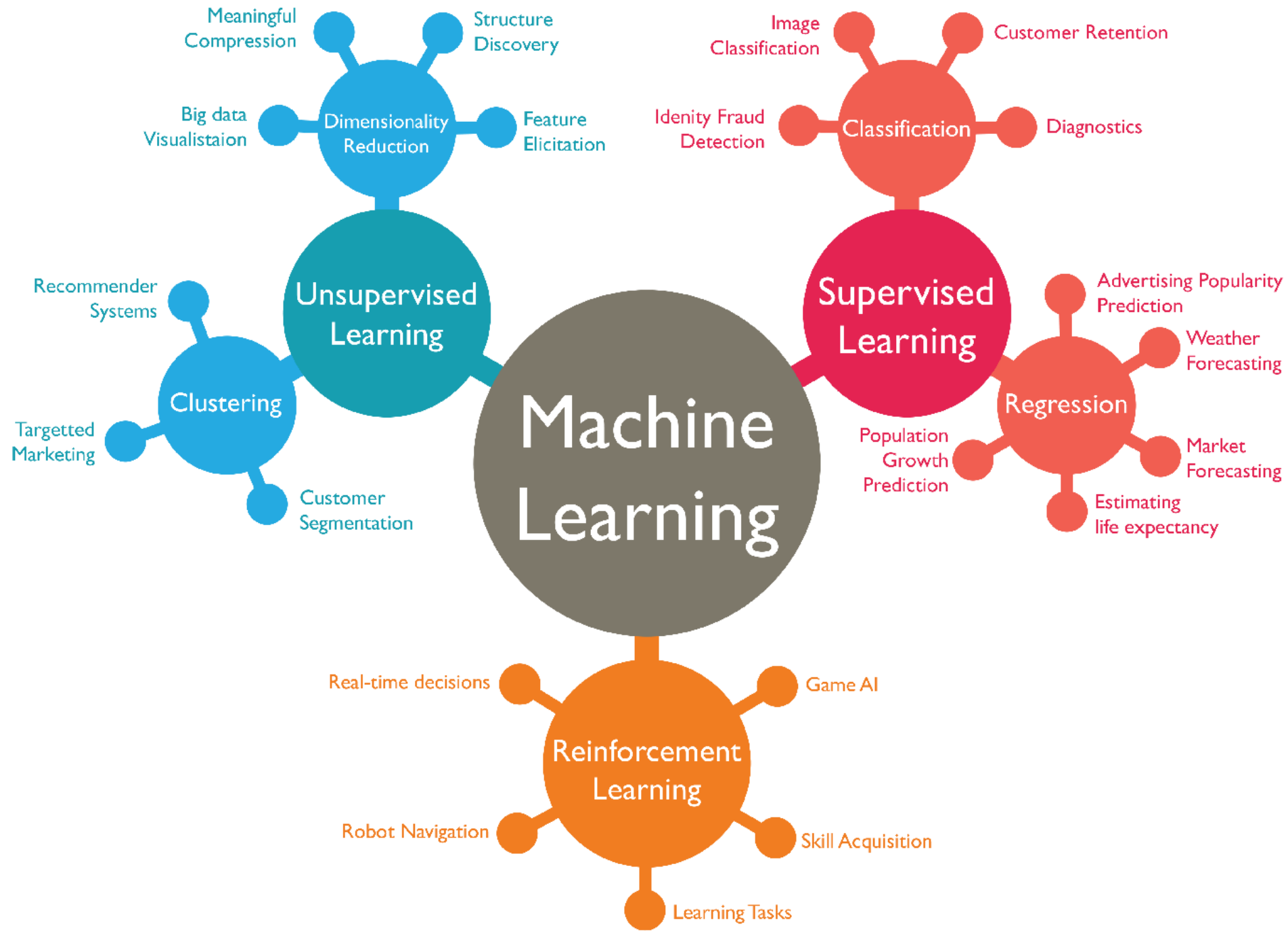
Unsupervised Learning