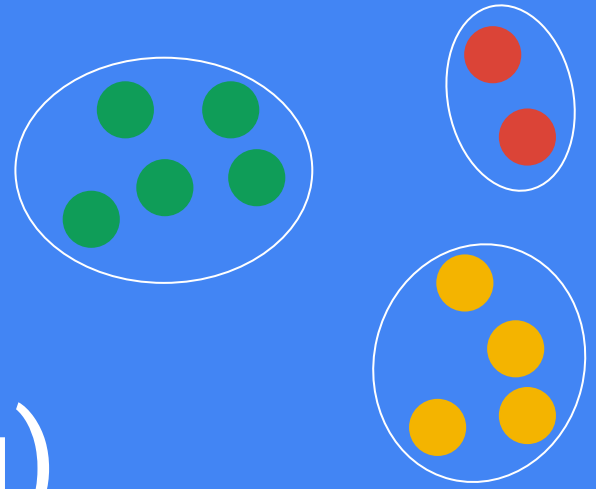
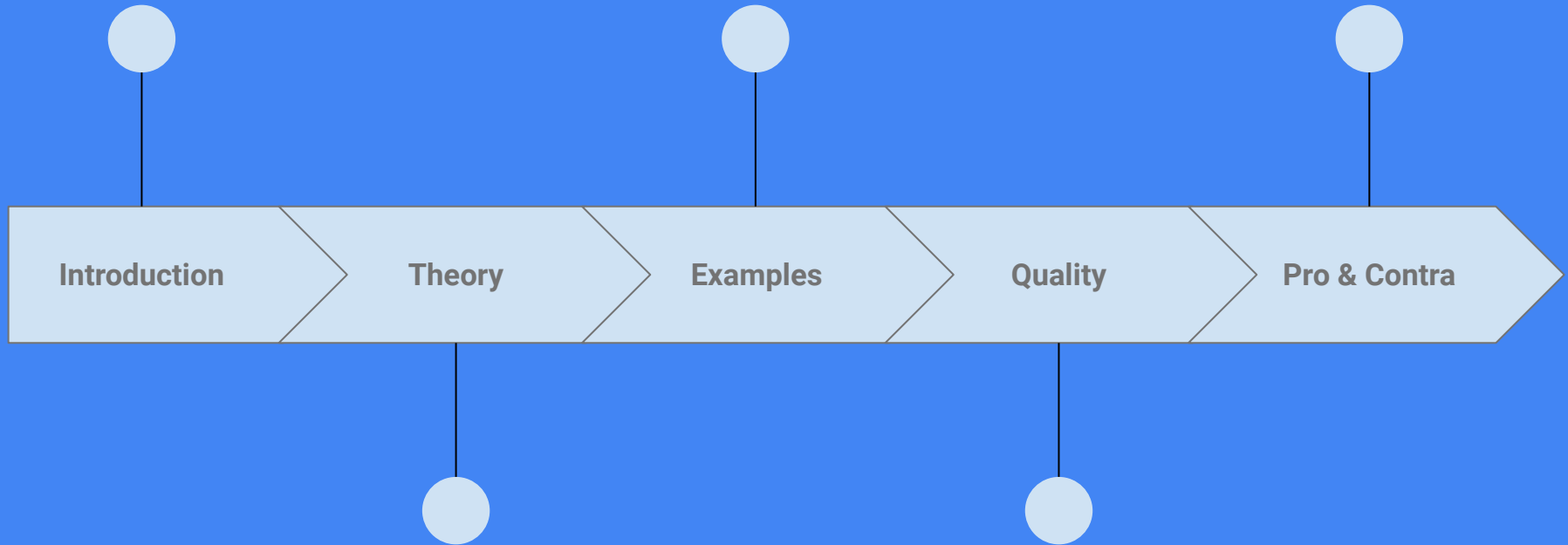


k-means (Clustering)

Knowledge Discovery (CENG-542)
Paper Presentation



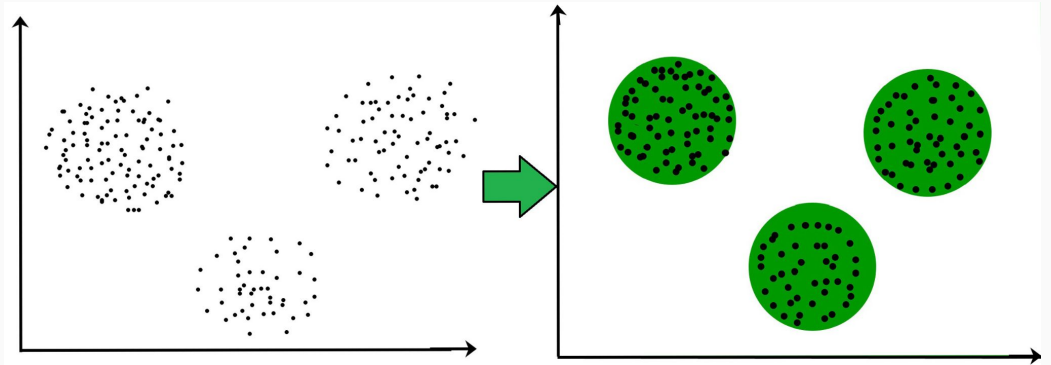
TOC (k-means)



Introduction

Motivation: to cluster given dataset

Question: How?



