

K-medoids

Given samples $\mathcal{X} = \{x(1), \dots, x(N)\}$, function $dist: \mathcal{X} \times \mathcal{X} \to \mathbb{R}^+$ and monotonic energy function $\psi: \mathbb{R}^+ \to \mathbb{R}^+$, find $\mathcal{C} \subset \{1, \dots, N\}$ where $|\mathcal{C}| = K$ to minimize

$$E = \sum_{i=1}^{N} \min_{i' \in \mathcal{C}} \psi(dist(x(i), x(i'))).$$

Applications for clustering sequences, graph vertices, sparse and dense vectors, etc. Two popular algorithms are,

- MEDLLOYD ((Hastie et al. (2001), Park and Jun (2009)): like Lloyd's algorithm, but centroids are replaced by medoids
- CLARANS (Ng and Han (1994)): random swaps between centers and non-centers are proposed, and only accepted if $E(\mathcal{C})$ decreases.

K-means and K-means seeding

The K-means task is to find K centers, $\{c(1), \ldots, c(K)\}$, not necessarily elements of $\{x(1), \ldots, x(N)\}$, to minimize

$$E = \sum_{i=1}^{N} \min_{k \in \{1, \dots, K\}} \|x(i) - c(k)\|_{2}^{2}.$$
 (1)

Centers for the popular *Lloyd's* algorithm (a.k.a. the K-means algorithm) are commonly initialized or *seeded* as a subset of \mathcal{X} . Good seeding is critical for to avoid poor local minima.

Case (B) has lower seeding *and* final E. Most seeding algorithms attempt to minimize initial energy (k-means++, Bradley-Fayad, etc.). Minimizing seeding energy is the special case of K-medoids with

$$dist(x(i), x(i')) = ||x(i) - x(i')||_2$$
 and $\psi(v) = v^2$,

which motivates the use of popular and established K-medoids algorithms for K-means seeding.

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K-medoids for K-means seeding

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The CLARANS K-medoids algorithm

The algorithm iteratively proposed swapping a medoid $(x(i_{-}))$ with a non-medoid $(x(i_{+}))$. Energy reducing swaps are implemented.

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1: Initialize center indices \mathcal{C} \subset \{1, \ldots, N\}, where |\mathcal{C}| = K

2: E \leftarrow \sum_{i=1}^{N} \min_{i' \in \mathcal{C}} \psi(dist(x(i), x(i')))

3: while stopping criterion false do

4: sample i_- \in \mathcal{C} and i_+ \in \{1, \ldots, N\} \setminus \mathcal{C}

5: E^+ \leftarrow \sum_{i=1}^{N} \min_{i' \in \mathcal{C} \setminus \{i_-\} \cup \{i_+\}} \psi(dist(x(i), x(i')))

