k-median Clustering

TOP: Data Clustering 076/091

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Outline

1 Introduction

2 A Local Search Algorithm

A Robust Estimator

- *k*-center is very sensitive to outliers
- A quantity that is robust/not very sensitive: median
- Need to corrupt several data points to significantly change the median

A Robust Estimator

- *k*-center is very sensitive to outliers
- A quantity that is robust/not very sensitive: median
- Need to corrupt several data points to significantly change the median
- Hard to define in higher dimension
- Generalize another definition of the median

Another definition of median

Given a set X of numbers, median m minimizes the total/average distance

$$\sum_{p \in X} ||p - c||$$

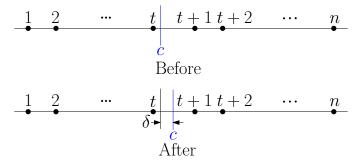
over all $c \in \mathbb{R}$.

Another definition of median

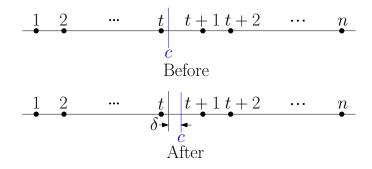
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$$\sum_{p \in X} ||p - c||$$

over all $c \in \mathbb{R}$.



Change in cost



- Change is $t \cdot \delta (n t)\delta = (2t n)\delta$
- It is -ve as long as t < n/2
- It is 0 if n/2 points on both sides of c

k-median Clustering

Given a set X of n points in the metric space (\mathcal{U} , d)

■ Find a set C of k points (cluster centers) in \mathcal{U} that minimizes,

$$cost(C) = \sum_{p} d(p, NearestCenter(p))$$

The centers in *C* are called medoids.

Discrete *k*-median Clustering

Given a set X of n points in the metric space (X, d)

■ Find a set *C* of *k* points (cluster centers) in *X* that minimizes,

$$cost(C) = \sum_{p} d(p, NearestCenter(p))$$

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An Algorithm for *k*-median (Arya et al. 2001)

Algorithm Local Search

```
Require: Set of points X
 1: Start with medoids M = \{m_1, \dots, m_k\} chosen arbitrarily
    from X
 2: repeat
        change \leftarrow false
 3.
 4:
        for x \in X \setminus M, m \in M do
 5.
             M' \leftarrow (M \setminus \{m\}) \cup \{x\}
             if cost(M') < cost(M) then
 6.
                 M \leftarrow M', change \leftarrow true, Break.
 7:
             end if
 8.
        end for
 g.
10: until change is false
11: return M
```

Time Complexity of Local Search

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■ Neighborhood size is O(nk): cost computation O(nk); Total $O(n^2k^2)$

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- Neighborhood size is O(nk): cost computation O(nk); Total $O(n^2k^2)$
- Complexity depends on the repeat-until loop: rate of cost decrement

Changing the cost checking condition

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 5.
             if cost(M') < cost(M)/2 then
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             end if
         end for
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```

- Overall ℓ iterations: sets of medoids $M_1, M_2, \ldots, M_{\ell}$
- Exponential Decrease: $cost(M_{\ell}) < cost(M_{\ell-1})/2 < cost(M_{\ell-2})/2^2 < \ldots < cost(M_1)/2^{\ell-1}$

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- $= cost(M_{\ell}) \ge OPT$
- If $Cost(M_1) \le n \cdot OPT$, $\ell = O(\log_2 n)$
- Complexity is $O(n^2k^2 \log n)$

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- k-median-cost(C) $\leq n \cdot 2 \cdot \text{OPT-}k$ -center cost (pay $2 \cdot \text{OPT-}k$ -center n times)

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- k-median-cost(C) $\leq n \cdot 2 \cdot \text{OPT-}k$ -center cost (pay $2 \cdot \text{OPT-}k$ -center n times)
- Then, by Ineq (1), k-median-cost(C) $\leq n \cdot 2 \cdot \text{OPT-}k$ -median cost

Analysis of Local Search

■ What is the approximation factor?

Analysis of Local Search

- What is the approximation factor? 5
- If we swap 2 medoids, 4-approximation
- If we swap p medoids, (3 + 2/p)-approximation
- But, time complexity $O(n^{p+1}k^{p+1}\log n)$
- The analyses are beyond the scope