Special Topics in Biostatistics and Bioinformatics
Week III

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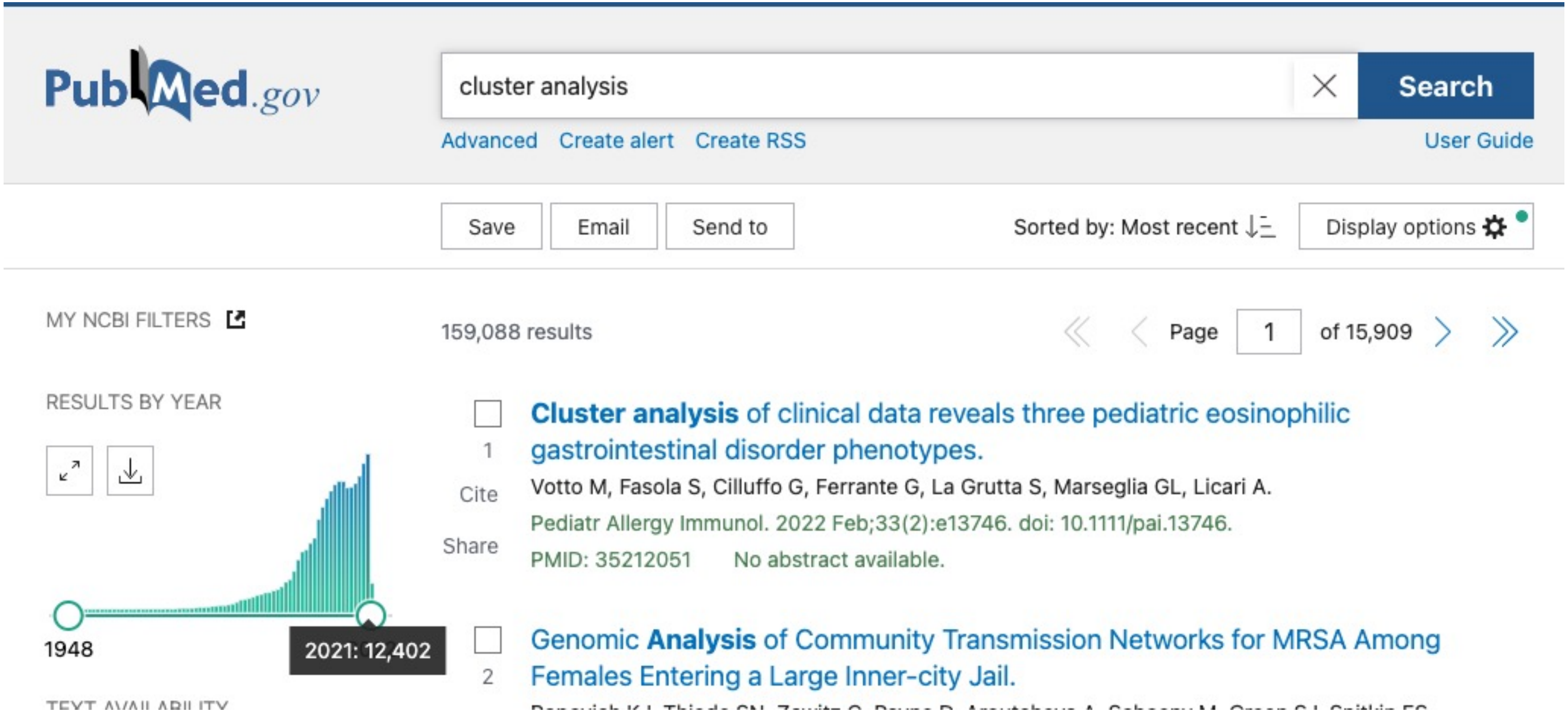
17 March 2022

ACIBADEM
MEHMET ALİ AYDINLAR
ÜNİVERSİTESİ

Clustering

find “close” samples or genes etc.