6: if E^+ < E then

7: \mathcal{C} \leftarrow \mathcal{C} \setminus \{i_-\} \cup \{i_+\}

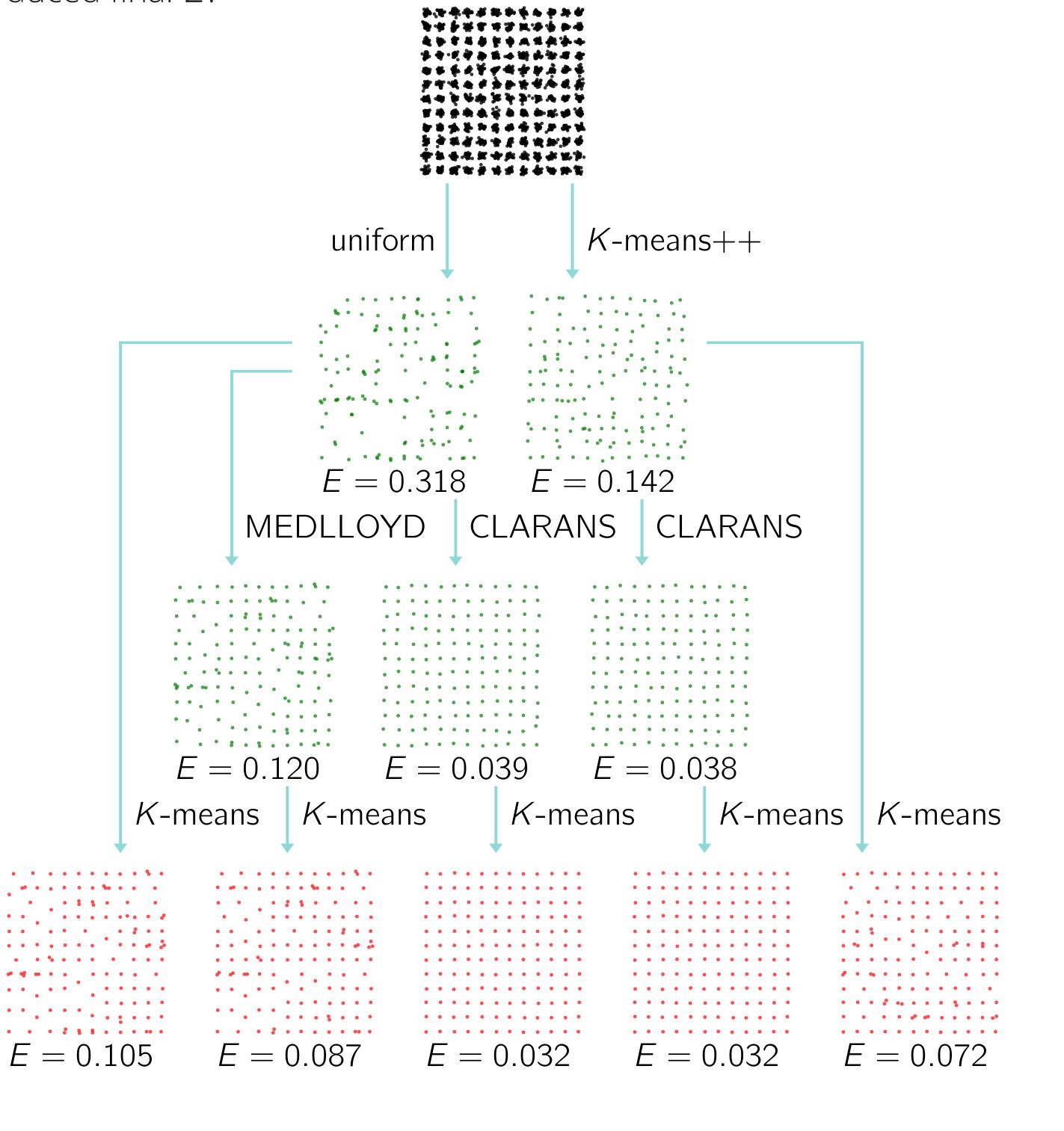
8: E \leftarrow E^+

9: end if

10: end while
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Five routes to *K*-means local minima

(Below) Clustering with $K=12^2$ centers on a 2-d grid, K=N/25. First row, the generated samples. Second row, uniform and K-means++ seedings. Third row, K-medoids refinements. Fourth row, final K-means clusterings. CLARANS refinement results in reduced final E.



Accelerating the CLARANS algorithm

There are many more *evaluations* (line 5) than actual *implementations*. Assuming balanced clusters, unoptimised evaluation complexity is O(N). When *dist* satisfies the triangle inequality, we present a technique with evaluation complexity O(K), implementation complexity O(N). It requires recording,