with scikit-learn

Alia Hamwi

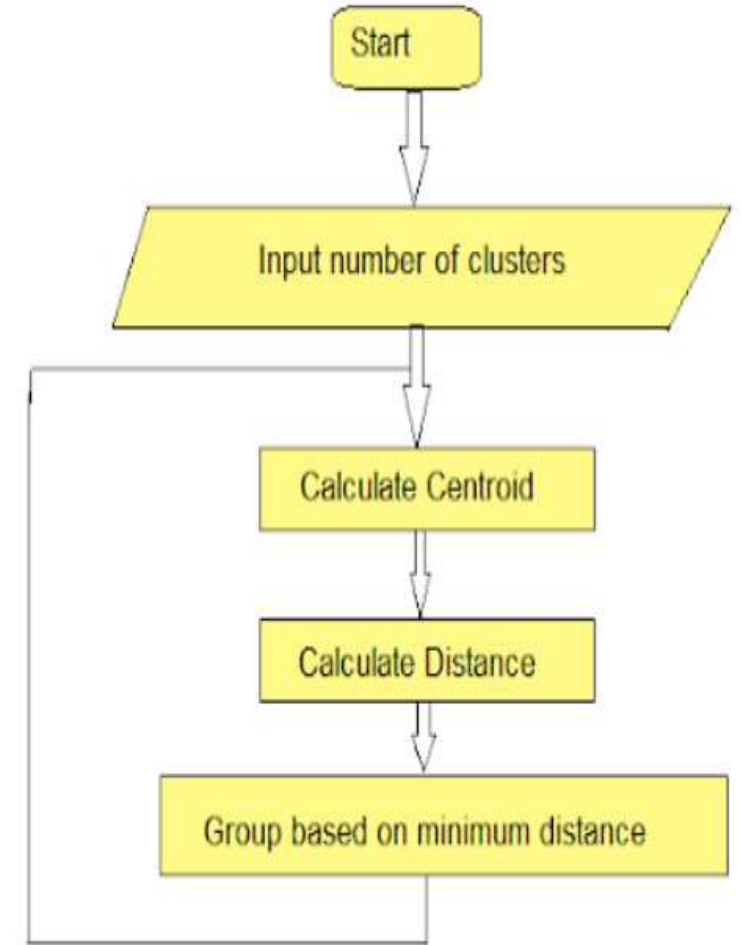
