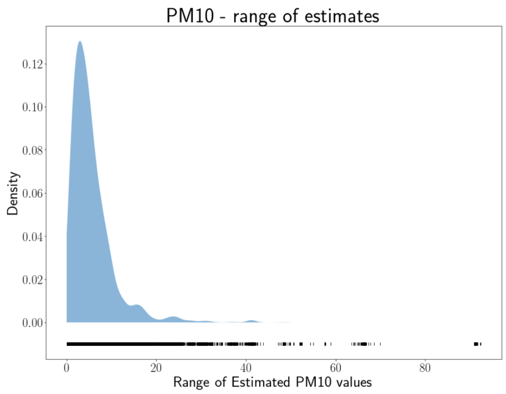
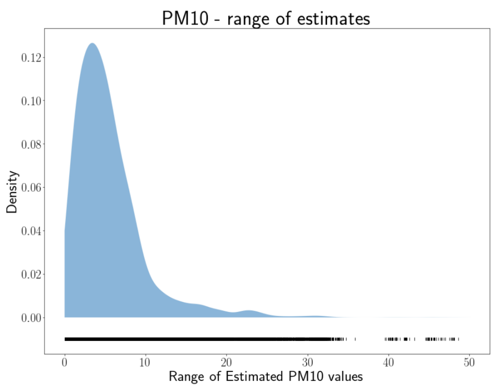
ToolkitName - A toolkit for spatial interpolation and sensor placement



(a) Range of Estimates of annual average PM10



(b) Range of Estimates of Maximum Quarterly PM10.

Figure 1: The top figure (a) above shows the ranges of estimates being positively skewed for annual average PM10. The figure (b) above shows a similar trend. The authors report that for both the above graphs, most of the range of estimates of PM10 is less than 15 $\mu gm/m^3$ with the majority less than 7 $\mu gm/m^3$. We observe similar trends and the above plots we obtain are consistent with the authors' observations.

ABSTRACT

Sensing is central to the SenSys and related communities. However, despite recent advancements, fine-grained spatial sensing remains a challenge, owing to cost, maintenance, among other factors. Thus, estimating the sensed phenomenon at unmonitored locations and strategically installing sensors is of prime importance. In this work, we introduce ToolkitName - an open source tool to lower the entry barrier for sensor deployments. ToolkitName provides a suite of algorithms for spatial interpolation and sensor placement. We replicate several existing papers on these two tasks to show the efficacy of ToolkitName. We believe that ToolkitName is an important step towards lowering entry barrier towards sensing and scientific reproducibility.

CCS CONCEPTS

• **Computing methodologies → Modeling methodologies**.

ACM Reference Format:

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1 APPENDIX

Figure 1 shows the range of estimates for PM10. We observe similar results as the authors.

Figure 2 shows interpolated empirical covariance matrix v/s NS kernel from the original paper.

Figure 3 shows the temperature and precipitation datasets over time.

Figure 4 shows deployment of 8 and 20 sensors for temperature and precipitation datasets respectively using MI and entropy.