put them into groups


PubMed.gov
cluster analysis
Search
Advanced
Create alert
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User Guide
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Email
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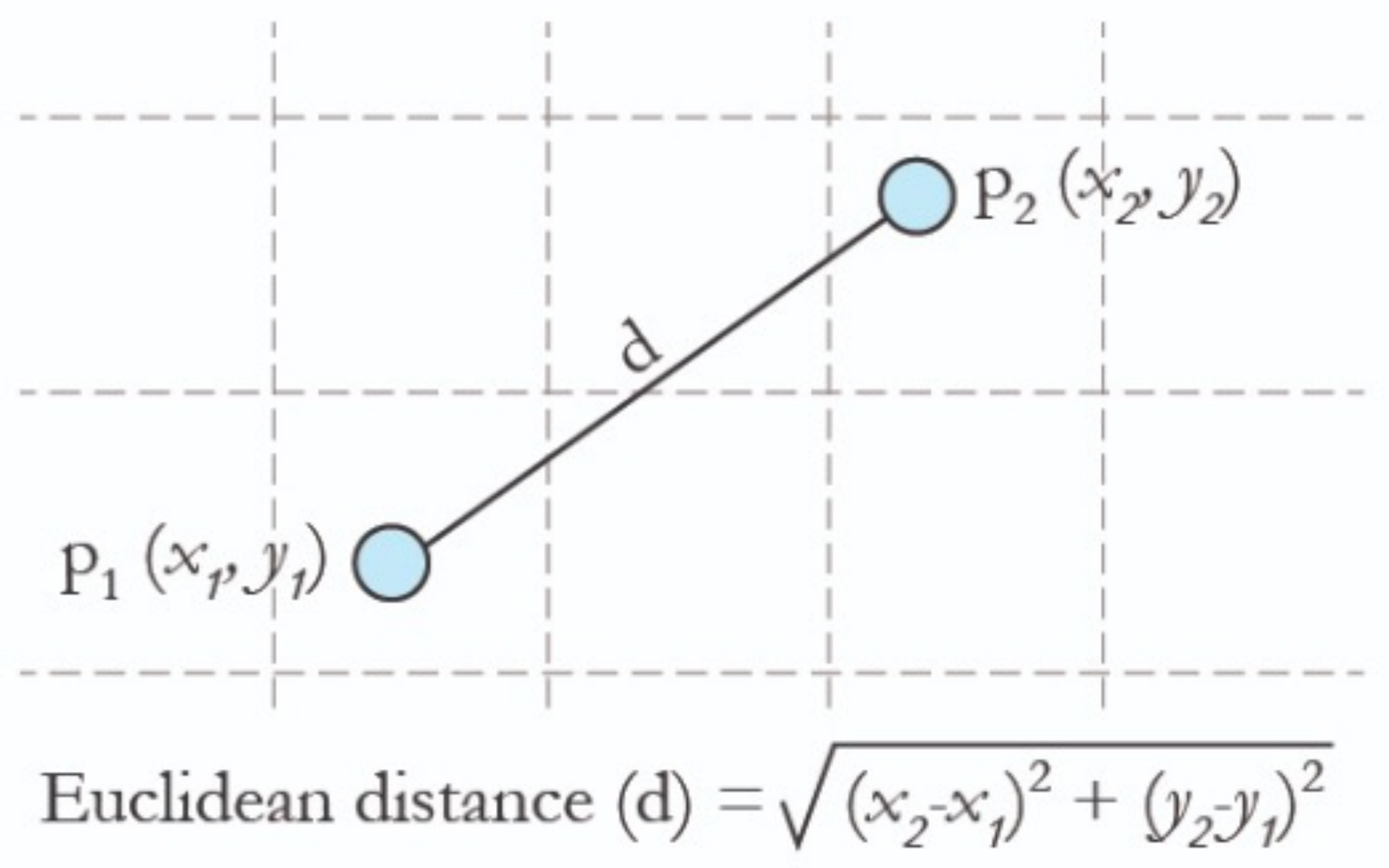
Sorted by: Most recent
Display options
MY NCBI FILTERS
159,088 results
Page
1
of 15,909
RESULTS BY YEAR
1948
2021: 12,402
Cluster analysis of clinical data reveals three pediatric eosinophilic gastrointestinal disorder phenotypes.
1
Cite
Share
Votto M, Fasola S, Cilluffo G, Ferrante G, La Grutta S, Marseglia GL, Licari A.
Pediatr Allergy Immunol. 2022 Feb;33(2):e13746. doi: 10.1111/pai.13746.
PMID: 35212051
No abstract available.
Genomic Analysis of Community Transmission Networks for MRSA Among Females Entering a Large Inner-city Jail.
2

https://www.tutorialexample.com/calculate-euclidean-distance-in-tensorflow-a-step-guide-tensorflow-tutorial/

Defining "distance"

Eucledian distance

$$d_{euc}(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

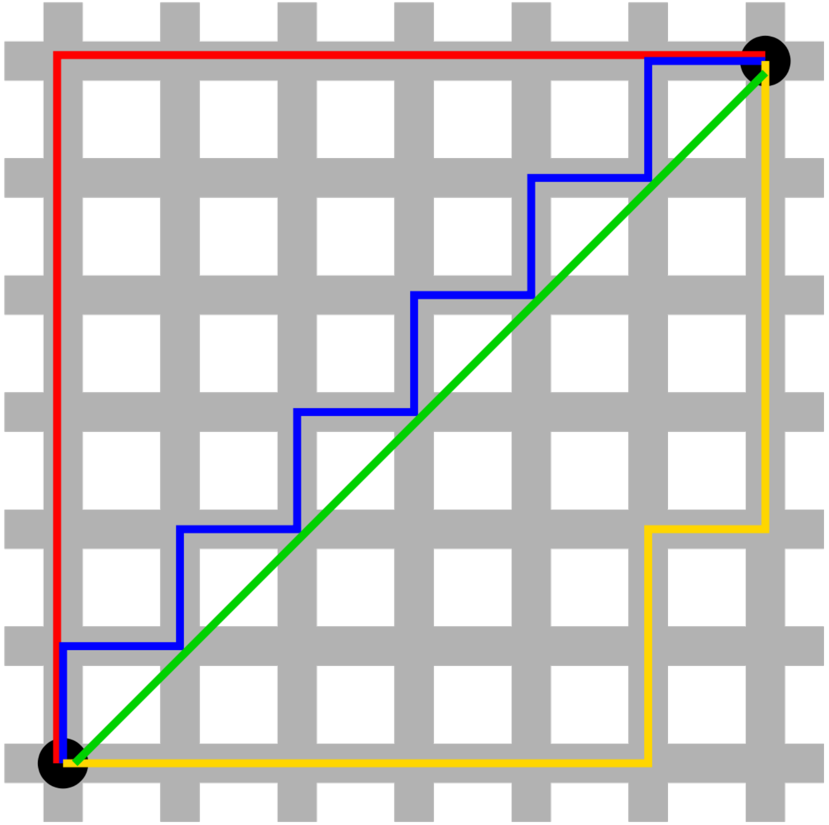


https://en.wikipedia.org/wiki/Taxicab_geometry

Defining "distance"

Manhattan distance

$$d_{man}(x, y) = \sum_{i=1}^{n} |x_i - y_i|$$



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

Defining “distance”

