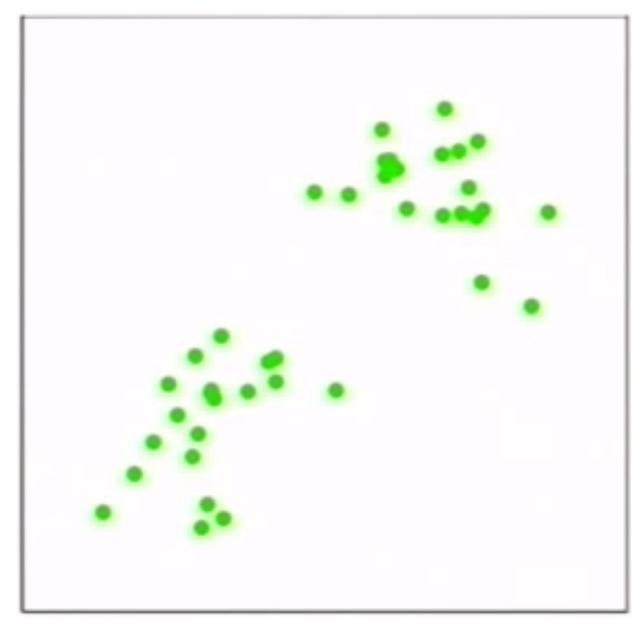
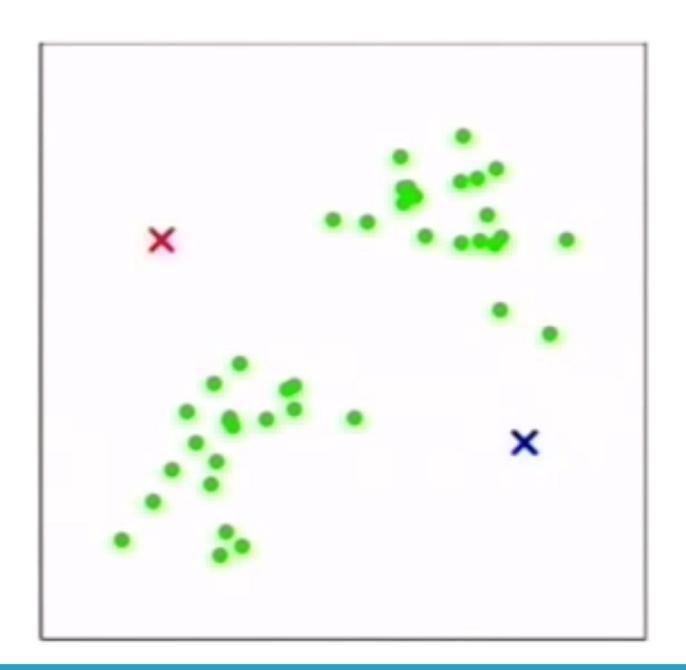
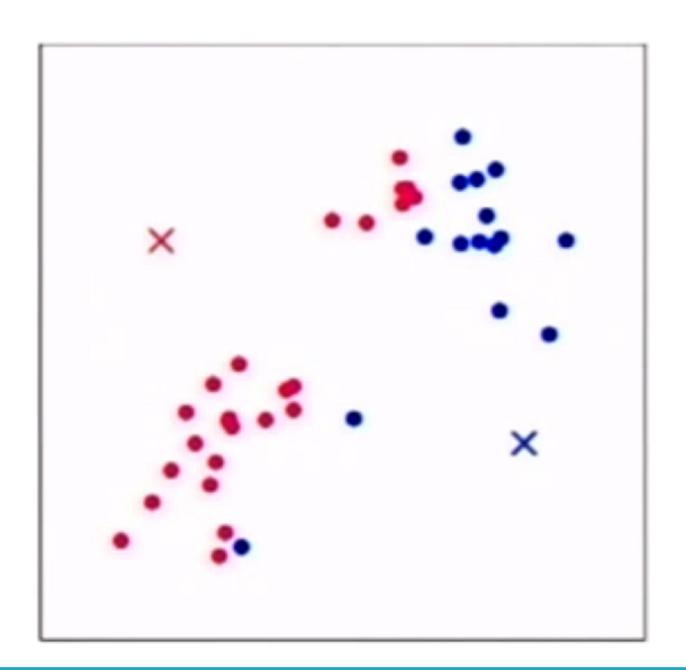
K-Means Clustering