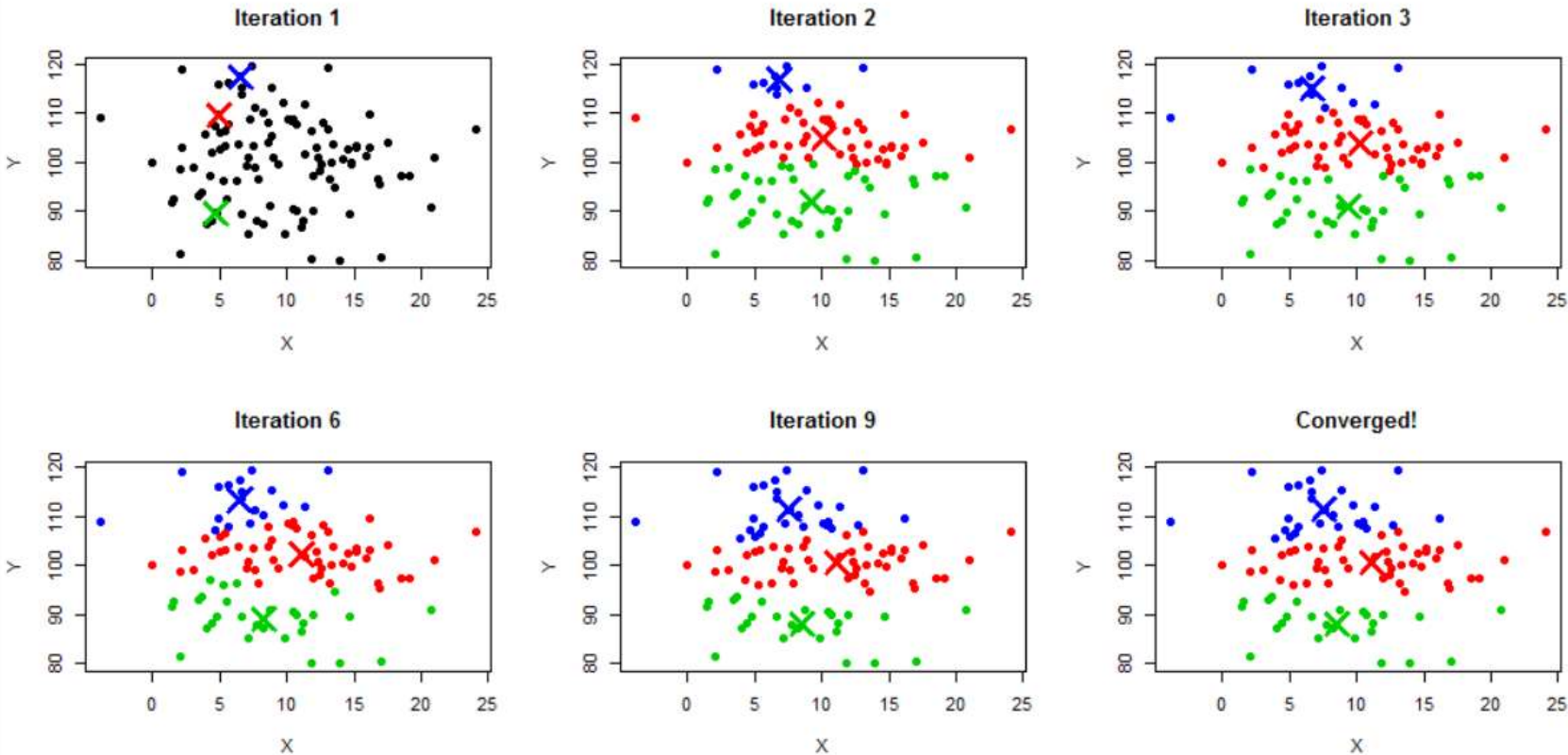
Types of Learning