Minkowski distance

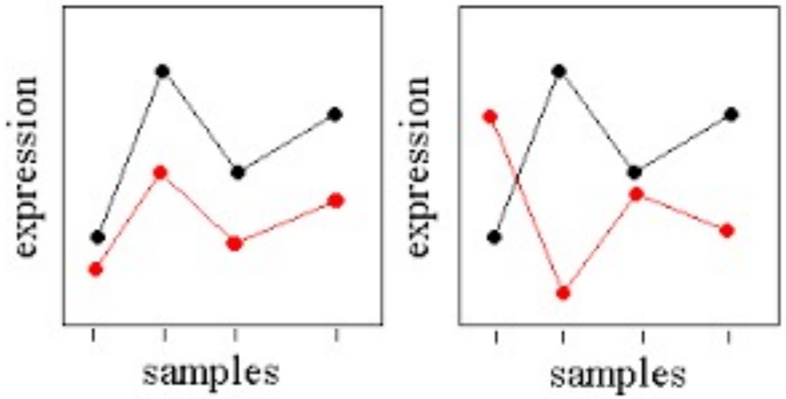
$$d_{mink}(x, y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}}$$

http://www.improvedoutcomes.com/docs/WebSiteDocs/Clustering/Clustering_Parameters/Pearson_Correlation_and_Pearson_Squared_Distance_Metric.htm

Other "dissimilarity" measures

Pearson correlation distance

$$d_{cor}(x,y) = 1 - \frac{\sum_{i=1}^{n}(x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$



https://www.datanovia.com/en/lessons/clustering-distance-measures/

Other "dissimilarity" measures

Eisen cosine correlation distance

$$d_{eisen}(x,y) = 1 - \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} {x_i}^2 \sum_{i=1}^{n} {y_i}^2}}$$

Spearman correlation distance

$$d_{spear}(x,y) = 1 - \frac{\sum_{i=1}^{n}(x_i' - \bar{x'})(y_i' - \bar{y'})}{\sqrt{\sum_{i=1}^{n}(x_i' - \bar{x'})^2 \sum_{i=1}^{n}(y_i' - \bar{y'})^2}}$$

Kendall correlation distance

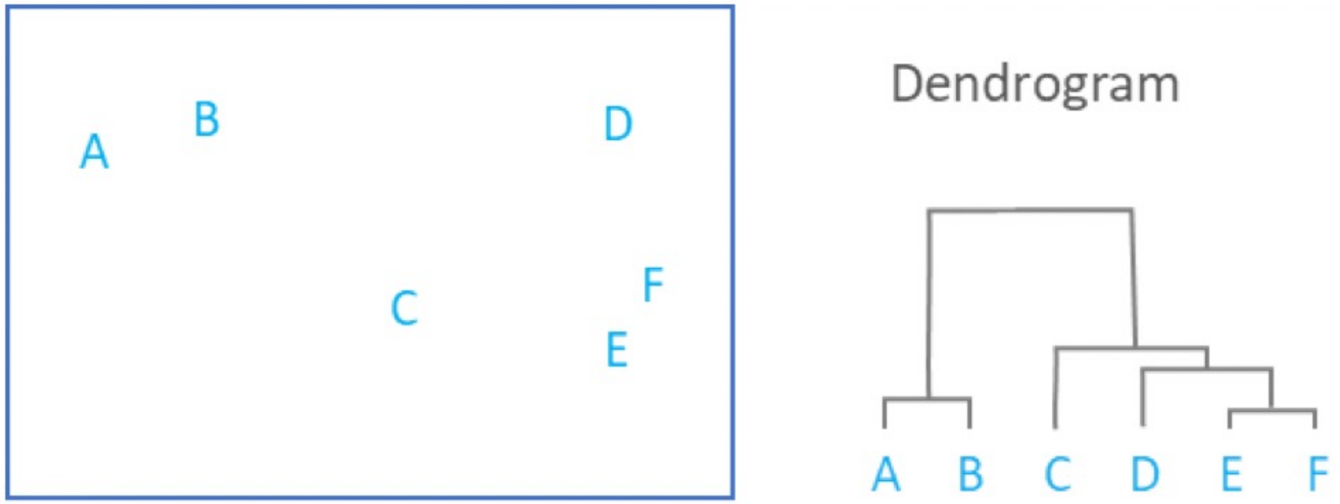
$$d_{kend}(x,y) = 1 - \frac{n_c - n_d}{\frac{1}{2}n(n-1)}$$

Clustering Methods

- Hierarchical clustering
- Centroid-based clustering
- Distribution-based clustering
- Density-based clustering
- Grid-based clustering
- Fuzzy clustering