Random Initialization (Partitioning)

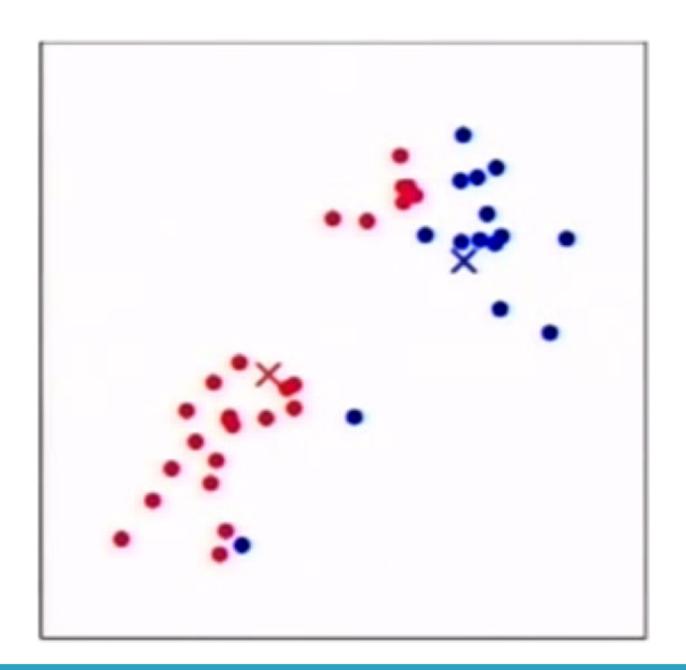


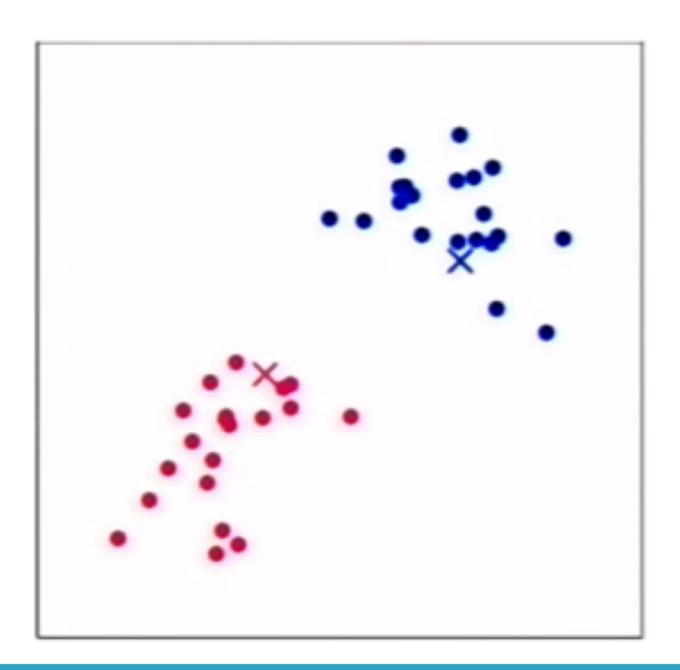
© M. Jordan

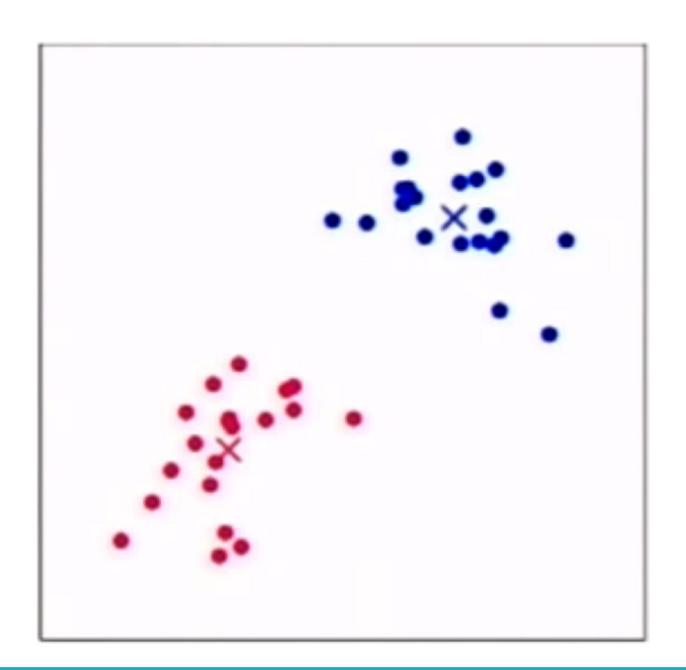




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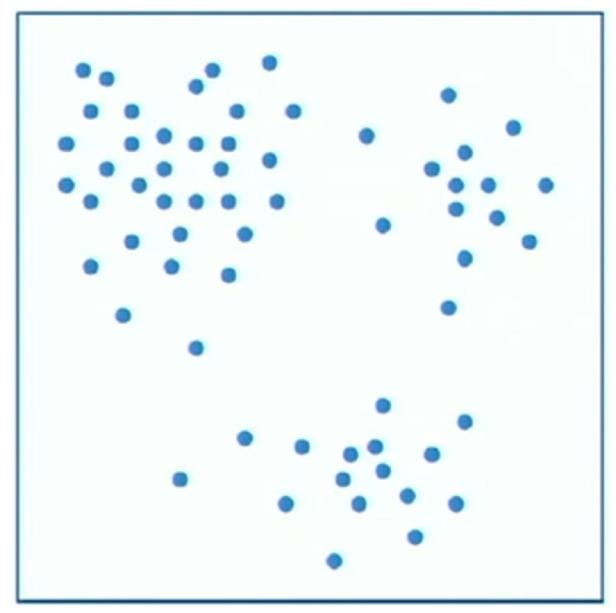




