Developing a Big Data Analytic Model and a Platform for Particulate Matter Prediction: A Case Study

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Abstract

While we’ve made progress over the last century, qualities of air and drinking water are getting worse. For the health of the people, many countries recommend to wear a mask or not to go out in case of bad air quality. However, the lack of real-time measurement and poor prediction of the concentration of fine dust provide inaccurate alarm and information to residents. The real-time air quality measurement data is the big data of new field which should be complemented with the national meteorological data in order to meet the demands for the customers and public through the other relevant data. In this study we aim to build a system to predict PM (particulate matter)—microscopic dust generated by human activities, such as the burning of fossil fuels in vehicles, power plants and various industrial processes. We also develop an optimized path of sprinkler vehicles to improve air condition in a local city. The density of PM is affected by meteorological variables such as temperature, rainfall, humidity and wind speed. To predict the density of (fine) PM, we use machine learning techniques considering not only meteorological data from observatories, but spatial factors like pollutants, floating populations and traffic volumes of a certain location using LTE (Long Term Evolution) signals. We suggested a conceptual architecture of a system and illustrate a case study of preprocessing and analyzing the data gathering from a local province with results and discussions.

Keywords: Particulate matter, Big data, Prediction model, Artificial intelligence, Fine dust

1. Introduction

World Health Organization classified fine dust as the group 1 carcinogenic substance which causes a serious health risk along with direct impact on work productivity, academic performance and work efficiency. The inconvenience and the anxiety of the people due to the fine dust has been increasing, on the other hand the utilization/accumulation of the data on the air pollution regarding the fine dust and its countermeasures against the fine dust are not properly performed. The real-time measurement data about air quality is the big data of new field which should be complemented with the national meteorological data in order to meet the demands for public people and relevant industry.

The changes in the frequency of dust generation, changes in power usage patterns, outbreaks
of the disease, and the movement pattern of people can be provided valuable information not only to the private sectors such as energy companies, electronics companies, medical institutions, and insurance companies, but also to the public sectors like local governments and schools. Air quality can be increased by dispatching and re-routing watering vehicles to appropriate areas on after predicting the future air pollution.

The study is to find out the correlations between the data and various activities of the people (such as health, economic activity, productivity, work efficiency) directly and indirectly by installing the air quality measurement which can be monitored for 24/7. With combining the air quality measurement data and various data in other fields can create the new big data with high value. This project stands for proposing a new value-added service through integration and analysis of data that relates to the fine dust and its relevant behaviors. To provide the public with a guidance/guidebook by establishing a big data platform of the fine dust, and to provide administrative guidance/guidebook to the public institutions and local governments and inform the integrated service of indoor and outdoor air management.

This study is organized as follows: Section 2 reviews related works of particular matter. Section 3 suggests a research framework regarding a big data analytic system and a model for predicting particular matter. In Section 4, we cover analytic results. We discuss the results and conclude our study with future research directions in Section 5.

## 2. Related Work

The literatures in predicting the density of particulate matter have several research directions. Main directions in these studies can be classified by prediction models and type of data used as shown in Table 1.

A machine learning approach is the most popular way of predicting the concentration of PM (particulate matter). Artificial neural network (ANN) is a common technique to represent features of forecasting the density of PM [1][10].

The second popular approach is a statistical analysis. Land use regression (LUR)—originally developed as a means to assess exposures from traffic-related air pollution—is a typical method to assess air pollution epidemiology [11][15].

Figures 1 and 2 show the number of annual papers published in relation to particulate matter and the word cloud used in the keywords, respectively.

### Table 1. Main research directions in predicting the density of PM

| Category        | Description                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| **Prediction model** | Artificial neural network, Support vector machine                           |
| Statistical     | Land use regression                                                          |
| Ensemble        | Random forest                                                               |
| **Type of data** | Satellite data, Geographical                                               |
| Spatial data    | Traffic                                                                      |
| Pollutants data | Traffic                                                                      |
| Meteorological data | Temperature, Rainfall, Humidity, Wind speed                     |
| Temporal data   | Pollutants, Populations, Vehicles                                           |
| Combined        | Spatial + Pollutants + Meteorological + Temporal data                      |

Figure 1. Number of published articles (1970–2018).