…

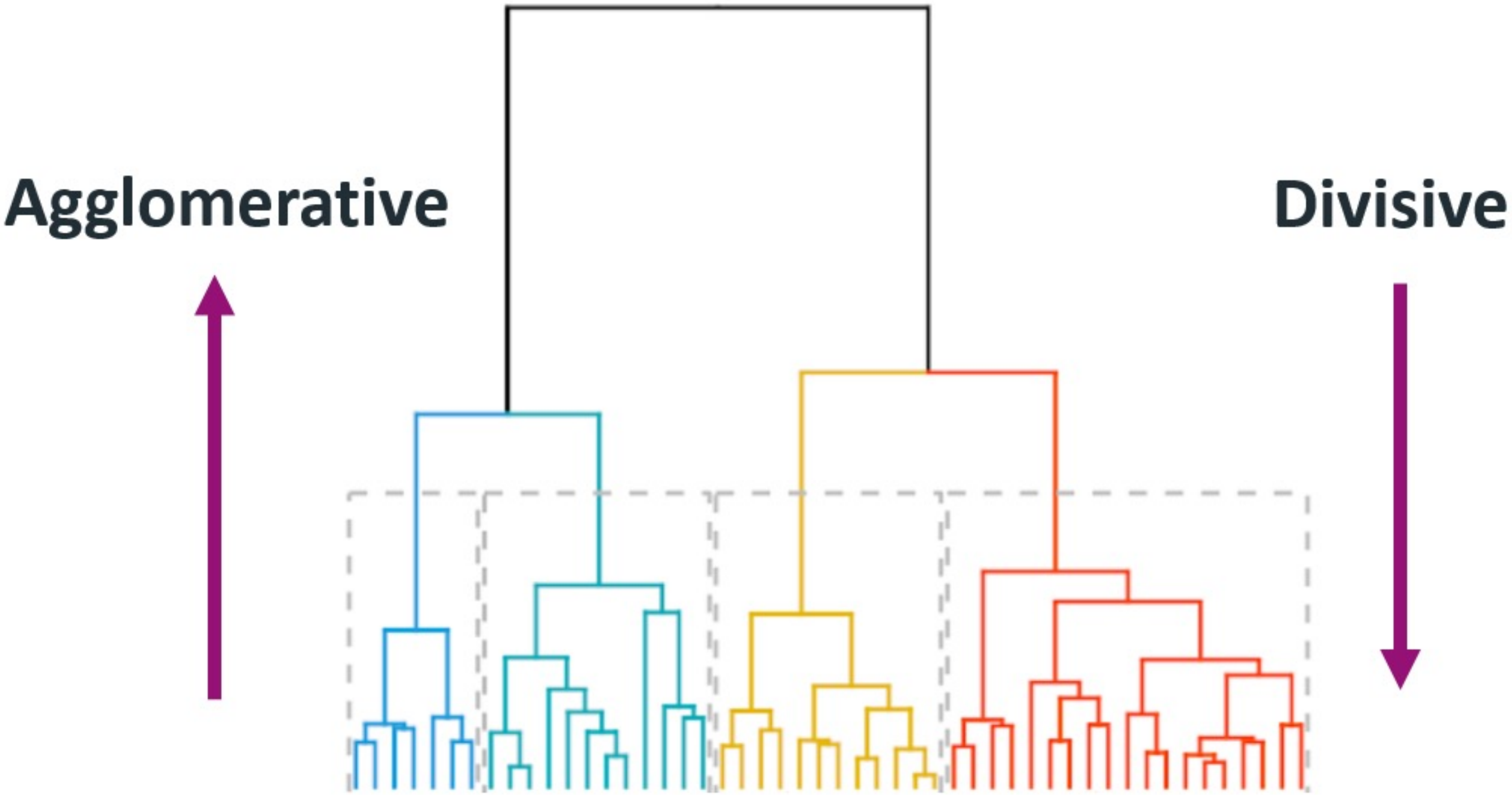
Hierarchical clustering



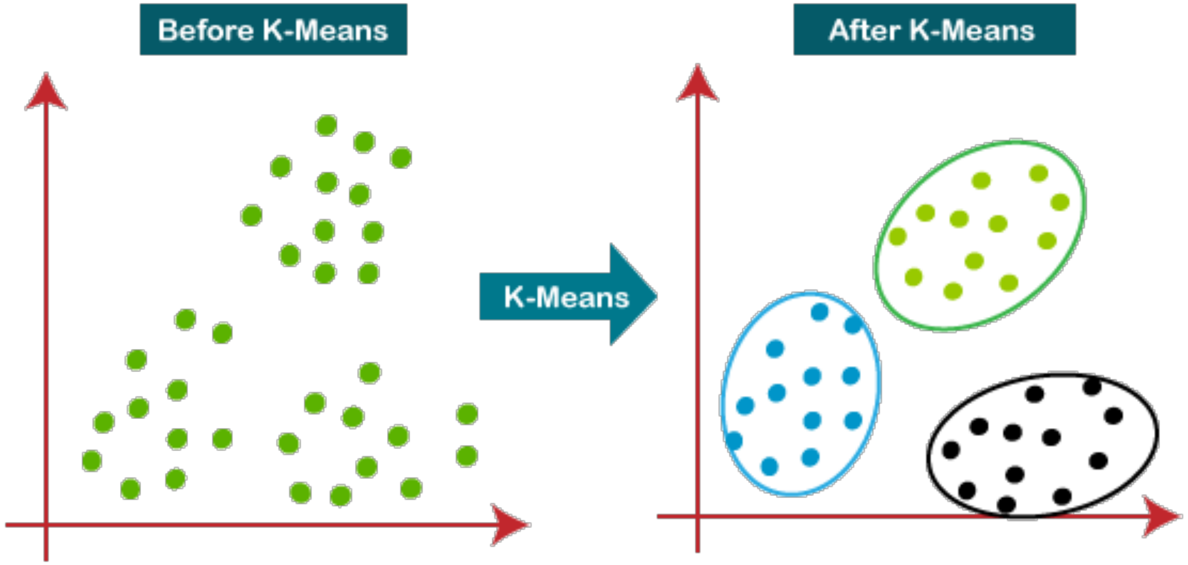
- Find the “closest” points
- Merge
- Repeat

https://harshsharma1091996.medium.com/hierarchical-clustering-996745fe656b

Hierarchical clustering



K-means clustering



- Initialize k cluster “centers” (random seeds)
- Assign each value to the closest center
- Update centers
- Reassign values
- Repeat