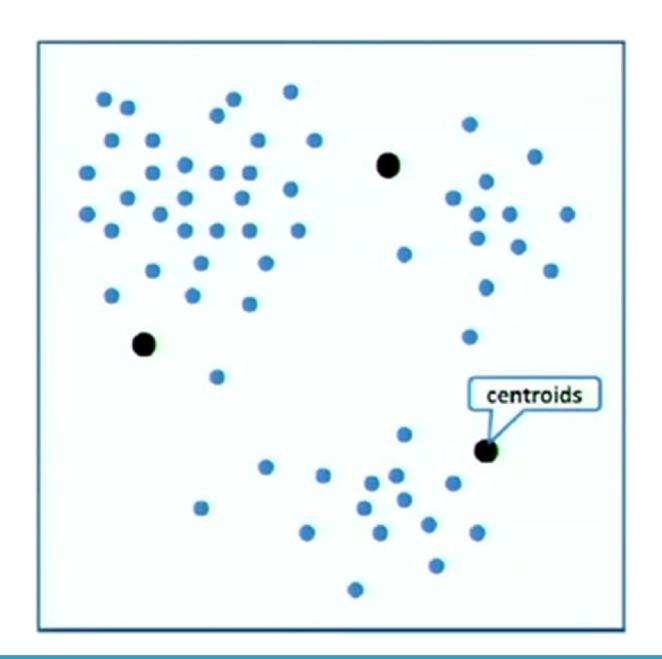


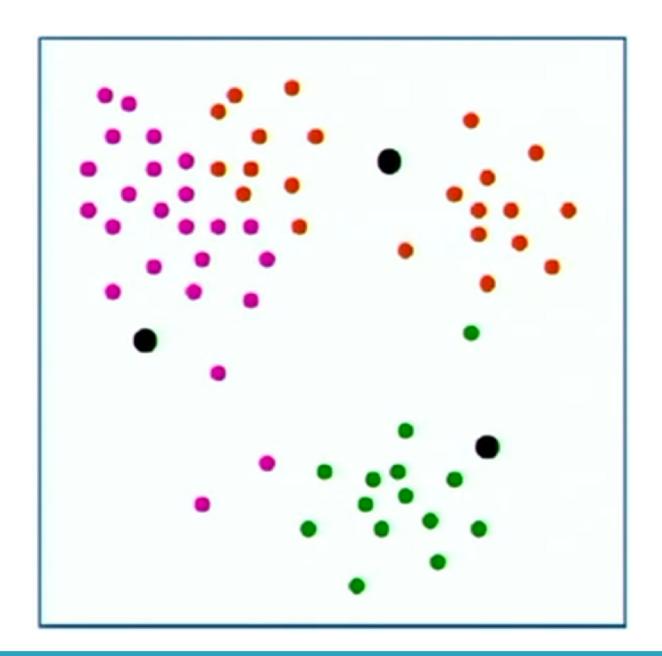
Forgy Initialization

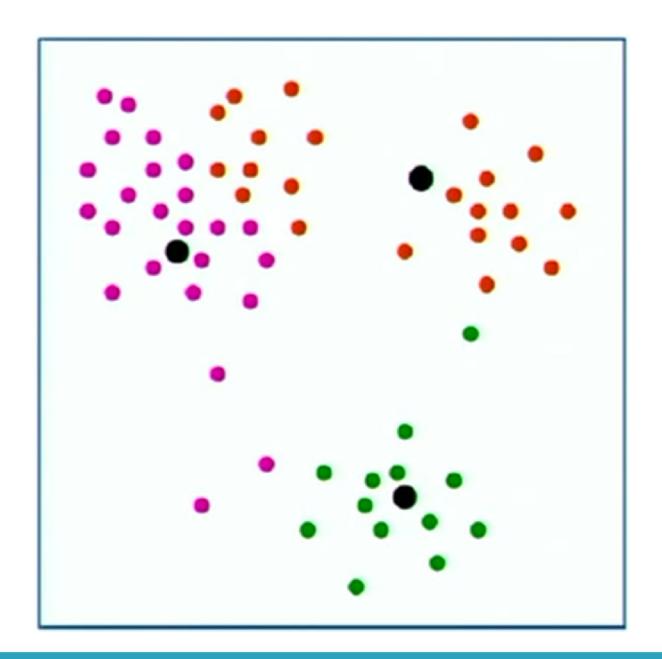
Second Example (Erroneous!)