Figure 2. Word cloud of keywords in PM related articles.
3. A Research Method

We suggest the conceptual architecture of a big data analytic system for particulate matter as shown in Figure 3. To analyze the density of particulate matter in the air, it is required to gather data from various sources such as Korean government, Meteorological Agency, Internet of Things (IoT) sensors, human activities and pollutants. A lot of data have spatio-temporal characteristics—values with geological location and/or with time stamp. While some of data is stored in databases and transferred through FTP (file transfer protocol), others are collected by sensors and transmitted through LTE networks automatically.

Heterogeneous and large volume of data should be stored in huge repository and accessible through networks. We suggest the mash-up data is preprocessed and stored in cloud service for ubiquitous access to shared pools of configurable system resources. A pre-processing process can include data quality assurance, normalization, and standardization.

Correlation analysis is an inevitable process for variable reduction. Multiple competing machine learning models need to be used to enhance the prediction accuracy. The target variable is the density of PM10 or PM2.5 with a 1-hour time gap between input variables. Since the target values are valid only in device locations, we need to estimate the target values of shaded areas considering spatial characteristic of estimated locations such as distances from multiple adjacent devices, floating population, traffic volumes and number of pollutants. After building a feasible analytic results, we will disseminate the outcomes to the public through open API (application programming interface).

Currently, a limited number of devices and lack of prediction mechanism cause wide shaded areas. We considered two models to estimate the density of shaded areas: (i) naive model of predicting an average density value from nearest two devices’ values, and (ii) interpolation model of a weighted average value from \( n \)-nearest devices’ values. Weight will be the closeness between a shaded spot and an IoT device. Figure 4 shows an

**Figure 3.** A conceptual architecture of big data analytic system for particulate matter (PM).

**Figure 4.** An As-Is model and To-Be models of predicting the densities of particulate matter in shaded areas.
As-Is model and To-Be models of predicting the densities of particulate matter in shaded areas.

\[ V_i = \frac{\sum_i w_i V_i}{\sum_i w_i}, \quad (1) \]

where \( w_i = \frac{1}{d_i} \).

\( V_i \) denotes the measure value of spot \( i \) and \( d_i \) means the Euclidean distance between estimation spot and spot \( i \). Eq. (1) means adjacent values will affect the predicted value in inverse proportion to the distance.

4. A Case Study

A case study is a nation-wide project to propose a new value-added service through integration and analysis of data that relates to particulate matter and its relevant behaviors. Fine dust measuring equipment is installed by the government at 320 branches nationwide and it measures the average value of the air quality every hour. In recent years, new IoT air quality measuring instruments have been introduced into the market, in combination with IoT technology.

The aim of project is to provide the public with a guidance/guidebook by establishing a big data platform of the fine dust, and to provide administrative guidance/guidebook to the public institutions and local governments and inform the integrated service of indoor and outdoor air management. The specification of the big data system is shown in Table 2.

We chose Jeju Island as a project area. Jeju Island is the cleanest area in Korea and is isolated from other areas, making it the easiest area to control and observe pollutants. Table 3 shows the raw data and details for predicting particulate matter. In order to predict the value after 1 hour, we collected the input values measured hourly.

4.1 Gathering and Preprocessing Raw Data

We used the density of (fine) PM (PM2.5, PM10) as both an input variable and a target variable. The densities are measured by IoT devices linked to LTE network and is transmitted automatically. There is a 1-hour gap between the two variables. The two variables, way of measuring density and characteristics of device location, were excluded since they are not influential to the target variable.

The meteorological data–temperature, amount of rainfall, humidity, wind speed–were downloaded from the government’s FTP server. If there is a missing value, it is replaced with another date value in the same time zone.