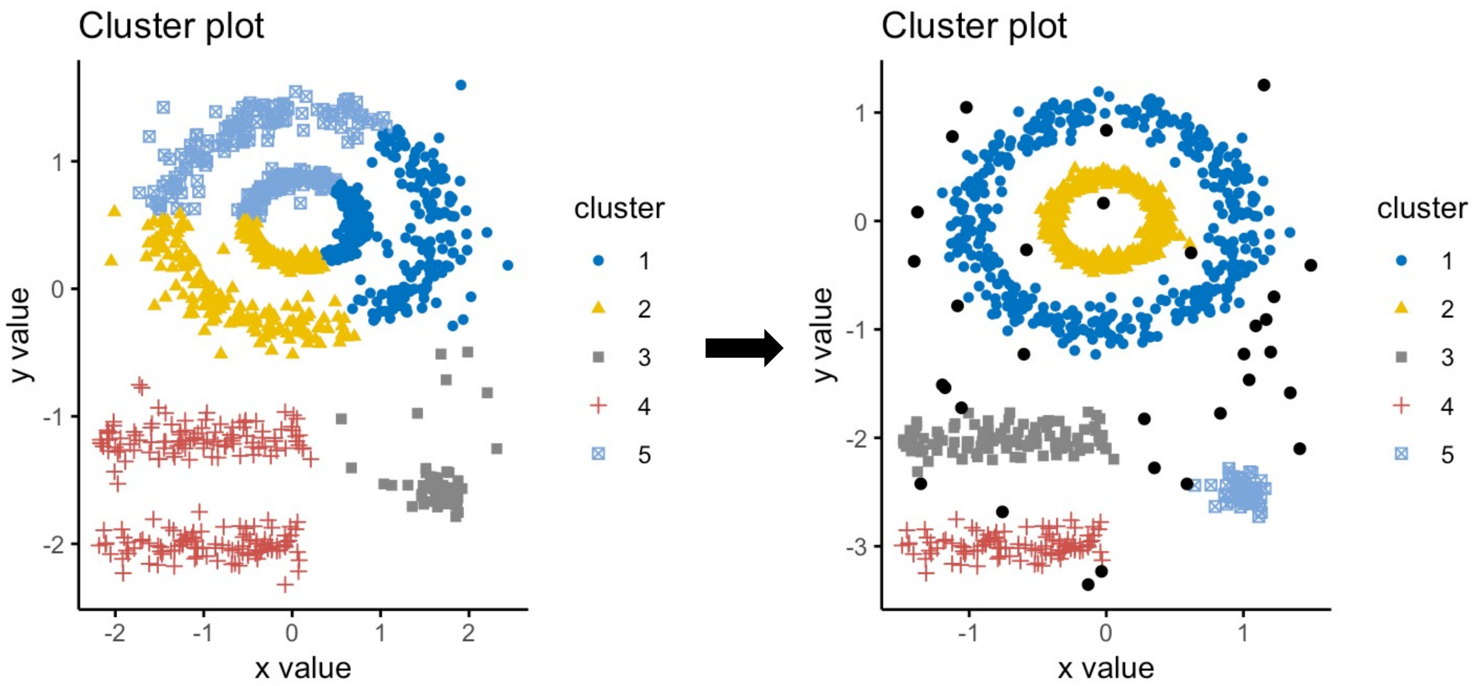
https://www.datanovia.com/en/lessons/dbscan-density-based-clustering-essentials/

Other Approaches

- Hierarchical K-means Clustering
- Hierarchical clustering on principal components

- Fuzzy Clustering
  - Fuzzy c-means

- DBSCAN



https://www.datanovia.com/en/lessons/determining-the-optimal-number-of-clusters-3-must-know-methods/

Determining the optimal number of clusters

- Visualization
- Elbow method
  - location of a bend in total within-cluster sum of square
- Average silhouette method
  - Maximum average silhouette
- Gap statistic method
  - the smallest value of k such that the gap statistic is within one standard deviation of the gap at k+1: $Gap(k) \geq Gap(k+1) - s_{k+1}$.

Dimensionality Reduction

Overcoming the curse of dimensionality

https://towardsdatascience.com/the-curse-of-dimensionality-50dc6e49aa1e

Curse of dimensionality

- Cannot visualize observations

- Overfitting – terrible out of sample performance.
- Observations become harder to cluster — too many dimensions causes every observation to appear equidistant from all the others

https://towardsdatascience.com/the-curse-of-dimensionality-50dc6e49aa1e

Curse of dimensionality

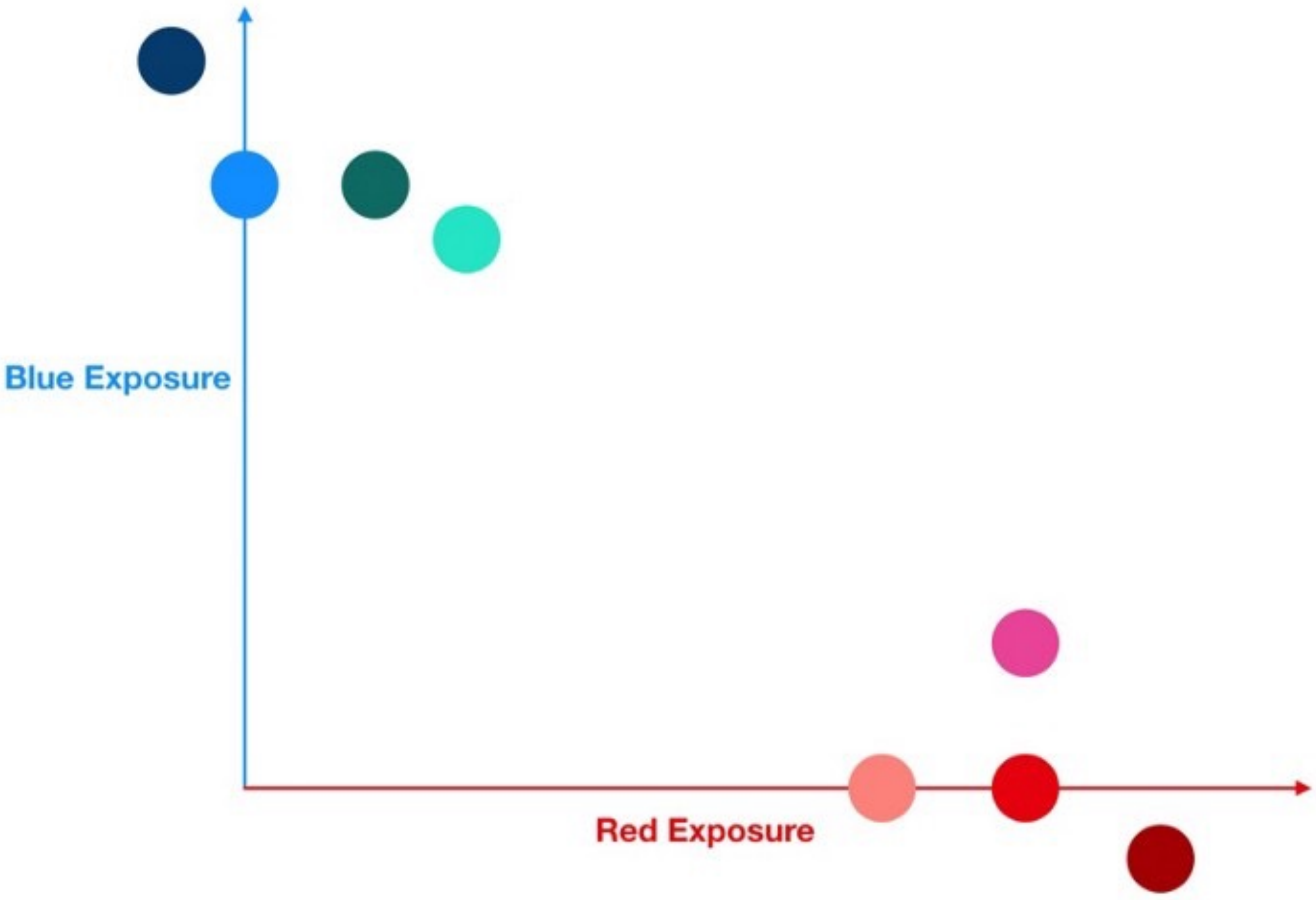
	Red	Maroon	Pink	Flamingo	Blue	Turquoise	Seaweed	Ocean
	1	0	0	0	0	0	0	0
	0	**1**	0	0	0	0	0	0
	0	0	**1**	0	0	0	0	0
	0	0	0	**1**	0	0	0	0
	0	0	0	0	**1**	0	0	0
	0	0	0	0	0	**1**	0	0
	0	0	0	0	0	0	**1**	0
	0	0	0	0	0	0	0	**1**

