Optimal Citizen-Centric Sensor Placement for Air-Quality Control

Relevant Algorithms

Why?

Generally, the measurements can be obtained either through low-cost mobile wireless sensors or fixed-location sensors with sophisticated measurement equipment. In this study, we focus on deployment strategies for **fixed-location sensors as measurements of such are more accurate and reliable.**

- Reference [7] proposed a near optimal sensor placement strategy for temperature monitoring by maximizing mutual information under size constraint
- Reference [9] studied the wind monitoring problem

all the studies mentioned above aim to place sensors or stations at the most informative locations defined either in terms of entropy or mutual information. **By modeling each location as a random variable, the proposed approach would require the covariance between any two random variables, usually through a strong Gaussian Process assumption on the underlying field and more importantly requires a pilot study to obtain the field information, which is impractical due to complex procedures and high costs.**

- **Can’t use totally citizen centric approach**, on the basis of previous studies it is observed that when the individual satisfaction is an exponential decay function of his/her distance to the nearest sensor, the objective function has the nice monotone and submodular property that
allows greedy algorithms to solve the problem efficiently with provable approximation guarantee

- **Two other citizen-centric objectives**
    1. Better protecting the vulnerable people
    2. Better monitoring traffic emissions to assess if ambient air quality standards have been met.

> 💡 So, finally our study **follows 3 citizen-centric objectives**:
> 1. Better assessing the vulnerable people’s exposure to air pollution
> 2. Maximizing overall satisfaction in air quality information available to the public
> 3. Better monitoring traffic emissions in order to assess if air quality objectives or ambient regulatory standards have been met

▼ Section II: BACKGROUND

Monotonicity

In simpler terms, the monotonicity property implies that adding an element to a set cannot decrease the value of the function. The function should either stay the same or increase when new elements are added

▼ explained a little more

Monotonicity is a desirable property in optimization problems. When optimizing a function over a set of variables, the monotonicity property ensures that adding new variables or increasing the values of existing variables will not decrease the objective function's value. This property simplifies the search for optimal solutions and allows for the use of efficient algorithms.

the monotonicity property provides a useful criterion for ensuring consistency and predictability in various mathematical and real-world contexts. It helps establish relationships between sets and their associated values, leading to valuable insights and facilitating the development of efficient algorithms and models.

Submodularity

Intuitively, submodularity implies that the incremental gain obtained by adding an element to a smaller set is greater than or equal to the incremental gain obtained by adding the same element to a larger set.

▼ application

1. Optimization: Submodularity is widely used in optimization problems, particularly in combinatorial optimization. Many problems, such as facility location, network design, sensor placement, and information gathering, can be formulated as submodular optimization problems. The submodular structure allows for the development of efficient algorithms to find near-optimal solutions.

2. Greedy algorithms: The submodularity property enables the design of efficient greedy algorithms for submodular maximization problems. Greedy algorithms iteratively select elements that provide the most gain given the current solution. The greedy approach guarantees a provable approximation guarantee for maximizing submodular functions.

Overall, submodularity is a powerful property that captures the diminishing returns characteristic and finds applications in various fields, including optimization, machine learning, AI, game theory, and economics. Its use enables the development of efficient algorithms and provides insights into the structure and behavior of optimization problems involving set functions.

▼ Section III: CITIZEN-CENTRIC PLACEMENT OBJECTIVES

▼ A. MAXIMIZING OVERALL CITIZEN SATISFACTION

Assumption (based on other study):

satisfaction ∝ 1/distance from individual

An individual’s satisfaction of a sensor placement scheme g(d) is a function of his/her distance to the nearest sensor d. Intuitively, the closer the nearest station is, the more
people are satisfied with the resolution of the information. Hence we require the satisfaction function g(d) to satisfy the following:

• g(d) be a monotonically decreasing function, i.e., for any d1 ≤ d2, g(d1) ≥

g(d2).

- for any d ≥ 0, g(d) ≥ 0.
- g(0) = 1

Exponential Decay Function

$$g(d) = \exp(-d/\theta)$$

where θ is an exponential decay parameter controlling the decay speed. By default we can set θ = 1. A smaller θ will cause the satisfaction function to decrease more rapidly as the
distance increases.