AirNet: a machine learning dataset for air quality forecasting

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Abstract

In the past decade, many urban areas in China have suffered from serious air pollution problems, making air quality forecast techniques a hot spot. Conventional approaches rely on the numerical method to estimate the pollutant concentration and require lots of computing power. To solve this problem, we applied deep learning methods which have already achieved major breakthroughs in many other areas. Deep learning requires large-scale datasets to train an effective model. In this paper, we introduced a new dataset, entitled as 'AirNet'[1], containing the 0.25 longitudinal and latitudinal degree grid map of mainland China, with more than two years of continued air quality measurement and meteorological data. We published this dataset as an open resource for machine learning researches and set up a baseline to a 5-day air pollution forecast. Through our experiments, it was demonstrated that this dataset could facilitate the development of new algorithms on forecasting the air quality.

1 Introduction

In recent years, along with economic development, air pollution in developing countries such as China and India has become a severe problem threatening the public health(Pun et al. (2014), Lv et al. (2016)).

The air quality forecasting techniques are being upgraded rapidly as the demand for measuring pollution increases. On one side, some models like HYSPLIT-4 and KF, utilize atmospheric dynamic processes, which try to figure out the accumulation and dissipation mechanisms of air pollutants (Lv et al. (2015); Djalalova et al. (2015)). Some people also used the hidden Makov model like the FL method, to predict pollutant concentrations (Sun et al. (2013); Yetilmezsoy & Abdul-Wahab (2012)). However, due to the complexity of air transport dynamics, the conventional forecasting models demand excessive computing resources. In addition, its accuracy depends on the model structure itself and cannot improve regardless of the amount of training data.

On the other hand, the deep learning approach (LeCun et al.) has achieved exceptional results in unstructured information processing, such as computer vision, speech recognition, and natural language processing (Hinton et al. (2012); Zhang & LeCun (2015); Krizhevsky et al. (2012)).In these tasks, the deep learning method has outperformed conventional machine learning methods. Inspired by this, people attempted to apply deep learning models such as the Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM), to do meteorological forecasting Shangzan et al. (2017), including the estimation of precipitation probability and air pollution.

Notably, to apply deep learning techniques effectively, a good model requires a large-scale dataset (Liu et al. (2017)). However, to our knowledge, such a dataset is absent in the air quality forecast field so far. A good dataset could greatly incent the industry to develop the new models and offer a unified assessment standard, as in the case of ImageNet (Deng et al. (2009)) in the computer vision field . To facilitate research and data collection, we processed

[1] AirNet: http://airnet.caiyunapp.com

Table 1: GFS Field Description

NUMBER	FIELD	DESCRIPTION
001	tmp	Temperature [K]
002	rh	Relative Humidity [%]
003	ugrd	U-Component of Wind [m/s]
004	vgrd	V-Component of Wind [m/s]
005	prate	Precipitation Rate [kg/m2/s]
006	tcdc	Total Cloud Cover [%]

and published an air quality dataset, 'AirNet', in an attempt to fill this gap. Furthermore, we conducted experiments to validate the capability of this dataset, and set up a baseline for air pollution prediction on the AirNet dataset.

1.1 Related Work

Shi et al. (2015) proposed RNN and convolutional LSTM to forecast the precipitation in future two hours, which they formalized as a spatiotemporal issue. The air quality forecast is similar to weather forecast, but two factors make air quality forecast more difficult and distinct from estimating precipitation; 1) the time span of air quality forecast is longer than weather forecast, the former often forecasts in four or five days, sometimes even goes beyond ten days. 2) additional influential factors must be considered in air quality forecast, such as the dynamic of air pollutants and the interaction with meteorological conditions. Modeling with AirNet dataset, the difference will be explicated in Section 5 below.

Ong et al. (2016) applied RNN to predict PM2.5 with environmental sensor data, which improved the results accuracy. Kurt & Oktay (2010)'s research on forecasting air pollution with neural networks demonstrated the method's feasibility and superiority. Liang et al. (2015) released a dataset containing the value of PM2.5 which is only measured in Beijing. After this, Liang et al. (2016) published a larger dataset to analyze the pollutant factor in five cities of China. All datasets used above are point-wise data, which do not allow us to model in a spatially explicit manner. In addition, as Table 2 shows, these datasets are too small to train a deep neural network. Thus it became essential and urgent to set up a larger scale training dataset to enhance the accuracy of the forecast results.

1.2 Contribution and Review

In this paper, we delivered a dataset, 'AirNet', containing more than two years of 7 indices of air quality data from 1498 stations, which is at least 40 times larger than most previous datasets. We set up a baseline based the LSTM model with AirNet dataset. The results demonstrated the effectiveness of the deep learning model for the air quality forecast.