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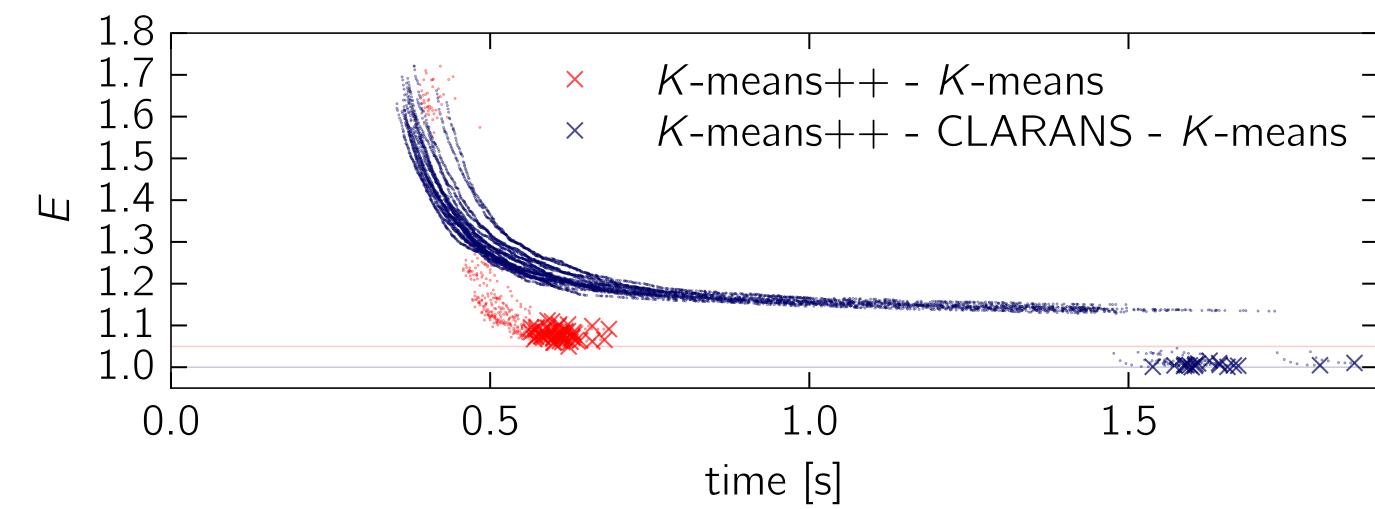
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- for non-centers (such as x(1) below), distance to nearest (d_1) and second nearest (d_2) centers
- for centers (such as x(2)), maximum over cluster of d_1 and d_2 (R_1 and R_2 respectively), and distances to all centers.

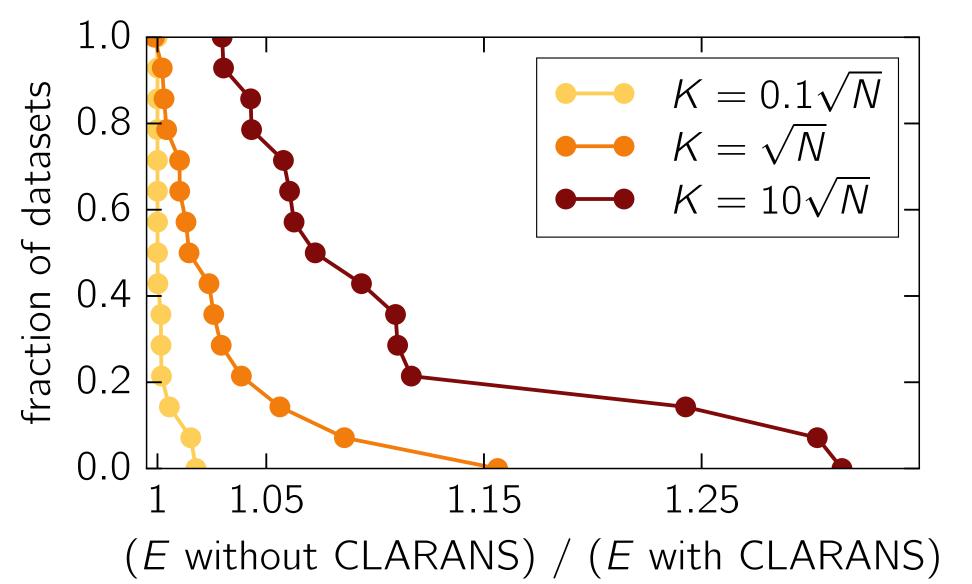


Results

(Below) An experiment with an RNA dataset, $N = 16 \times 10^4$, d = 8 and $K = 4 \times 10^2$. With 50 runs seeded with K-means++ (red), and several runs with CLARANS between K-means and K-means++ (blue). The best run without CLARANS has 5% higher E.



(Below) Summary of experiments on 16 publicly available datasets. Each point is an experiment with same setup as for RNA above, horizontal position is reduction in E obtained using CLARANS. Datasets have dimensions $d: 2 \rightarrow 90$, $N: 1484 \rightarrow 488565$.





code on github