- Unsupervised learning
 - Given: training data (without desired outputs)

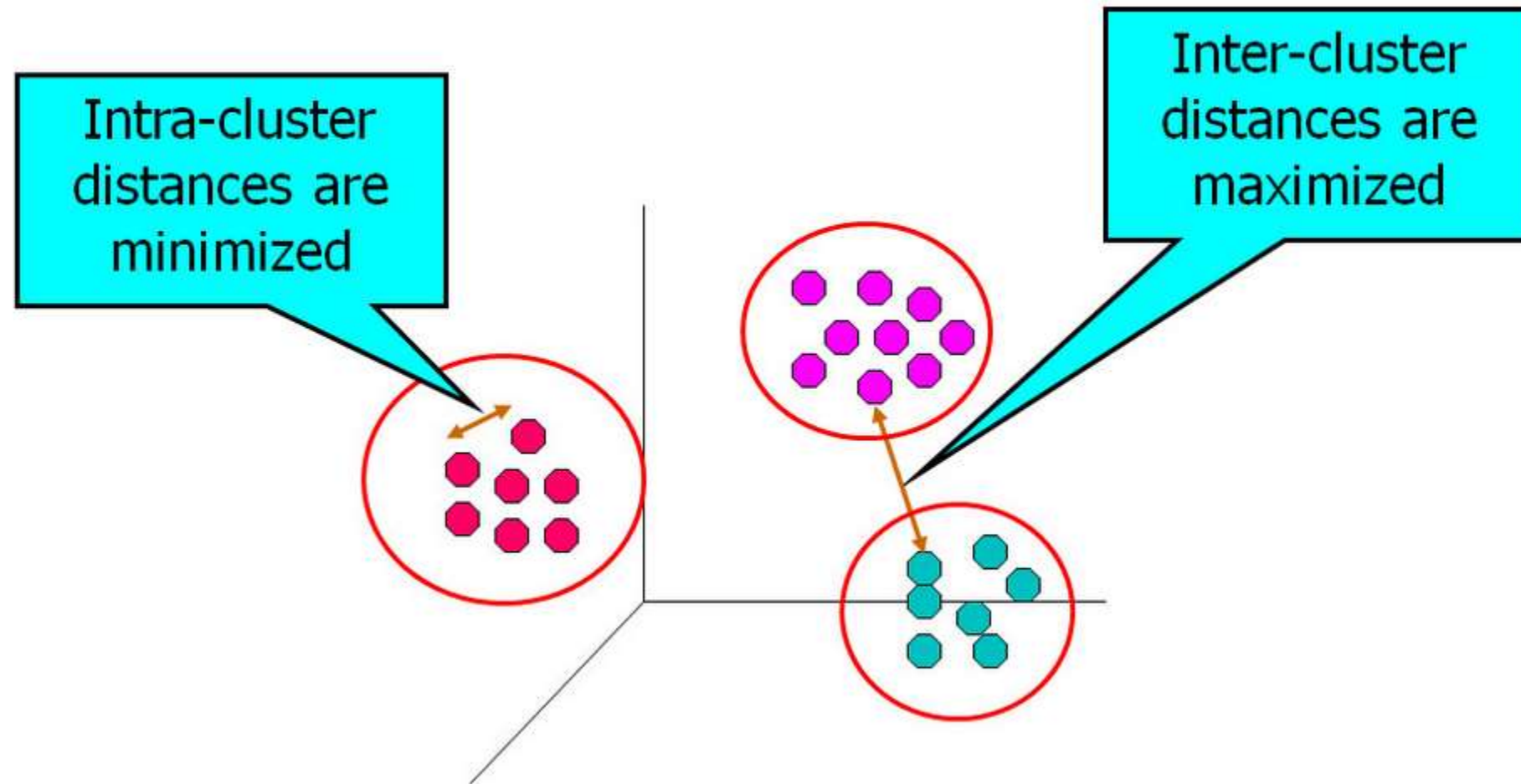




Clustering: K-means

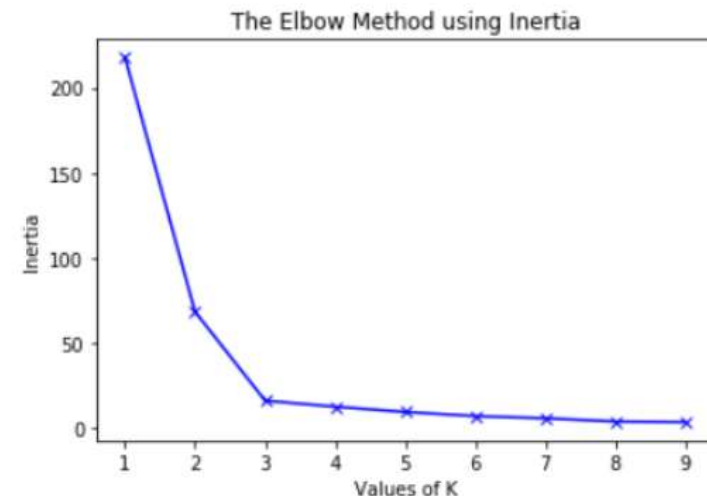


Measuring Performance of K-means



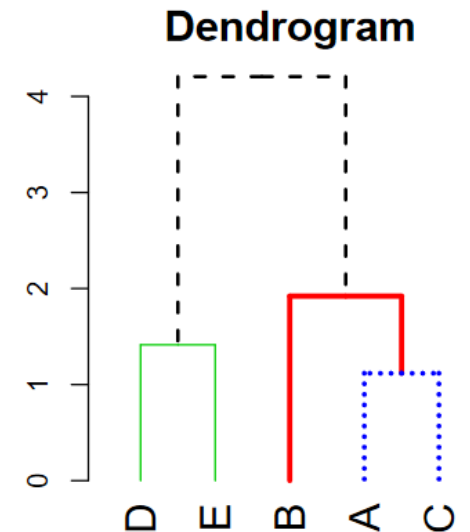
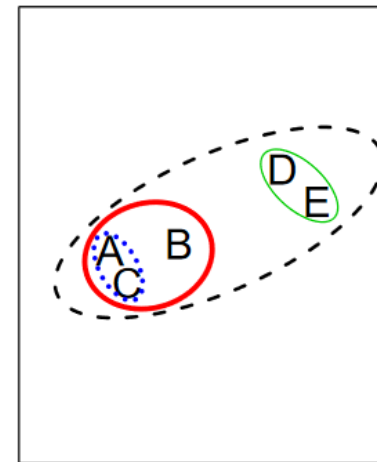
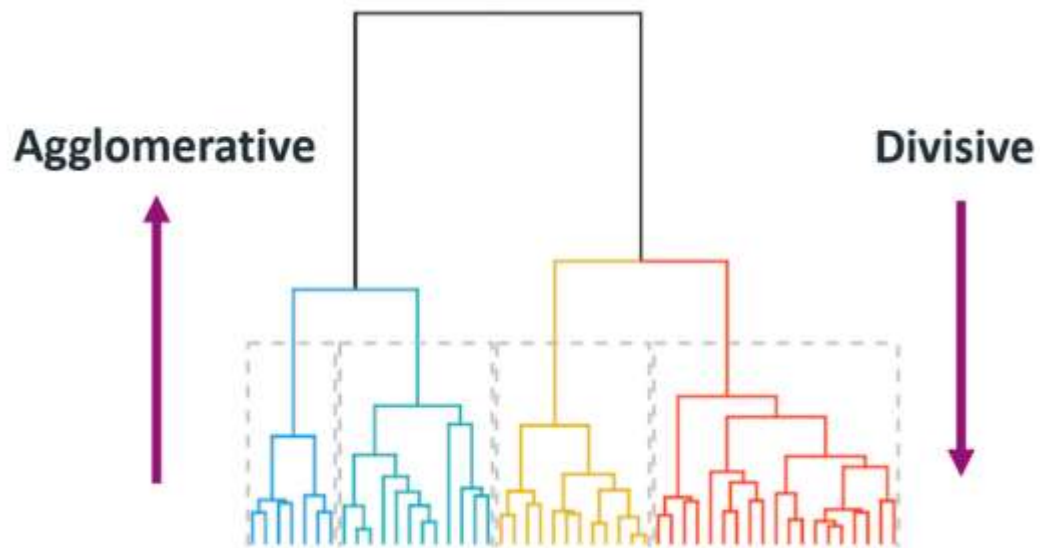
How to Choose K (# of Clusters)

- To determine the optimal number of clusters, we have to select the value of k at the “elbow” ie the point after which the distortion/inertia start decreasing in a linear fashion. Thus for the given data, we conclude that the optimal number of clusters for the data is **3**.
- inertia tells how far away the points within a cluster are. Therefore, a small of inertia is aimed for.



