

# Seeding Strategies for Lloyd's kmeans

C++ implementation of Ostrovsky, Rabani, Schulman and  
Swamy's ideas

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# Overview

Five approaches to seed Lloyd's k-means

- ▶ A: Random Sampling
- ▶ B: Greedy Deletion
- ▶ C: Linear time algorithm
- ▶ D: Linear time constant factor algorithm
- ▶ E: Polynomial Time Approximation Scheme (PTAS)

# A: Random Sampling

$O(knd)$

1. Select two random points  $c_1$  and  $c_2$  with probability  $\|c_1 - c_2\|^2$
2. Perform a ball-k-means step
3. Repeat: add another point  $c_{i+1}$  with probability  $\min_{j \in \{1 \dots i\}} \|c_{i+1} - c_j\|^2$

## A: Random Sampling

lloyd\_SampleKSeeder 6\_init.svg - 220706

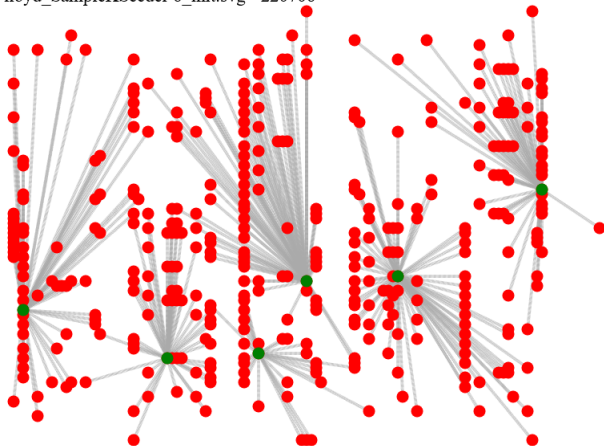


Figure: SVG-Output of SamplekSeeder on pbl395.tsp ( $k=6$ )

## B: Greedy Deletion

```
1 Pointset GreedyDelSeeder::seed(Pointset init) const {
2     Pointset sites = init;
3     while (sites.size() > (unsigned int) k) {
4
5         // B1: get best and second best center for each
6         // customer
7         Partition part = Partition(&customers, sites);
8
9         // B2: pick the center for which Tx is minimum
10        int bestid = part.getMinTx();
11
12        // B3: delete chosen partition and move points to
13        // centroid of voronoi region
14        part.delete_set_from_partition(bestid);
15        sites = part.centroids();
16    }
17    return sites;
18 }
```

## B: Greedy Deletion

Running time: outer loop  $(n - k)$  iterations  $\Rightarrow O(n)$

Partitioning:  $O(n^2 d)$

No speed loss for second best

$\Rightarrow$  together:  $O(n^3 d)$

## C: Linear time algorithm

```
1 Pointset LTSeeder::seed() const {
2
3     //C1
4     double e = instance.eps();
5     double p1 = sqrt(e);
6     int N = (int)(2 * k / (1 - 5 * p1) + 2 * log(2 / p1)
7         / pow((1 - 5 * p1), 2));
8
9     SampleKSeeder samplekseeder(instance, N);
10    Pointset S = samplekseeder.seed();
11
12    //C2
13    Partition partition = Partition(&customers, S);
14    Pointset sdach = partition.centroids();
15
16    GreedyDelSeeder greedydelseeder(instance, k);
17
18    return greedydelseeder.seed(sdach);
19 }
```

## C: Linear time algorithm

$$O(nkd + k^3d)$$

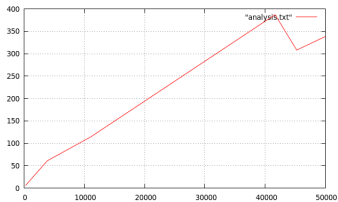


Figure: complexity in #customers

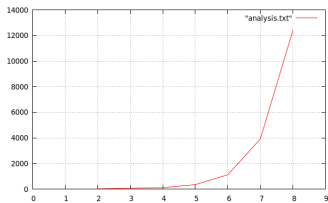


Figure: complexity in #sites



## D: Linear time constant factor algorithm

```
1 Pointset DSeeder::seed() const {  
2     // D1 (obtain k initial centres using last seeding  
3     strategy)  
4     Pointset init = (LTSeeder(instance, k)).seed();  
5     // D2 (run a ball-k-means step)  
6     return ballkmeansstep(init);  
7 }
```

## D: Linear time algorithm

lloyd\_DSeeder\_final6.svg - 97949.3

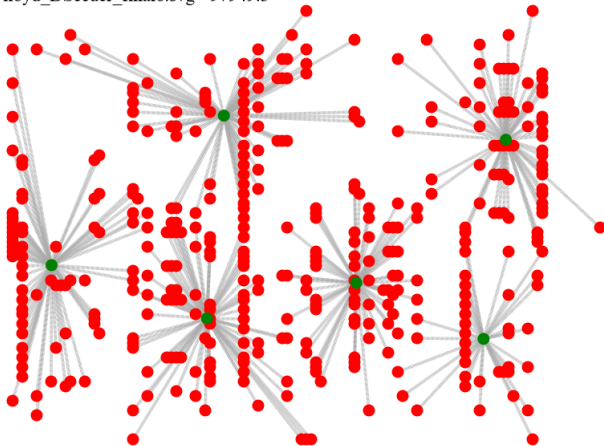


Figure: SVG-Output of DSeeder on pbl395.tsp ( $k=6$ )

## E: Polynomial Time Approximation Scheme (PTAS)

```
1 Pointset ESeeder::seed() const {  
2     SampleKSeeder samplek(instance, k);  
3     Partition part = Partition(&customers, samplek.seed()  
4         );  
5     return part.centroid_estimation(instance.omega,  
6         instance.eps);  
7 }
```

## centroid estimation

```
1 for s in sites:
2     select expanded Voronoi region V[s]
3     choose a random subset R[s] of V[s]
4     foreach subset A of size 1/wb:
5         T[s] = T[s], centroid(A)
6 foreach set B in  $\{\{x_1, \dots, x_k\} : x_i \text{ in } T[i]\}$ :
7     if error(B) < error (best) then best = B
```

# PTAS analysis

Ostrovski et al:

error at most  $(1 + \omega) * OPT$  with probability  $\gamma^k$   
(for some constant  $\gamma$ )

## E: PTAS

$$O(2^{\frac{4k}{\beta\omega}} n * d)$$

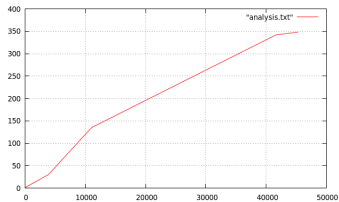


Figure: complexity in #customers

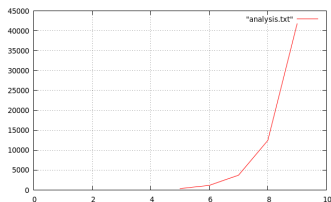


Figure: complexity in #sites