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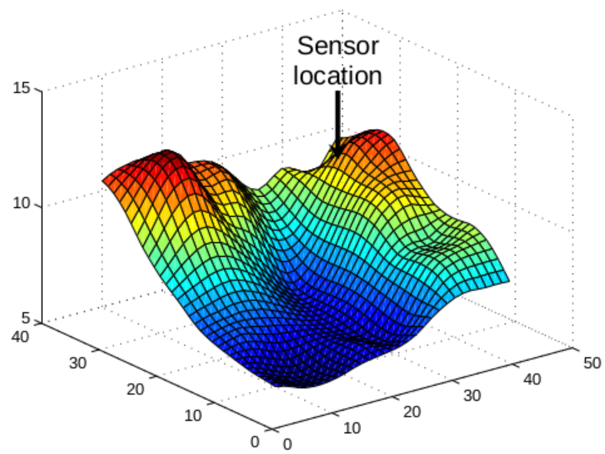
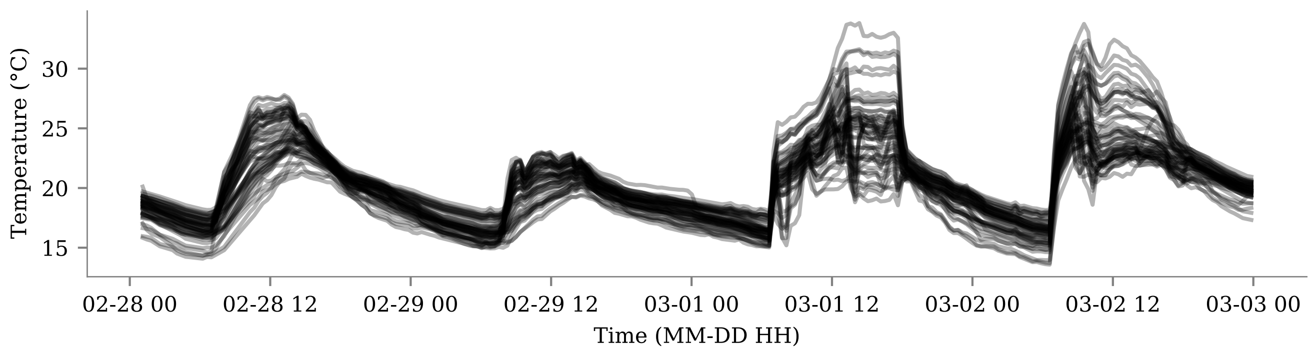
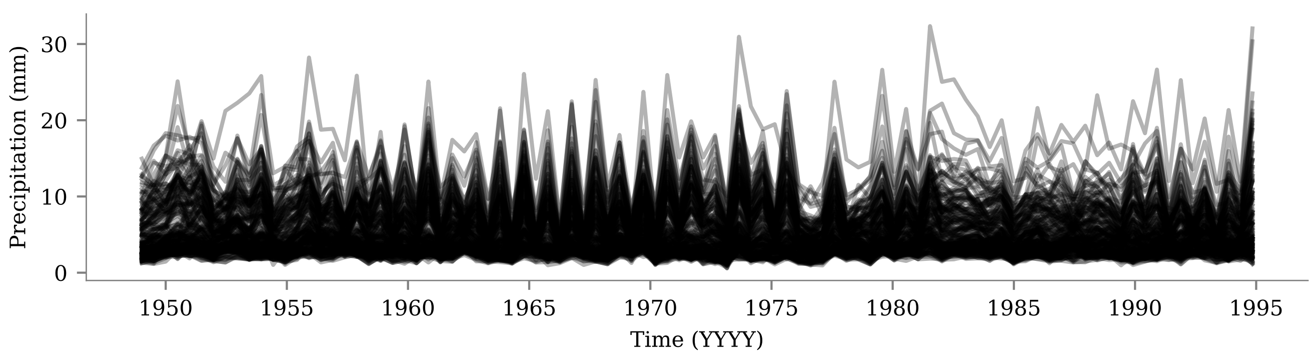


Figure 2: Example kernel function learned from the Berkeley Lab temperature data: (a) learned covariance function K (x, ·), where x is the location of sensor 41; (b) "ground truth", interpolated empirical covariance values for the same sensors. Observe the close match between predicted and measured covariances (caption is copied from the original source).