Data use the previous time value in case of missing values. Human movements (floating population and estimated traffic volume) are measured by the number of people and vehicles connected to the mobile phone base stations. The numbers are

| Category                        | Detail                      |
|---------------------------------|-----------------------------|
| Operating system                | CentOS release 6.9          |
| Database                        | postgres (PostgreSQL) 8.4.20|
| Application language            |                             |
| Batch Job                       | Shell script, crontab       |
| Preprocessing                   | Stored procedure            |
| Analysis language               | Python 3.6.3                |
|                                 | Library: scikit learn v0.19.1|

| Category                      | Details                                      | Metric | Volume (instance) |
|-------------------------------|----------------------------------------------|--------|-------------------|
| Air quality measurement data  | Time span: 2017/06/02-2017/09/25             | PM10   | 439 MB            |
|                               | Number of devices: 58                        | PM2.5  | (319 million cases)|
|                               | Measurement frequency: 1 min                 |        |                   |
| Pollution source data         | Time span: 2017/04/01-2017/09/30             | Floating population | 1 GB  |
|                               | Measurement frequency: 1 hr                  | Estimated traffic volume | (1.049 billion cases)|
|                               | Time span: 2017/09                         | Pollution volume | 76 kB  |
|                               | Measurement Frequency: 1 hr                  | Pollution grade | (6,000 sources) |
|                               | Temperature                                | Latitude-Longitude |        |
| Meteorological data           | Time span: 2017/06/02-2017/09/25             |        | 484 kB            |
|                               | Measurement Frequency: 1 hr                  | Temperature | (112,000)|
|                               | Cumulative rainfall                         | Humidity |                   |
|                               | Humidity                                    | Wind speed |                   |
5. Building Models and Predicting the Density

Figure 6 depicts the procedure of building models and predicting the density of particulate matter. 70% data was used for developing a prediction model and 30%, for performance test. Three competing models—neural network, multiple linear regression, and decision tree—compared their accuracies. The best model is used to predict 1-hour-later density of particulate matter.

The neural network model showed better $R^2$ and root-mean-squared error (RMSE) values than other models and was adopted as a fine dust prediction model. Although the performance difference is not large compared with other models, it is considered that the neural network is most suitable considering the improvement through continuous data accumulation. Table 4 shows the performance comparison results.

The density of target spot can be estimated by interpolation using Eq. (1). We gathered the density data from 58 IoT devices. However, we still need some interpolations to estimate the densities of shaded areas as shown in Figure 7. Considering accessibility and stability of density data, we use 5 adjacent measured densities to estimate the density of a shaded spot.
Table 4. Prediction accuracies

| Target variable | Model            | Training set | Test set  |
|-----------------|------------------|--------------|-----------|
|                 | R^2              | RMSE         | R^2       | RMSE     |
| PM10            | Neural network   | 0.70823      | 9.90440   | 0.715764 | 9.89117  |
|                 | Linear regression| 0.70293      | 9.94345   | 0.712042 | 9.87822  |
|                 | Decision tree    | 0.68144      | 10.28459  | 0.688197 | 10.28040 |
| PM2.5           | Neural network   | 0.71921      | 6.76133   | 0.71845  | 6.75422  |
|                 | Linear regression| 0.71337      | 6.79357   | 0.71265  | 6.76922  |
|                 | Decision tree    | 0.71740      | 6.74638   | 0.71656  | 6.72331  |

Figure 7. Location of IoT sensors and coverages.

6. Conclusion

We proposed an analytic system architecture for predicting PM density. Three data mining models are built and compared to find the best model for PM prediction. We also suggested an interpolation method to cover up the shaded areas. We expect that this study will be expanded to conduct a nationwide verification and to suggest some practical implications after further researches.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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References

[1] M. D. Adams and P. S. Kanaroglou, “Mapping real-time air pollution health risk for environmental management: combining mobile and stationary air pollution monitoring with neural network models,” Journal of Environmental Management, vol. 168, pp. 133-141, 2016. [https://doi.org/10.1016/j.jenvman.2015.12.012](https://doi.org/10.1016/j.jenvman.2015.12.012)

[2] G. Grivas and A. Chaloulakou, “Artificial neural network models for prediction of PM10 hourly concentrations, in the Greater Area of Athens, Greece,” Atmospheric Environment, vol. 40, no. 7, pp. 1216-1229, 2006. [http://dx.doi.org/10.1016/j.atmosenv.2005.10.036](http://dx.doi.org/10.1016/j.atmosenv.2005.10.036)

[3] H. He, W. Z. Lu, and Y. Xue, “Prediction of particulate matter at street level using artificial neural networks cou-
pling with chaotic particle swarm optimization algorithm,” *Building and Environment*, vol. 78, pp. 111-117, 2014. http://dx.doi.org/10.1016/j.buildenv.2014.04.011

