A Bayesian LSTM Model to Evaluate the Effects of Air Pollution Control Regulations in China

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***Abstract*—Rapid socio-economic development and urbanization have resulted in serious deterioration in air-quality in many world cities, including Beijing, China. This preliminary study is the first attempt to examine the effectiveness of air pollution control regulations implemented in Beijing during 2013 – 2017 through a data-driven regulatory intervention analysis. Our proposed machine-learning model utilizes proxy data including Aerosol Optical Depth (AOD) and meteorology; it can explain 80% of the $PM_{2.5}$ variability. Our preliminary results show that air pollution control regulatory measures introduced in China and Beijing have reduced $PM_{2.5}$ pollution in Beijing by 23% on average.**

***Index Terms*—air pollution control regulation, effects of regulatory interventions, Bayesian LSTM**

I. Introduction

Over the past few decades, rapid socio-economic development and urbanization have resulted in serious deterioration in air quality in Beijing, China. Air pollutants, especially $PM_{2.5}$ (particulates smaller than 2.5 micrometers in diameter), can lead to extremely detrimental health consequences, such as cancer, stroke, asthma or heart disease [1], [2]. In order to provide in a timely manner the critical health advice for Beijing's citizens based on scientific evidence, the introduction of real-time air pollution monitoring and reporting system in China has become crucial. Since April 2008, the US Embassy in Beijing has been publishing hourly $PM_{2.5}$ readings using a monitor mounted on its rooftop. In January 2013, Beijing officially launched a new air quality monitoring system. Since then $PM_{2.5}$ has been fully monitored by Beijing's automatic monitoring network, with hourly air pollution concentrations released by Beijing's Environmental Monitoring Center.

A number of air pollution control regulations have been introduced by the government in China to control air pollution, with increasing stringency over the last two decades. Many studies have examined the effect of regulation on pollution concentration in both the Chinese and international context. Two major approaches, namely, (1) the environmental engineering approach and (2) the environmental economic approach, have been adopted in these studies. The first approach evaluates the policy impacts on emission inventories by forecasting air qualities under different policy scenarios or constructing hypothetical air qualities in the absence of policy regulations, using physical and statistical modelling [3]. In contrast, the second approach utilizes experimental design, e.g., randomized experimental or quasi-experimental design, to estimate the causal effect of policy regulation, based on difference-in-differences estimation and regression discontinuity test, etc. [4]. These approaches, however often failed to model the complex relationship between air pollution and other confounders such as meteorology and time trends, and to account for the uncertainties in input data and model parameters [5].

Rapid development in machine learning has made the adoption of data-driven regulatory analysis possible, with applications in resource allocation and causal inference [6]. Machine-learning methods have been used to estimate individual treatment effects [7], [8]. Recently, deep-learning approaches have achieved state-of-the-art performance in air pollution estimation and forecasting [9], [10], [11], [12], including $PM_{2.5}$ estimation, utilizing satellite-based Aerosol Optical Depth (AOD) images as proxy data [13]. However, in such study [13], the temporal correlation between $PM_{2.5}$ pollution concentration and AOD is yet to be fully exploited by the neural network structure. Moreover, deep learning may also suffer from limited data source and low data quality when compared to other machine learning techniques. Incorporating the Bayesian approach into deep learning can reduce network overfitting due to data sparsity and noise, and provide uncertainty measure for the prediction [14]. However, a data-driven approach has yet to be applied to accurately estimate the counter-factual effects of air pollution regulatory interventions on air pollution concentrations with uncertainty estimation.

Using Beijing as a case study, this paper proposes a data-driven regulatory intervention analysis framework to study the causal relationship between air pollution control regulations and city-level $PM_{2.5}$ pollution concentration, based on available monitored air pollution data and proxy data such as AOD and meteorology. The effects of air pollution control regulations in Beijing during 2013 – 2017 are evaluated. The rest of the paper is organized as follows. Section II discusses our collected data and proposed method for regulatory intervention analysis. Section III presents our experimental results followed by discussions. Section IV gives the conclusion. To the best of our knowledge, this is the first attempt to evaluate the effects of air pollution control regulation using machine learning.