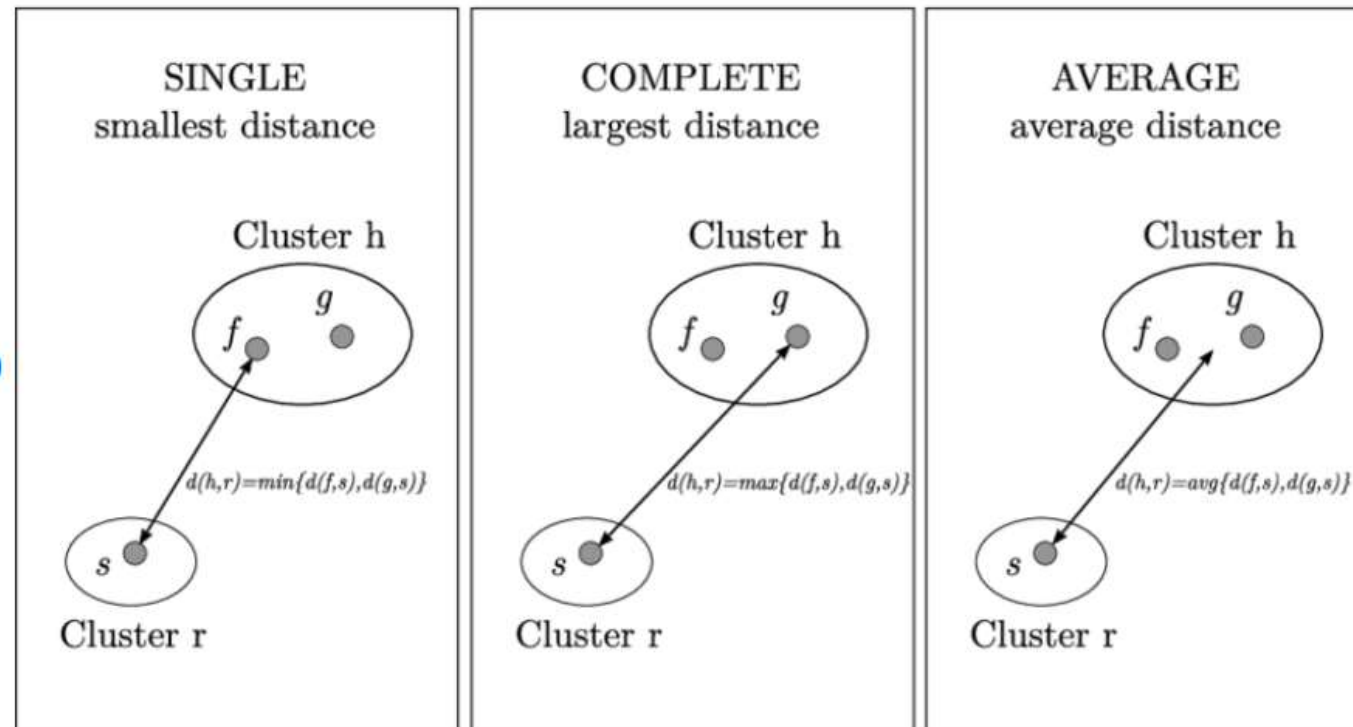
Hierarchical Clustering

- The approach in words:
 - Start with each point in its own cluster.
 - Identify the closest two clusters and merge them.
 - Repeat.
 - Ends when all points are in a single cluster.