https://towardsdatascience.com/the-curse-of-dimensionality-50dc6e49aa1e

Dimensionality Reduction

Latent Features

	Red	Blue
Red	1.00	0
Maroon	1.20	-0.10
Pink	1.00	0.20
Flamingo	0.80	0
Blue	0	1.00
Turquoise	0.25	0.90
Seaweed	0.15	1.00
Ocean	-0.10	1.20



Dimensionality Reduction

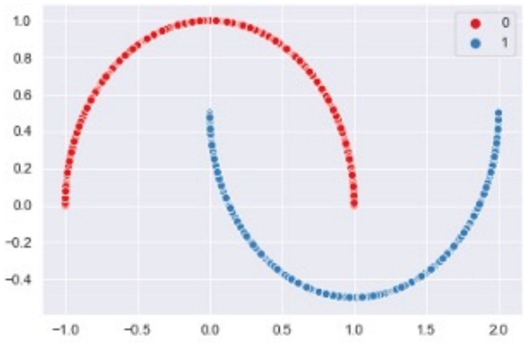
- Projection
  - Projecting every data point in high dimension onto a suitable lower-dimensional space, approximately preserving the distances
- Manifold Learning
  - Modelling the manifold on which the training instance lie
  - Assumption: most real-world high-dimensional datasets lie close to a much lower-dimensional manifold

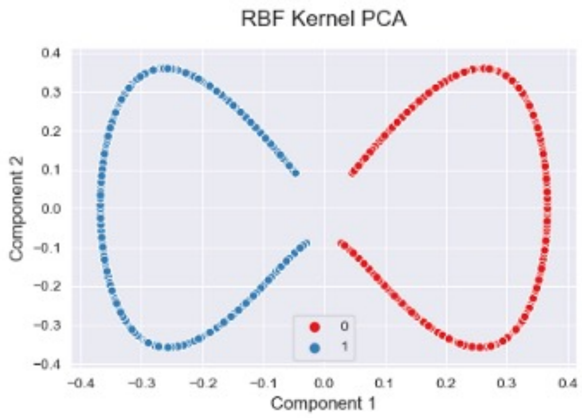
https://towardsdatascience.com/11-different-uses-of-dimensionality-reduction-4325d62b4fa6

Use Cases

- Visualization to observe relationships – 2D/3D
- Batch effect identification
- …