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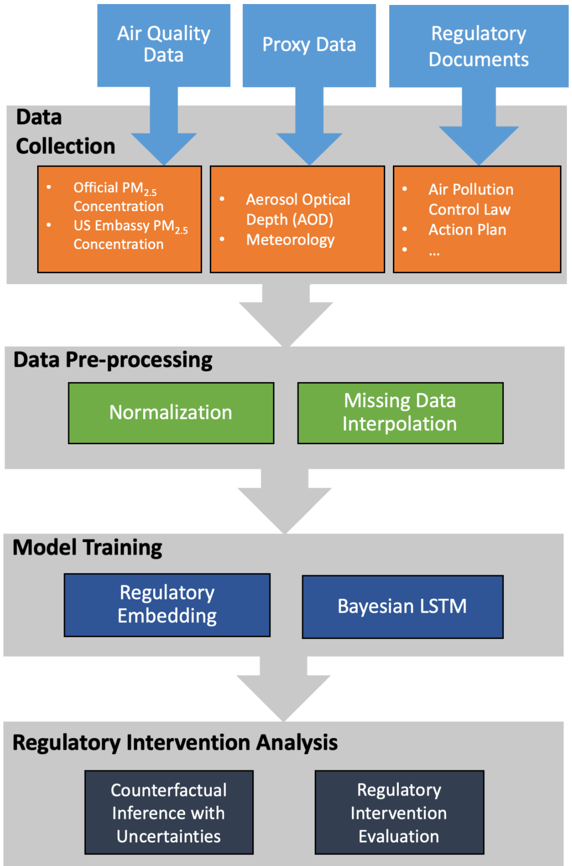

Fig. 1. The overall framework

II. Data and Methods

This study proposes a machine learning framework to provide counter-factual inference and evaluate the effects of air pollution regulatory intervention. Our proposed framework consists of four components, as shown in Figure 1, namely, data collection, data pre-processing, model training, and regulatory intervention analysis.

A. Data Collection

1) Air Quality: We collected official hourly station-level $PM_{2.5}$ concentration data from 1 January 2013 to 31 December 2017. In addition, we collected hourly $PM_{2.5}$ concentration data recorded at the US Embassy, Beijing from 9 April 2008 to 30 June 2017. Existing studies showed that Beijing's city-level $PM_{2.5}$ concentration is highly correlated with $PM_{2.5}$ concentration observed at the US Embassy, Beijing, suggesting that readings reported by the US Embassy can be used to reflect the level of air-quality throughout the city [15]. Based on our collected data, our preliminary analysis is also consistent with previous findings. Therefore, given that official $PM_{2.5}$ concentration data is not available until 2013, we used observations at the US Embassy, Beijing as the ground truth for city-level $PM_{2.5}$ pollution concentration in Beijing.

2) Proxy Data (AOD and Meteorology): Previous studies showed that AOD and meteorology data can be used in the statistical modelling of the effects of regulatory intervention on air pollution concentration in Beijing [3]. In this study, we collected AOD data from the NASA MODIS satellite database from 26 March 2008 to 21 May 2017. Eight features were selected based on data availability during the period of study. In addition, meteorology data, including temperature, pressure, humidity, visibility, precipitation, and wind speed, measured at the Beijing Capital International Airport, from 1 January 2008 to 31 December 2017, were collected.

3) Regulatory Documents: We identified five major air pollution control regulations at the city level or the national level from 2008 to 2017 [16]. These regulations focused on a range of areas such as emission control of coal-fired power plants, industrial facilities and vehicles, prevention and control of dusts, optimization of energy structures and traffic systems, technological innovations for clean environment, emergency plans for high pollution episodes, and legal responsibilities. They are listed as follows:

Regulation 1: Action Plan for Clean Air in Beijing during 2013 – 2017 (Issued on 11 September 2013)
Regulation 2: Air Pollution Prevention and Control Law in Beijing (Effective from 1 March 2014)
Regulation 3: Environmental Protection Law in China (Effective from 1 January 2015)
Regulation 4: Air Pollution Prevention and Control Law in China (Effective from 1 January 2016)
Regulation 5: Guidelines on Vertical Integration and Reform for Monitoring of Law Enforcement of Environmental Protection Units under Provincial Governance (Issued on 14 September 2016)

B. Data Pre-processing

The input data consists of two parts: one is a vector representing the historical proxy data (including AOD and meteorology), while another is a vector representing the regulatory intervention. The output is a real value representing the corresponding city-level daily $PM_{2.5}$ concentration. At first, each feature in the historical proxy data is normalized into the range of zero to one. Then, linear temporal interpolation is used to complete the missing values in the historical proxy data.

