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EDA and a Tailored Data Imputation Algorithm for Daily Ozone Concentrations (Conference Paper)

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Abstract

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Air pollution is a critical environmental problem with detrimental effects on human health that is affecting all regions in the world, especially to low-income cities, where critical levels have been reached. Air pollution has a direct role in public health, climate change, and worldwide economy. Effective actions to mitigate air pollution, e.g. research and decision making, require of the availability of high resolution observations. This has motivated the emergence of new low-cost sensor technologies, which have the potential to provide high resolution data thanks to their accessible prices. However, since low-cost sensors are built with relatively low-cost materials, they tend to be unreliable. That is, measurements from low-cost sensors are prone to errors, gaps, bias and noise. All these problems need to be solved before the data can be used to support research or decision making. In this paper, we address the problem of data imputation on a daily air pollution data set with relatively small gaps. Our main contributions are: (1) an air pollution data set composed by several air pollution concentrations including criteria gases and thirteen meteorological covariates; and (2) a custom algorithm for data imputation of daily ozone concentrations based on a trend surface and a Gaussian Process. Data Visualization techniques were extensively used along this work, as they are useful tools for understanding the multi-dimensionality of point-referenced sensor data.

SciVal Topic Prominence

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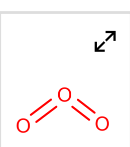

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Air pollution | Data imputation | Gaussian process | Sensor data

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Funding text #1

The Air Data project from the U.S. Environmental Protection Agency (EPA) collects air quality and weather measurements from more than 4000 outdoor monitors across the United States, Puerto Rico, and the Virgin Islands [22]. The data provided cover a time period from 1980 to 2017 in hourly, daily and annual aggregation. For this study, we downloaded the pre-generated daily files for the year 20162. The available files are grouped in two categories: (1) Criteria Gases such as Ozone, Sulfur dioxide (SO2), Carbon monoxide (CO), and Nitrogen dioxide (NO2); and (2) Particulates, such as PM2.5 (particles with a diameter of 2.5 μm or less), PM10 (particles with a diameter of 10 μm or less) [22].

Funding text #2

Motivated by the general challenge of studying spatio-temporal modeling of air pollution concentrations measured from cheap sensor networks, we decided to assemble a real-life data set made up of ozone concentrations taken from the Air Data project from the U.S. Environmental Protection Agency (EPA) plus weather covariates taken from the NCEP/NCAR Reanalysis Project (NNRP). The biggest problem with this data set, was the missing values in the target variable (ozone). This problem was addressed by means of a tailored algorithm inspired by the hierarchical models. Throughout this study we extensively applied several Exploratory Data Analysis techniques and multivariate analysis to understand the data and the relationships between the features.

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