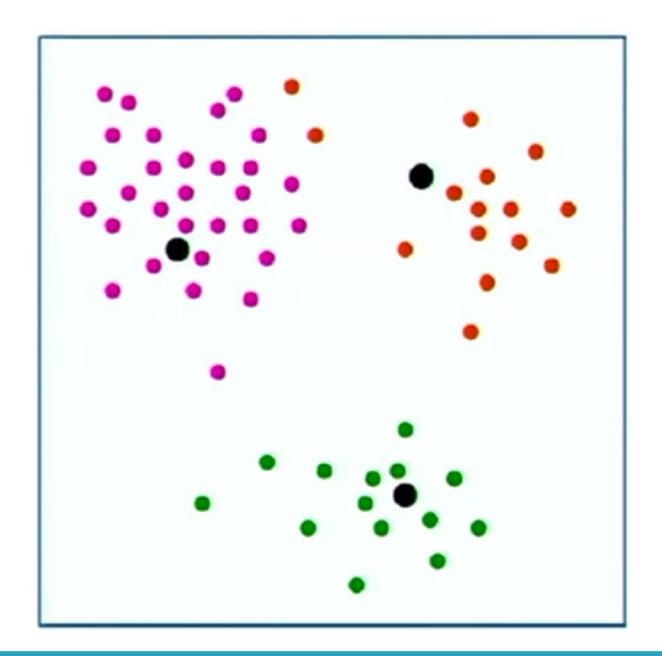


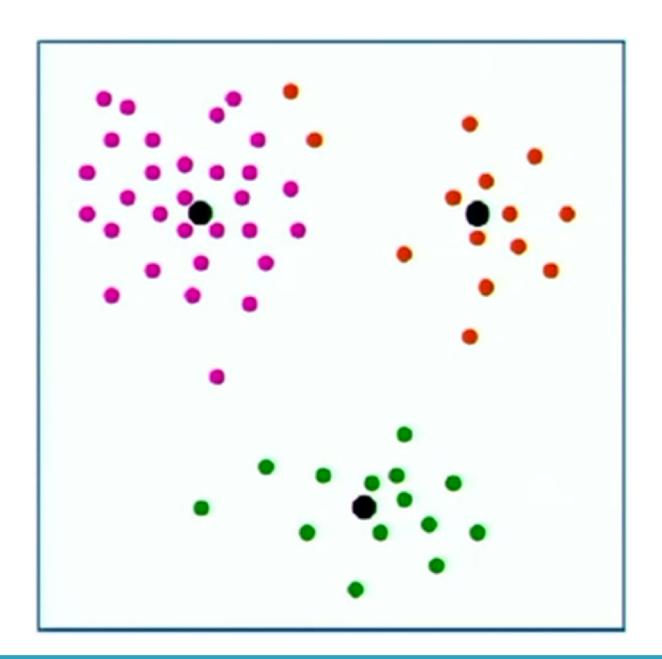
© R. Bekkerman

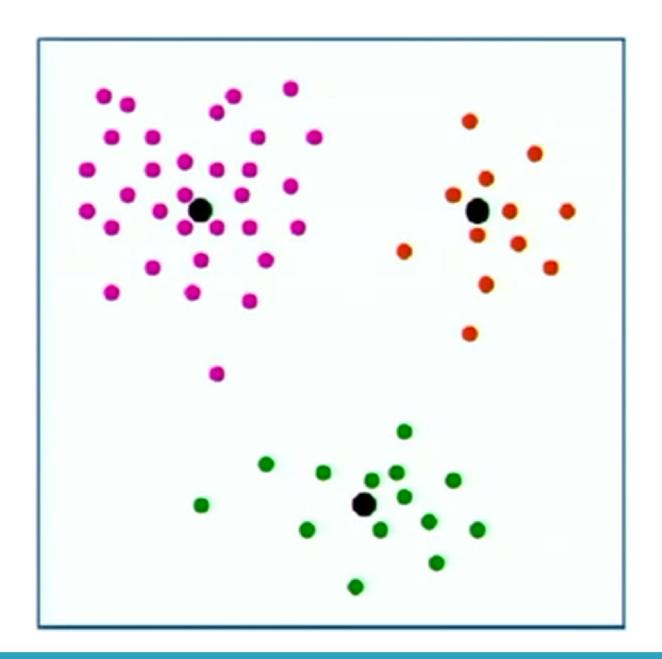


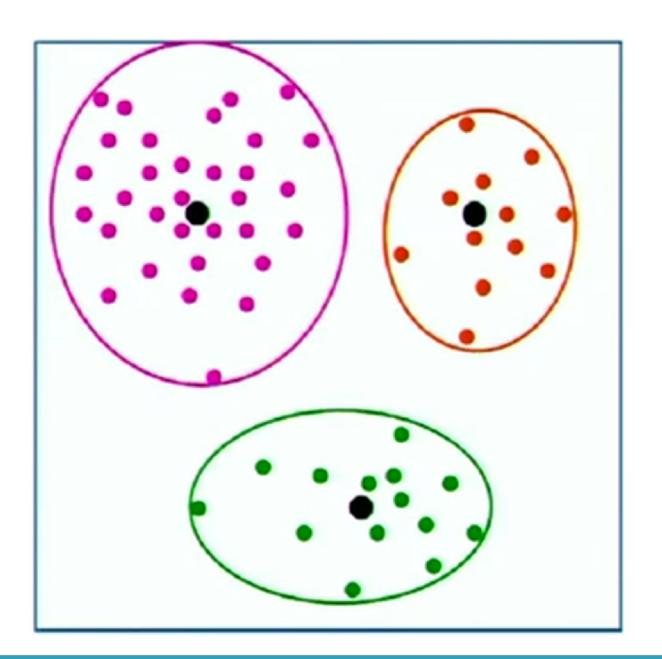