[4] J. Hooyberghs, C. Mensink, G. Dumont, F. Fierens, and O. Brasseur, “A neural network forecast for daily average PM10 concentrations in Belgium,” *Atmospheric Environment*, vol. 39, no. 18, pp. 3279-3289, 2005. http://dx.doi.org/10.1016/j.buildenv.2014.04.011

[5] X. Leng, J. Wang, H. Ji, H., Q. Wang, H. Li, X. Qian, F. Li, and M. Yang, “Prediction of size-fractionated airborne particle-bound metals using MLR, BP-ANN and SVM analyses,” *Chemosphere*, vol. 180, pp. 513-522, 2017. https://doi.org/10.1016/j.chemosphere.2017.04.015

[6] J. B. Ordieres, E. P. Vergara, R. S. Capuz, and R. E. Salazar, “Neural network prediction model for fine particulate matter (PM2.5) on the US–Mexico border in El Paso (Texas) and Ciudad Juarez (Chihuahua),” *Environmental Modelling & Software*, vol. 20, no. 5, pp. 547-559, 2005. http://dx.doi.org/10.1016/j.envsoft.2004.03.010

[7] P. Perez and J. Reyes, “Prediction of maximum of 24-h average of PM10 concentrations 30 h in advance in Santiago, Chile,” *Atmospheric Environment*, vol. 36, no. 28, pp. 4555-4561, 2002. http://dx.doi.org/10.1016/S1352-2310(02)00419-3

[8] U. A. Sahin, C. Bayat, and O. N. Ucan, “Application of cellular neural network (CNN) to the prediction of missing air pollutant data,” *Atmospheric Research*, vol. 101, no. 1-2, pp. 314-326, 2011. http://dx.doi.org/10.1016/j.atmosres.2011.03.005

[9] A. Suleiman, M. R. Tight, and A. D. Quinn, “Assessment and prediction of the impact of road transport on ambient concentrations of particulate matter PM10,” *Transportation Research Part D: Transport and Environment*, vol. 49, pp. 301-312, 2016. http://dx.doi.org/10.1016/j.trd.2016.10.010

[10] Y. Zhan, Y. Luo, X. Deng, H. Chen, M. L. Grieneisen, X. Shen, L. Zhu, and M. Zhang, “Spatiotemporal prediction of continuous daily PM2.5 concentrations across China using a spatially explicit machine learning algorithm,” *Atmospheric Environment*, vol. 155, pp. 129-139, 2017. https://doi.org/10.1016/j.atmosenv.2017.02.023

[11] C. Ho, C. Chan, C. Cho, H. Lin, J. Lee, and C. Wu, “Land use regression modeling with vertical distribution measurements for fine particulate matter and elements in an urban area,” *Atmospheric Environment*, vol. 104, pp. 256-263, 2015. https://doi.org/10.1016/j.atmosenv.2015.01.024

[12] M. Hochadel, J. Heinrich, U. Gehring, V. Morgenstern, T. Kuhlbusch, E. Link, H. Wichmann, and U. Kramer, “Predicting long-term average concentrations of traffic-related air pollutants using GIS-based information,” *Atmospheric Environment*, vol. 40, no. 3, pp. 542-553, 2006. https://doi.org/10.1016/j.atmosenv.2005.09.067

[13] X. Meng, Q. Fu, Z. Ma, L. Chen, B. Zou, Y. Zhang, et al., “Estimating ground-level PM10 in a Chinese city by combining satellite data, meteorological information and a land use regression model,” *Environmental Pollution*, vol. 208, pp. 177-184, 2016. https://doi.org/10.1016/j.envpol.2015.09.042

[14] H. Merbitz, S. Fritz, and C. Schneider, “Mobile measurements and regression modeling of the spatial particulate matter variability in an urban area,” *Science of the Total Environment*, vol. 438, pp. 389-403, 2012. http://dx.doi.org/10.1016/j.scitotenv.2012.08.049

[15] G. Pereira, H. J. Lee, M. Bell, A. Regan, E. Malacova, B. Mullins, and L. D. Knibbs, “Development of a model for particulate matter pollution in Australia with implications for other satellite-based models,” *Environmental Research*, vol. 159, pp. 9-15, 2017. http://dx.doi.org/10.1016/j.envres.2017.07.044

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