Multi-Swap K-means++

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K-means

Input: $x_1, x_2, ..., x_n \in \mathbb{R}^d$ Output: $c_1, c_2, ..., c_k \in \mathbb{R}^d$

that minimize

$$\sum_{i=1}^{n} \min_{j=1...k} ||x_i - c_j||_2^2$$





K-means

Output: $c_1, c_2, \ldots, c_k \in \mathbb{R}^d$ that minimize N $\sum_{j=1}^{n} \min_{j=1...k} ||x_i - c_j||_2^2$



0 0



K-means

Output: $c_1, c_2, ..., c_k \in \mathbb{R}^d$ that minimize $\sum_{i=1}^{n} \min_{j=1...k} ||x_i - c_j||_2^2$

Lloyd's Algorithm

maintain $c_1 \dots c_k$ and alternate between

1) $C_j \leftarrow \{x_i \text{ captured by } c_j\}$ for each j

2) $c_j \leftarrow mean(C_j)$ for each j



0



Seeding Strategy For $j = 1 \dots k$:

Sample x_i proportionally to $\min_{\ell < j} ||x_i - c_{\ell}||_2^2$





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Set $c_j \leftarrow x_i$

Lloyd's Algorithm Only improves current solution. **K-means++ seeding** $O(\log k)$ -approximation!





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Single-Swap KM++ Repeat $\tilde{O}(k)$ times: Sample 1 more center c_{k+1} Swap-out the least useful c_j

C-approximation! ($C \approx 500$)





Multi-Swap K-means++ [this work]

Lloyd's Algorithm Only improves current solution. Single-Swap K-means++ C-approximation! ($C \approx 500$)

Multi-Swap KM++ Repeat poly(k) times: Sample p more centers $c_{k+1}...c_{k+p}$ Swap-out the least useful $c_{j_1}...c_{j_p}$

9-approximation!





Our Theorems

Multi-Swap K-means++ $(9 + \varepsilon)$ -approx in time $nd \cdot poly(k)$. A practical 10.5-approx in time $nd \cdot poly(k)$.



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A Tight Result for Local Search [KMNPSW SoCG 02] proved that 9-approx is tight for local search.

Our Experiments

Multi-Swap K-means++ seeding

1.10 -1.05 1.00 0.95 · KM++ MSLS-G-p=1, 0.12 s Cost 0.90 MSLS-G-p=4, 0.23 s MSLS-G-p=7, 0.32 s 0.85 MSLS-G-p=10, 0.43 s 0.80 · 0.75 -0.70 -10 20 30 40 50 0 LS Iterations

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Seeding + Lloyd's postprocessing