2 Dataset Extraction

2.1 Dataset collection

At first, we collected the data from China National Environmental Monitoring Center (CNEMC) which run the 1498 monitor stations spreading in the whole country. Every station monitors air quality in real-time and reports the quality of air quality every hour. Therefore we wrote a spider to fetch the data from the Data-Publish platform[2]. Secondly, we gathered the meteorological data from the Global Forecast System (GFS) which contains the 7 meteorological condition features as in Table 1.

[2]URL: http://106.37.208.233:20035

Table 2: Air pullutant dataset charactisc

	Stations	Polutant	Time-span	Samples
AirNet	1498	PM2.5,PM10, NO2, CO, O3, SO2, AQI	2015-4-1 2017-9-22	10593856
BeijingPM25	2	PM2.5	2010-1-1 2014-12-31	43824
Five-Cities PM25	16	PM2.5	2010-1-1 2015-12-31	262920

2.2 Alignment Data

For air quality data from CNEMC, in each city, there are several monitoring stations of the real-time air pollutant concentration per hour.

The GFS data format is a 3-dimension matrix, released by National Oceanic and Atmospheric Administration (NOAA) every six hours. Every release contains the meteorological condition features forecasting for 10 days in every 3 hours, and 16 days in every 12 hours. For each meteorological condition features like TEMP, there are 1038240 values at one time point globally. We converted this data to a matrix which equals the volume of (180 * 4 + 1) * (360 * 4), where 180 is the radial latitude, 360 is the radial of longitude, and 4 is the invert of the 0.25 resolution. Subsequently, the global forecasting model's geospatial information was also obtained.

These two kinds of data sources are distinct. GFS data is a 3 dimensional matrix while the air quality data is a two dimensional matrix at a time point, where one dim is station ID, and the other is air quality indices. Therefore we had to align these two datasets. For each GFS data time point, we selected required air quality data for all stations in China and interpolate them into a matrix covering the whole country.

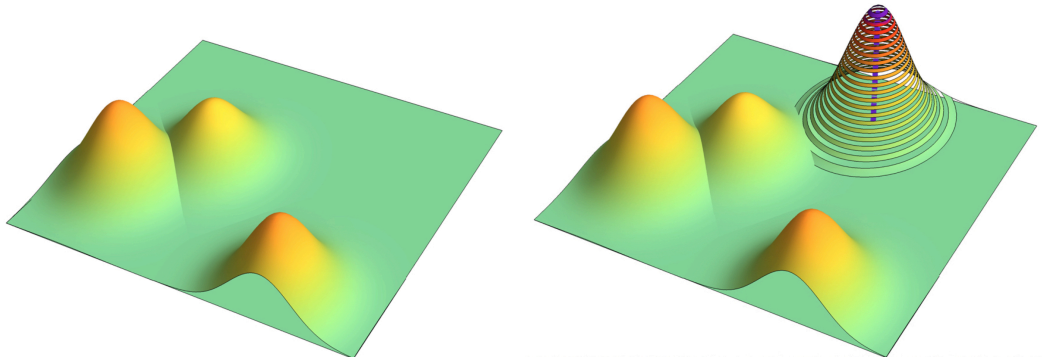

Figure 1: Use radial basis function to interpolate Air data from point-wise to a matrix.

Radial Basis Function is used to interpolate Air data to a matrix as shown in Figure 1. After that, we concatenated the gfs dataset with air quality dataset as in Figure 2, thus we produced a four-dimensional dataset (latitude, longitude, timesteps, features). Latitude ranges from 75 degrees to 132 degrees. The range of north latitude is from 18 degrees to 51 degrees. The grid resolution is 0.25 degree and the data was collected from April 1, 2015, to September 1, 2017. Every 3 hours there is one frame; on every frame we have 6 GFS features, and 7 types of the air quality indices. In total, we had a matrix with the dimension of (132, 228, 7072, 13). We took partial features of the day January 23, 2017 as an example in Figure 2

Some statistic features of the AirNet[3] was shown in Table 2.

[3]BeijingPM25: https://archive.ics.uci.edu/ml/machine-learning-databases/00381/; Five-Cities PM25: https://archive.ics.uci.edu/ml/machine-learning-databases/00394/