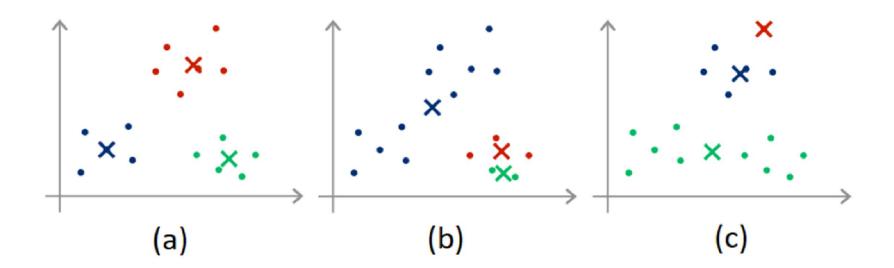






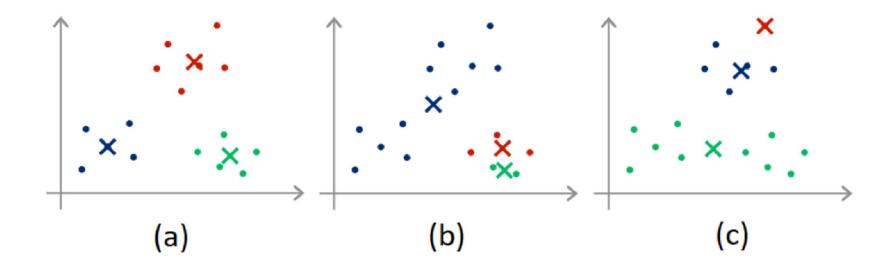


Poor initialization may lead to poor clustering



Solution?