C. Model Training

The pre-processed data is fed into a Bayesian deep learning model for training. In this study, we focus on the Bayesian RNN, which is a particular type of Bayesian deep learning model capable of modelling time-series data [17]. A Bayesian RNN model with network structure f and parameters θ is denoted as f_θ. During the period of study, each observation of air quality and other covariates at day t consists of the proxy features x_t, and the status of K regulatory interventions $I_t = \{I_t^1, \ldots, I_t^k\}$, e.g., $\{\text{Regulation 1 is adopted}, \text{Regulation 2 is not adopted}, \ldots\}$. An embedding layer is used to map the regulatory status vector to a vector of continuous values [18], so that the proxy features and the regulatory embedding can be combined into a single vector:

$$c_t = \text{Concatenate}(x_t, \text{Regulatory-Embedding}(I_t))$$

The model input consists of the observations over the past L days (including current day t): $X_{t-L,t} = \{c_{t-L}, \dots, c_t\}$, and the corresponding factual outcome y_t, i.e., observed city-level daily $PM_{2.5}$ concentration. The Bayesian RNN model f_θ aims to find the optimal posterior distribution of the network weight parameters θ, given the observed pairs $(X_{t-L,t}, y_t)$. We use LSTM as the recurrent unit in the network. A Bayesian multilayer perceptron (MLP) is used to predict y_t, based on the final hidden state of Bayesian LSTM. Conceptually, our proposed model is as follows:

$$\begin{cases} h_t = \text{Bayesian-LSTM}(c_t, h_{t-1}) \\ y_t = \text{Bayesian-MLP}(h_t) \end{cases}$$

To train our proposed model, we follow [17], [19]. In the network, each weight parameter is a random variable with a Gaussian prior, and the weight at each time step has the same distribution. A diagonal Gaussian distribution is used as the variational posterior, and Bayes by Backprop is adopted to update the weight parameters of the network while minimizing the loss in terms of Mean Squared Error (MSE) and Kullback–Leibler (KL) divergence cost.

D. Regulatory Intervention Analysis

Counter-factual outcomes, in the absence of regulatory intervention, are predicted to quantify the net effects of regulatory intervention, based on the fitted model f_θ after training. More specifically, regulatory intervention analysis is performed according to the following steps. First, we randomly draw a sample from the posterior of the network weight parameters to obtain a model f_{θ_i}. Next, we construct the corresponding regulatory status vector under different hypotheses (e.g., without any air pollution control measures), combined with proxy data, to re-estimate $PM_{2.5}$ concentration using this model. Next, we compare the difference between the average factual outcome (observed air quality) and the average estimated counter-factual outcome (hypothetical air quality) to evaluate the average intervention effect (AIE) of a regulatory intervention:

$$\text{AIE}_i = \text{E}_{t \in T}[y_t] - \text{E}_{t \in T}[f_{\theta_i}(\tilde{X}_{t-L,t})]$$

where θ_i is a sample from the posterior distribution, T is in the *ex post* period and $\tilde{X}_{t-L,t}$ is the input at day t with hypothetical regulatory status. This is repeated N times, so that we can calculate the mean and the variance of AIE samples, to reflect the uncertainties of the model parameters [20]. The final estimation of AIE with uncertainties can be calculated as follows:

$$\begin{cases} \mu_{\text{AIE}} = \frac{1}{N}\sum_{i=1}^{N} \text{AIE}_i \\ \sigma^2_{\text{AIE}} = \frac{1}{N}\sum_{i=1}^{N}(\text{AIE}_i - \mu_{\text{AIE}})^2 + \text{data uncertainty} \end{cases}$$

where data uncertainty refers to the irreducible noise inherent in the data, which could be estimated by the residual sum of squares on an independent validation dataset [21]. Finally, 95% Confidence Interval (CI) of AIE is calculated as follows:

$$[\mu_{\text{AIE}} - t_{\frac{\alpha}{2}}\sigma_{\text{AIE}}, \mu_{\text{AIE}} + t_{\frac{\alpha}{2}}\sigma_{\text{AIE}}]$$

where α is set to 5%, $t_{\frac{\alpha}{2}}$ is the critical value derived from the corresponding Student's t distribution.

