

Efficient Online Learning for Dynamic k -Clustering

Dimitris Fotakis, National Technical University of Athens

Georgios Piliouras, Singapore University of Technology and Design

Stratis Skoulakis, Singapore University of Technology and Design

ICML 2021

k -Clustering Problems

Clustering problems

Open k centers minimizing the distance from n clients.

- n clients on a metric space $d : V \times V \mapsto \mathbb{R}$.
- Open k centers, $F \subseteq V$ with $|F| = k$.
- Each client connects to the closest center, $d(i, F) = \min_{j \in F} d_{ij}$,

$$\text{minimize } \underbrace{\left(\sum_{i=1}^n d^p(i, F) \right)^{1/p}}_{\text{the } p\text{-norm of distances}} \quad \text{where } p \geq 1$$

Extensively studied for various p -values.

- k -median for $p = 1$.
- k -means for $p = 2$.
- k -center for $p = \infty$.

Clustering problems

Open k centers minimizing the distance from n clients.

- n clients on a metric space $d : V \times V \mapsto \mathbb{R}$.
- Open k centers, $F \subseteq V$ with $|F| = k$.
- Each client connects to the closest center, $d(i, F) = \min_{j \in F} d_{ij}$,

$$\text{minimize } \underbrace{\left(\sum_{i=1}^n d^p(i, F) \right)^{1/p}}_{\text{the } p\text{-norm of clients' distances}} \quad \text{where } p \geq 1$$

Many efficient approximation algorithms.

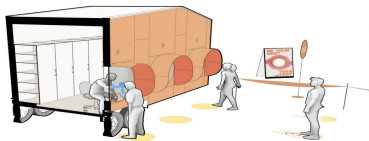
k -Clustering under Uncertainty

In most practical settings, the positions of the clients are unknown,

- clients are located according to some unknown probability distribution.
- clients change positions over time.

example

Locate the k Covid-Test Units over a city.



k -Clustering under Uncertainty

In most practical settings, the positions of the clients are unknown,

- clients are located according to some unknown probability distribution.
- clients change positions over time.

Place k -centers in such agnostic settings??

We can cast **k -Clustering** as Online Learning Problem.

k -Clustering as Online Learning Problem

A learner selects the positions of the centers and an adversary selects the positions of the clients.

At each round $t \geq 1$,

1. The learner chooses the positions of the centers, $F_t \subseteq V$ with $|F_t| = k$.
2. The adversary selects the positions of the clients, denoted as R_t .
3. The learner suffers the connection cost of the clients,

$$C(R_t, F_t) = \left(\sum_{i \in R_t} d^p(i, F_t) \right)^{1/p}$$

where $d(i, F_t) = \min_{j \in F_t} d_{ij}$.

Online Learning Algorithm

Takes as input the past positions of the clients R_1, \dots, R_{t-1} and outputs the positions of the centers at round t (denoted as F_t).

Goal of Learner:

Select the centers according to an Online Learning Algorithm minimizing connection cost.

- If the learner uses the Multiplicative Weight Update algorithm then

Overall Connection Cost \sim Optimal Cost!!

- If the learner uses the **Multiplicative Weight Update algorithm** then

$$\underbrace{\sum_{t=1}^T C(R_t, F_t)}_{\text{the overall connection cost}} \leq \underbrace{\min_{F^*} \sum_{t=1}^T C(R_t, F^*)}_{\text{the optimal connection cost}} + O(\sqrt{T})$$

- **MWU needs $\Theta(|V|^k)$ time and space!! (Highly Inefficient)**

Can we achieve similar performance guarantees in polynomial-time?

Our Results

- We design a polynomial-time online learning algorithm $\text{poly}(|V|, k)$ such that

$$\sum_{t=1}^T C(R_t, F_t) \leq \rho \cdot \sum_{t=1}^T C(R_t, F^*) + O(\sqrt{T})$$

for $\rho = \min(k, \# \text{clients per round})$.

- constant ρ (independent from $k, \# \text{clients per round}$) cannot be achieved with polynomial-time online learning algorithms.

Thanks You :)