Hierarchical Clustering

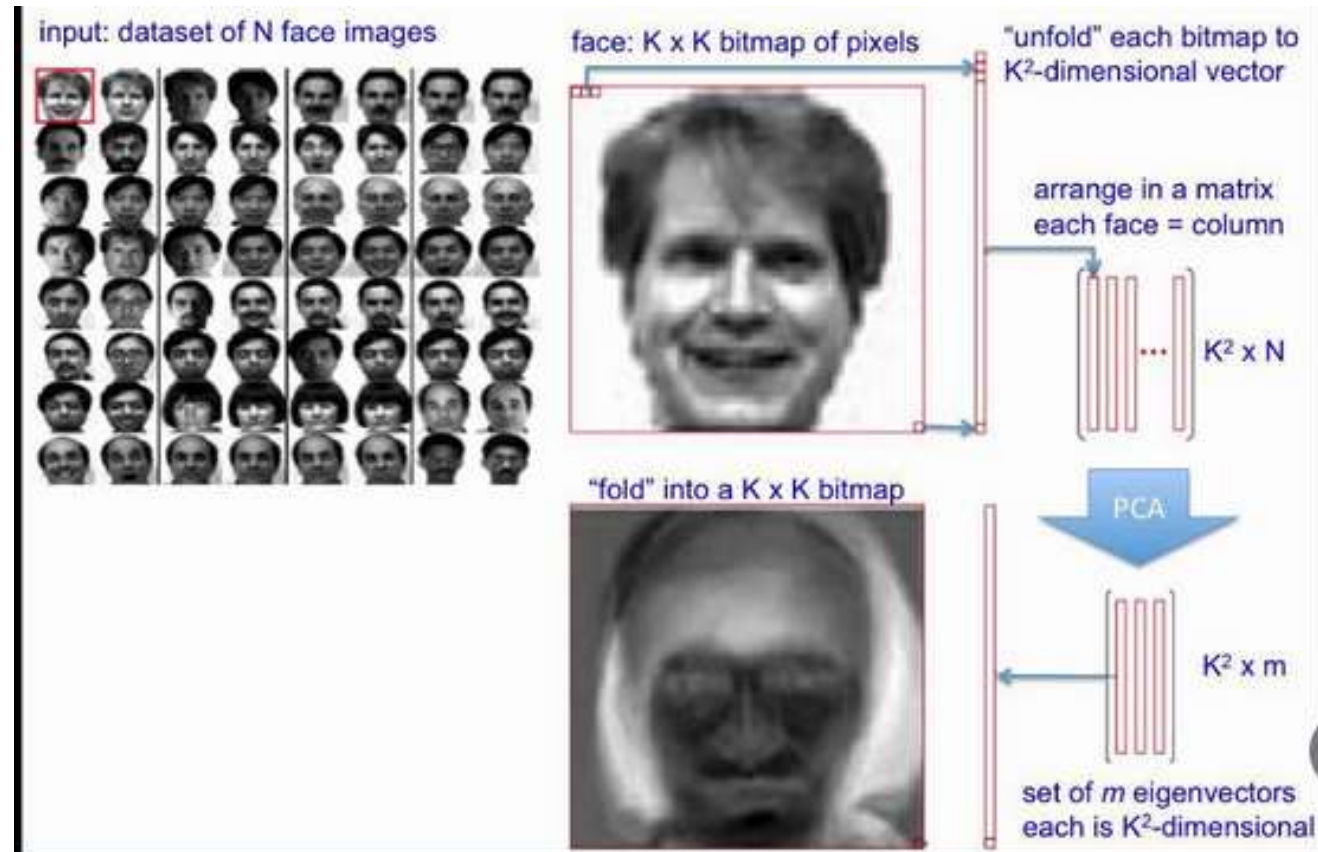
- Different linkage methods for hierarchical clustering



Principal component analysis (PCA)

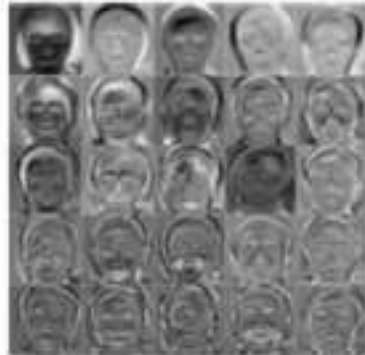
- PCA produces a low-dimensional representation of a dataset. It finds a sequence of linear combinations of the variables that have maximal variance, and are mutually uncorrelated
- Apart from producing derived variables for use in supervised learning problems, PCA also serves as a tool for data visualization.