<https://www.geeksforgeeks.org/clustering-in-machine-learning/>

Answer: k-means algorithm (iterative way to **partition** dataset)

Approach: unsupervised machine learning (no training phase)

k-means (Theory)

Data: has d dimensions

Distance Measurement: euclidian

Nature of algorithm: greedy

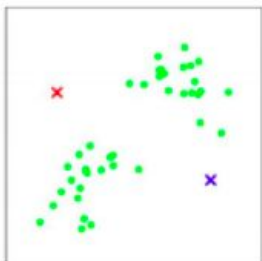
Pseudocode (k-means)

- (1) specify #clusters k
- (2) randomly pick k data points as centroids
- (3) **repeat**
- (4) **[assignment]** **for each** data point dp : assign dp to closest centroid
- (5) **[relocation]** **for each** cluster c : update c 's mean
- (6) **until** centroids do not change

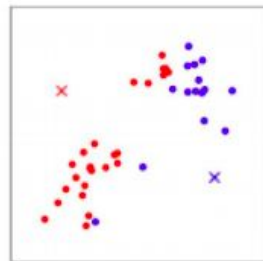
k-means – Example 1



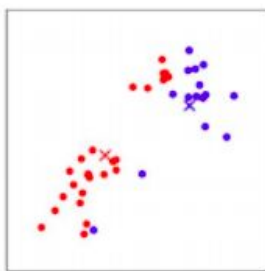
(a)



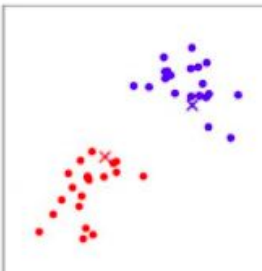
(b)



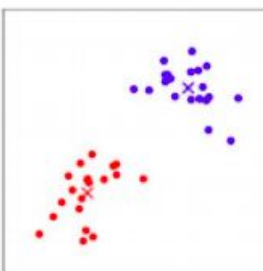
(c)



(d)



(e)



(f)

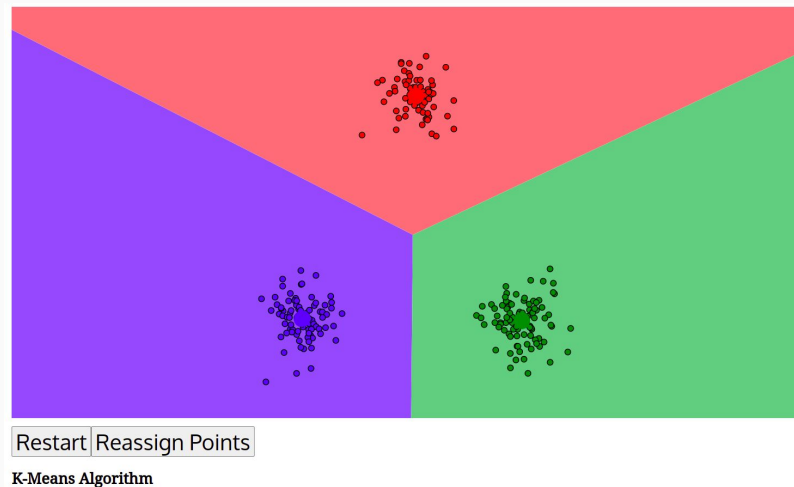
Pseudocode (k-means)

- (1) specify #clusters k
- (2) randomly pick k data points as centroids
→ (b)
- (3) **repeat**
 - (4) **[assignment]** for each data point dp : assign dp to closest centroid
→ (c), (e)
 - (5) **[relocation]** for each cluster c : update c 's mean
→ (d), (f)
- (6) **until** centroids do not change

k-means – Example 2 (interactive)

Experiment:

1. <https://www.naftaliharris.com/blog/visualizing-k-means-clustering/>
2. Press “*I’ll Choose*”
3. Press “*Gaussian Mixture*”
4. Try different starting points & different k
 - $k=6$, 2 centroids for each cluster
 - $k=6$, 4 in A, 1 in B, 1 in C
 - $k=3$
 - $k=2$
 - $k=1$ (worst cluster)

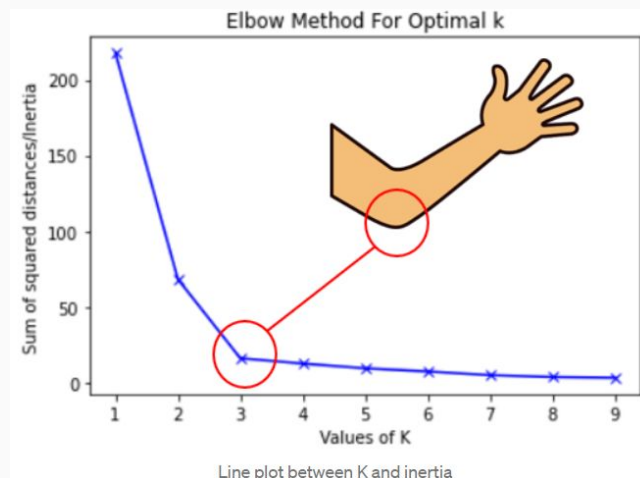


Quality

Quality measurement: within-cluster variation / within-cluster sum of squared error (WSS)

$$E = \sum_{i=1}^k \sum_{x \in \text{cluster } C_i} \text{dist}(x, \text{centroid of } C_i)$$

Elbow plot: plot WSS for different k



<https://www.analyticsvidhya.com/blog/2021/05/k-mean-getting-the-optimal-number-of-clusters/>

Pro & Contra

Pro	Contra
easy implementation	sensitive against outliers → preprocess data → use k-medoids algorithm
adapts to new data points	initial pick for centroids has impact on result → repeat algorithm
scalable (many data points)	affected from curse of dimensionality → reduce dimensions (e. g. PCA)
guaranteed convergence	not guaranteed to converge to the global optimum (often terminates at a local optimum) → repeat algorithm
runtime $O(k * n * \text{iterations})$	manually choose k → repeat algorithm & use elbow plot

Thank you!

Questions?

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