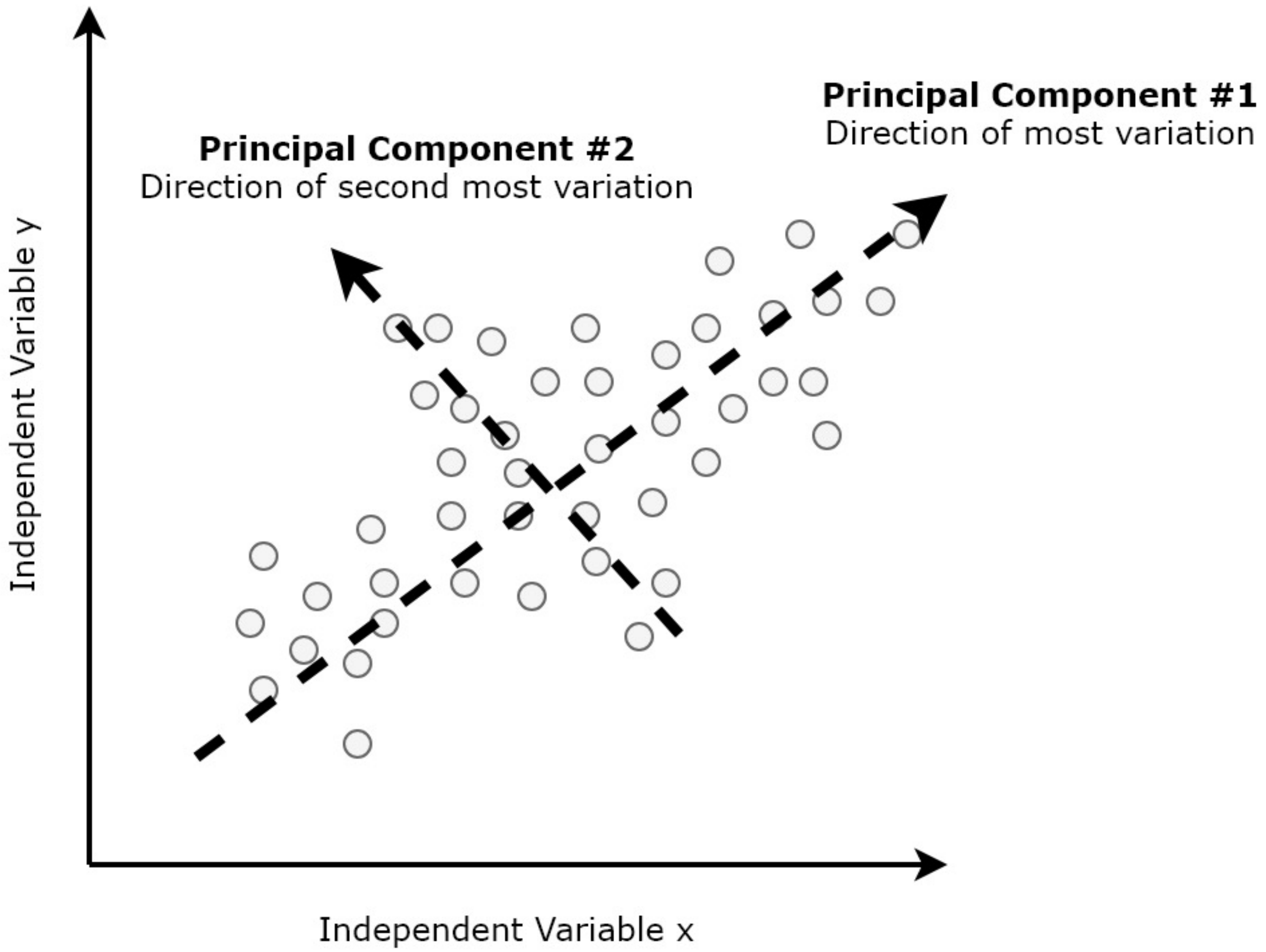
- transforms non-linear data into a linearly-separable form
- removes multicollinearity
- reduces the training time of models
- improves the accuracy of models





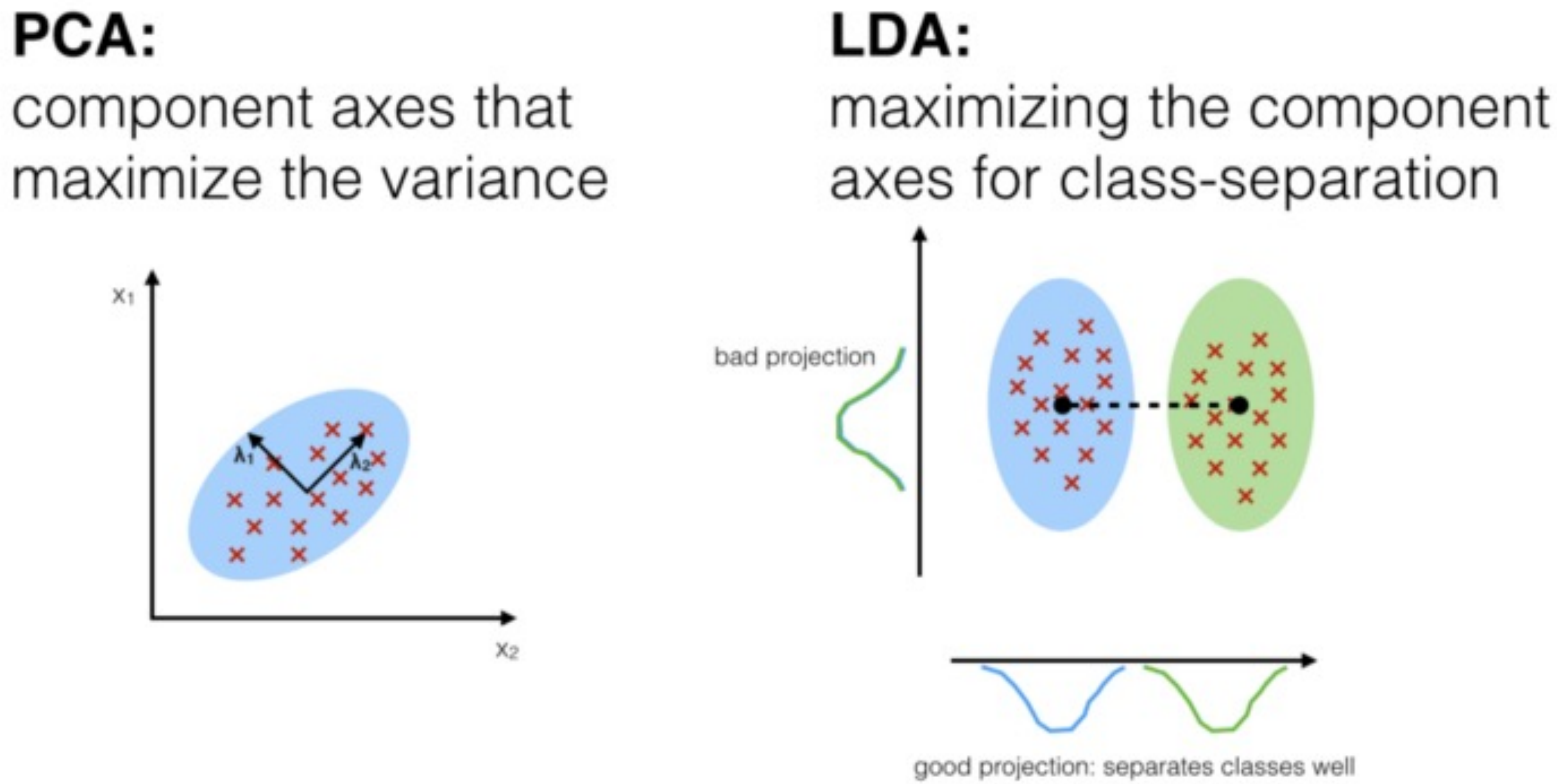
https://towardsdatascience.com/dimensionality-reduction-for-data-visualization-pca-vs-tsne-vs-umap-be4aa7b1cb29