Face recognition: Eigenfaces

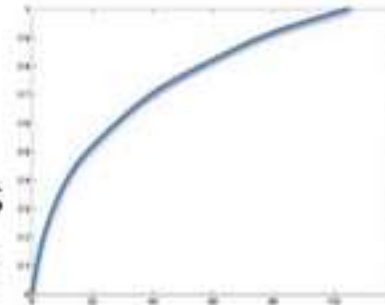


Face recognition: Eigenfaces

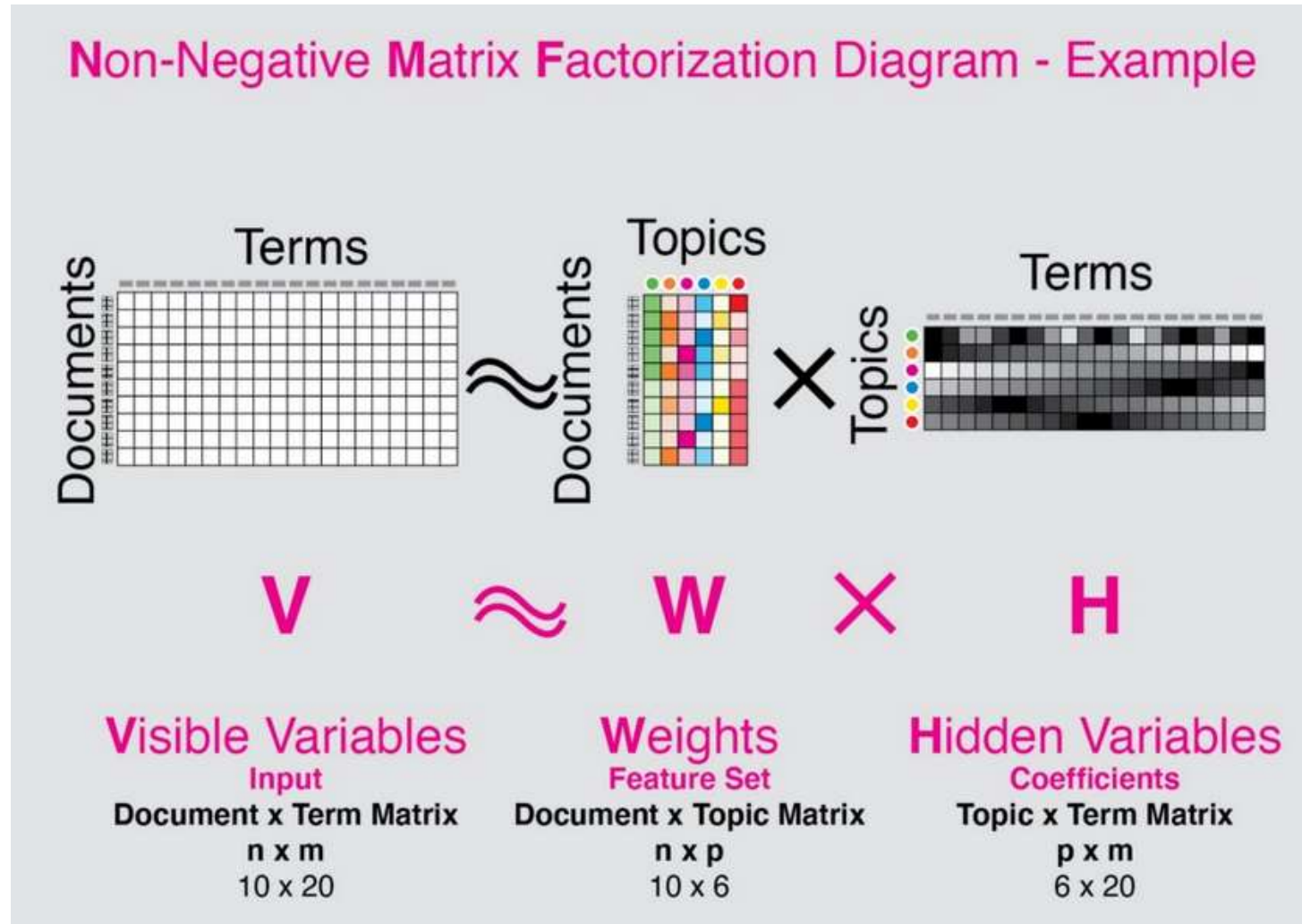

$$= \text{mean} + 0.9 * \img alt="Eigenface 1" data-bbox="411 311 474 421"/> - 0.2 * \img alt="Eigenface 2" data-bbox="536 311 599 421"/> + 0.4 * \img alt="Eigenface 3" data-bbox="666 311 729 421"/> + \dots$$



- Project new face to space of eigen-faces
- Represent vector as a linear combination of principal components
- How many do we need?



Non-negative Matrix-Factorization



Non-negative Matrix-Factorization

- In the example above, the Topics (p) are set to 6. Each column of the W matrix represents a probability that the topic is in the document. Each row of the W matrix represents a distribution of topic frequencies in each Document. Each row of the H matrix represent the distribution of term frequencies in each topic, and can be seen as the degree to which each term is activated in each topic.

References

- <https://towardsdatascience.com/nmf-a-visual-explainer-and-python-implementation-7ecdd73491f8>
- <https://www.pyimagesearch.com/2021/05/10/opencv-eigenfaces-for-face-recognition/>

Thank You