Poor initialization may lead to poor clustering



- Solution?
 - Multiple Initializations → randomness
 - K-means++, Intelligent K-means, Genetic K-means

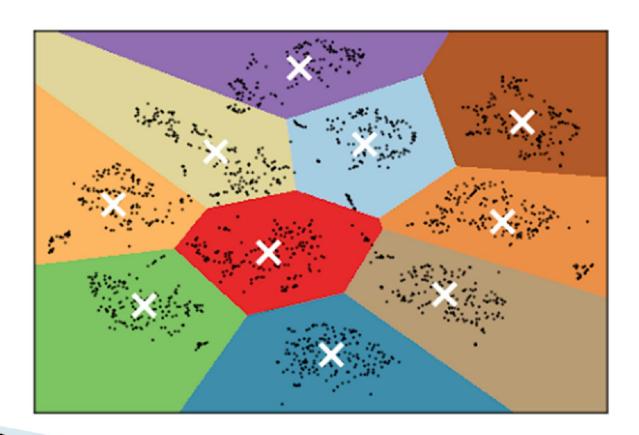
- Distance metrics
 - $oldsymbol{l}_1$ norm (Manhattan distance)
 - o *l*₂ norm (Euclidean distance)
 - Cosine similarity
- Centroids
 - Mean
 - Median
 - Medoid
 - O . . .

- Distance metrics
 - $oldsymbol{l}_1$ norm (Manhattan distance)
 - o *l*₂ norm (Euclidean distance)
 - Cosine similarity
- Centroids
 - Mean
 - Median → Outliers?
 - Medoid
 - Most commonly used on data when a mean or centroid cannot be defined, such as graphs.

K-means Properties

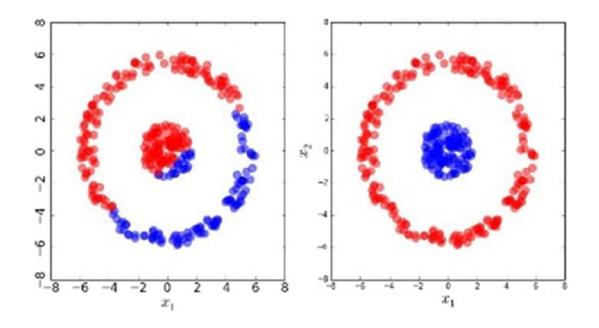
- Unsupervised
- Instance-based
- □ Time complexity: O(tkn)
- Non-parametric
- Linearly separable data

Linearly separable data



K-means Variations

■ Kernel K-means



■ Fuzzy C-means

k-means Clustering

<u>Video</u>

Sum of Square Error

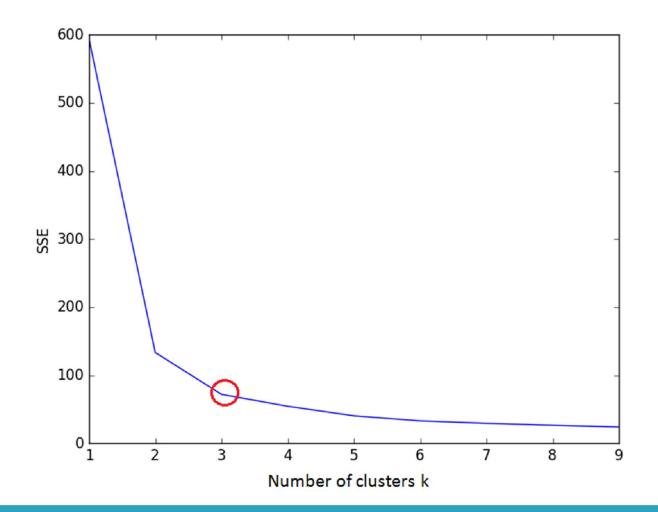
Sum of Square Error (SSE)

$$SSE = \sum_{k} \sum_{\bar{x}_i \in C_k} ||\bar{x}_i - C_k||^2$$

Goal: minimizing within-cluster distance

Optimal number of Clusters

Elbow method



Applications

- Document classification (news, ...)
- □ Sentiment analysis (customer reviews, ...)
- Anomaly detection
- Fraud detection
- Trend analysis