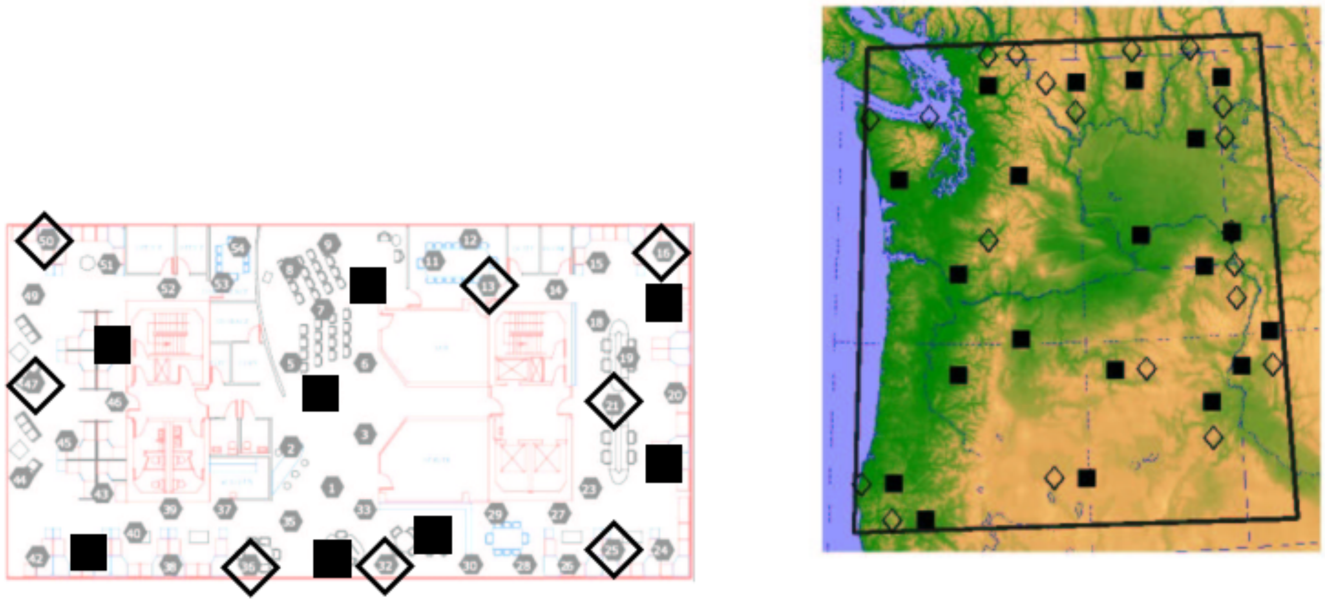


(a) Temperature



(b) Precipitation

Figure 3: Temperature and Precipitation datasets over time



(a) *Placements of temperature sensors* (b) *Placements of rain sensors*

Figure 4: Example sensor placements for temperature and precipitation data. Squares indicate locations selected by mutual information, diamonds indicate those selected by entropy. Notice how entropy places sensors closer to the border of the sensing field. (caption is copied from the original source)

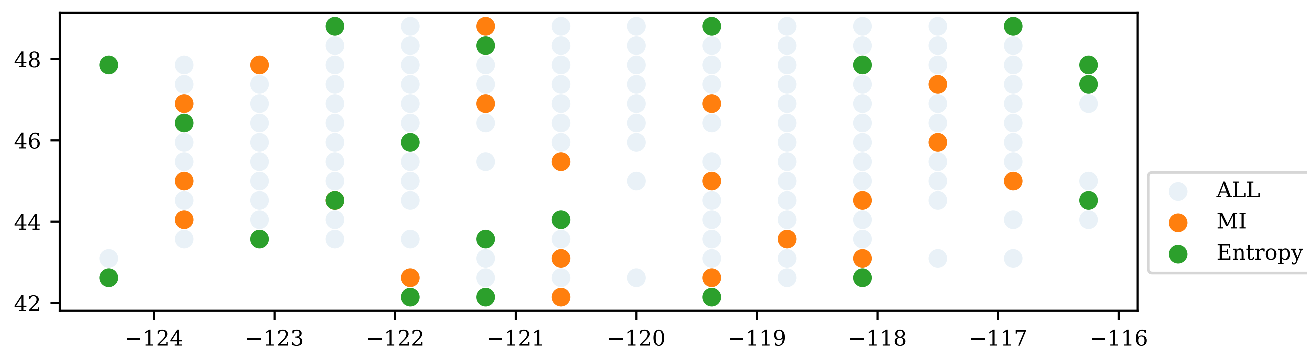


Figure 5: 20 sensors placed with Greedy algorithm using MI and entropy with precipitation dataset. Entropy has placed sensors near to the boundary. MI has placed sensors centrally.