III. Results

A. Experimental Setting

The proposed model was developed based on DeepMind Sonnet, a TensorFlow-based neural network library. In our experiment, multiple linear regression, which is commonly used in econometric modelling, was selected as the baseline model. To evaluate our proposed model, we used an 80/10/10 split of the available data as the training set, the validation set, and the test set. We used R^2, which measures the proportion of the variance in $PM_{2.5}$ pollution that can be explained by the proxy data and regulatory interventions, for model evaluation and comparison. We fine-tuned the hyper-parameters and chose the model with the highest R^2 of the validation set as the final model for further analysis.

For the input features, we set the number of lagged days L to 7. For Bayesian LSTM, we set the hidden units to 256, and the number of layers to 3. As shown in Section II-A3, we set the total number of regulatory interventions K to 5. We set the dimension of the embedding layer to 3. We set the sample size N to 100 to obtain a reasonable estimation of the mean and the variance of the distribution with regards to the average intervention effect of regulatory intervention.

B. Result of Regulatory Intervention Analysis

For the test set, the R^2 of the final fitted model was 80% when using the mean of the posterior over the network weight parameters for prediction, while the R^2 of the baseline model was only 70%. This suggested that our proposed model can better fit the data, and non-linear relationship might exist between $PM_{2.5}$ pollution concentration and proxy data. Hence, traditional econometric model might yield biased results based on the assumption of linearity.

We used the final fitted model to estimate/simulate the counter-factual outcomes based on the hypothesis that all regulatory interventions are not implemented, in order to examine the aggregate effect of regulatory intervention. Figure 2 showed the observed monthly air quality and simulated monthly air quality (without any regulatory interventions) during the period of study. Since the introduction of the first regulatory intervention, the average of observed daily $PM_{2.5}$ pollution was 82 $\mu g/m^3$, and the average of hypothetical daily $PM_{2.5}$ pollution was 107 $\mu g/m^3$ (95% CI: 96 $\mu g/m^3$ to 118 $\mu g/m^3$). The average intervention effect of all regulatory interventions was -25 $\mu g/m^3$ (95% CI: -36 $\mu g/m^3$ to -14 $\mu g/m^3$). This suggested that the aggregate effects of air pollution regulatory intervention introduced during this period

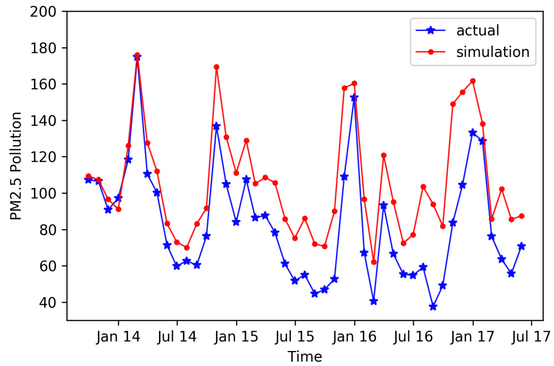

Fig. 2. The monthly trends of observed $PM_{2.5}$ pollution and simulated $PM_{2.5}$ pollution during 2013 – 2017

can lead to a 23% reduction in $PM_{2.5}$ pollution concentration on average.

C. Limitations

First, compared with traditional supervised learning, causal inference from observed data can be biased due to the lack of counter-factual outcomes. Selection bias (e.g., the proxy distribution during the period with/without regulatory intervention could be different) should be addressed in our proposed machine learning method for intervention modelling. Second, our study only examines the aggregate effect of air pollution control regulations during the period of study. More sophisticated analysis is needed to understand the individual effect of a particular regulatory intervention on air quality, and over a particular sector. Furthermore, proxy data are still very limited. Additional proxy data, such as remote sensing images from satellites, and industrial outputs published by the government's statistical bureau, can be included in the intervention modelling.

IV. Conclusion

This is the first study to investigate the effectiveness of air pollution control regulations in Beijing, China, using a machine learning approach. Our approach can model the complex relationship between $PM_{2.5}$ pollution concentration and many other factors that potentially affect pollution concentration, and predict the hypothetical $PM_{2.5}$ pollution concentration in the absence of any regulatory intervention (R^2 = 80%). Preliminary results of regulatory intervention analysis show that air pollution is reduced by 23% on average due to the aggregate effect of regulatory intervention during 2013 – 2017. In the future, we will propose more advanced machine-learning methods to address issues related to selection bias in observed data, and evaluate the individual effect of air pollution regulatory intervention.

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