Principal Component Analysis (PCA)



https://towardsdatascience.com/dimensionality-reduction-for-data-visualization-pca-vs-tsne-vs-umap-be4aa7b1cb29

Linear Discriminant Analysis (LDA)



https://towardsdatascience.com/dimensionality-reduction-for-data-visualization-pca-vs-tsne-vs-umap-be4aa7b1cb29

T-distributed stochastic neighbor embedding (t-SNE)

t-SNE reduces dimensionality while trying to keep similar instances close and dissimilar instances apart

van der Maaten, L.J.P.; Hinton, G.E. (Nov 2008). "Visualizing Data Using t-SNE" (PDF). Journal of Machine Learning Research. 9: 2579–2605.

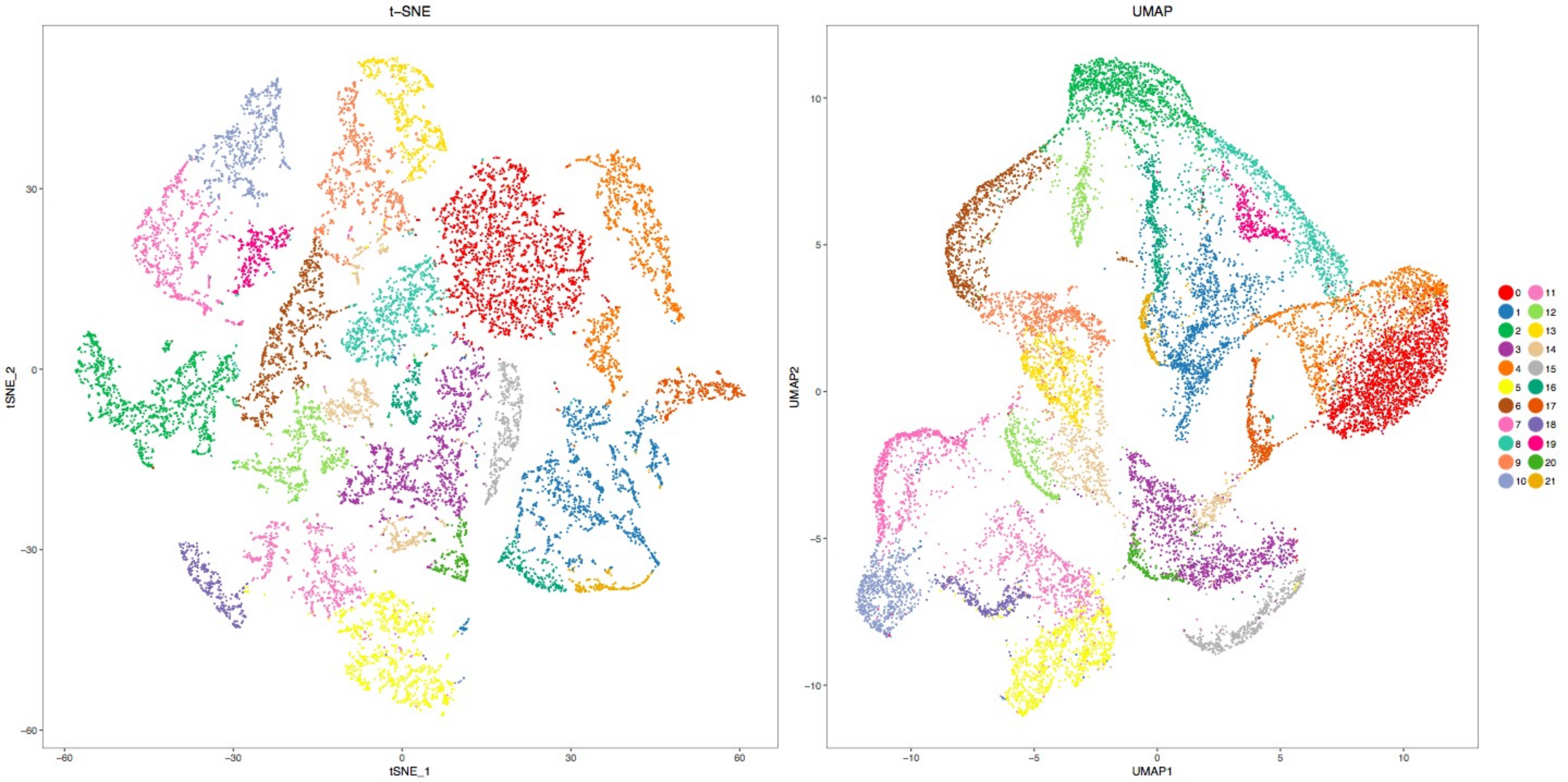
https://towardsdatascience.com/t-sne-clearly-explained-d84c537f53a

Uniform Manifold Approximation and Projection (UMAP)

McInnes, L., & Healy, J. (2018). UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. ArXiv e-prints.

- Similar to tSNE
- a number of advantages over tSNE
  - increased speed
  - scalability
  - better preservation of the data's global structure

https://pair-code.github.io/understanding-umap/



t–SNE
UMAP
tSNE_1
tSNE_2
UMAP1
UMAP2
−60
−30
0
30
60
−10
−5
5
10
0
1
2
3
4
5
6
7
8
9
10
11
12
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20
21

More Techniques

- Multidimensional Scaling (MDS)
- Independent Component Analysis (ICA)
- Non-negative Matrix Factorization (NMF)
- …