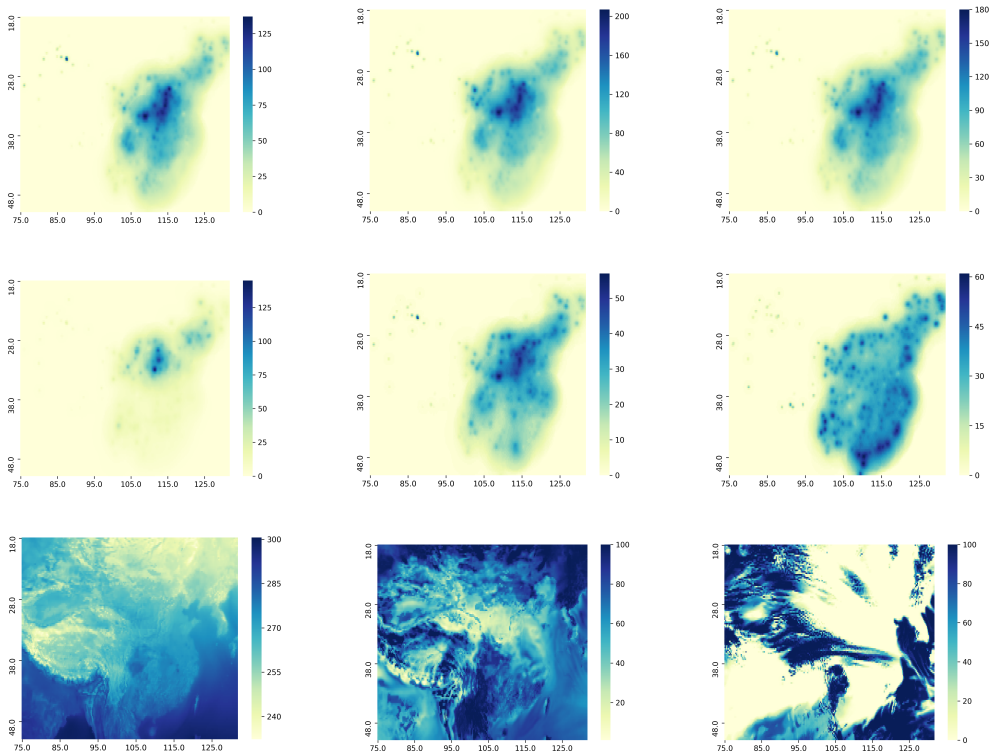

Figure 2: PM2.5, PM10, AQI, SO2, no2, o3, tmp, rh, tcdc in 20170123, mainland China, listed from left to right, top to bottom, respectively.

3 Machine learning task

3.1 Tasks Description

Air quality forecast is different to precipitation prediction because many factors will affect the concentration and distribution of the air pollutants. It is essential to take the future meteorological conditions into consideration rather than just the history of pollutant concentration. Based on such principles, we formalized the pollutant prediction as follows:

$$\begin{aligned} P\left(x_t\right) = P\left(x_t \mid x_{t-1}, x_{t-2} \ldots x_0; b_t, b_{t-1} \ldots b_0\right) \\ P\left(x_{t-1}, x_{t-2}, \ldots x_0\right) P\left(b_t, b_{t-1}, b_{t-2}, \ldots b_0\right) \end{aligned} \tag{1}$$

In this formula, the air pollutant concentrations was taken into the time step t as x_t. We converted the problem of the pollutant prediction as time sequential prediction problems, as in the case of giving the past pollutant concentration x_0 to x_{t-1}. Since future meteorological conditions are as important as history pollutant concentrations, the meteorological factors were taken as b_0 to b_{t-1} plus the predicted future meteorological condition b_t. We could produce future meteorological predictions through numerical methods, and feed the predicted data into the model, as time t increments, above step is repeated, so we could forecast air pollutant concentration as far as possible. In particular, our goal is to model and fit the conditional probability of the AirNet dataset.

3.2 Metrics

In the development of machine learning models, we use Mean Square Error as a loss function. Since the estimated pollutant value became more precise closer to the monitoring stations,

Table 3: Several concept about POD,FAR and CSI

	prediction >80	prediction <= 80
fact >80	hit	miss
fact <= 80	false alarm	

we modified the MSE using a new calculation method, as the Point-wise Mean Square Error (PMSE), which only calculates loss in the nearby stations. The experiments' results demonstrate that this improvement is evident and beneficial.

$$PMSE = \frac{1}{n}\sum_{i \in A}(\widehat{y}_i - y_i)^2 \qquad A := \{P \mid P \textit{ located in a monitor station place}\} \tag{2}$$

Additionally, we used the Probability of Detection (POD), the False Alarm Rate (FAR), and the Critical Success Index (CSI)Shi et al. (2015) as the metrics for the assessment. These metrics are intuitive for us to understand the performance of a system. We set the PM25 value 80 (ug/m3), as a threshold value to divide the air quality results into two levels, i.e. days with a pollutant concentration higher than 80, as the pollution days and vice versa, as in Table 3. Based on this definition, we designed the following formula:

$$POD = \frac{hits}{hits + misses + falsealarms} \tag{3}$$

$$FAR = \frac{falsealarms}{hits + falsealarms} \tag{4}$$

$$CSI = \frac{hits}{hits + misses} \tag{5}$$

4 Baseline

For the pollutant prediction described in 1, we developed a convolutional enhanced sequence model named 'WipeNet' with two steps. Firstly, to capture the air pollutant accumulation and dissipation relationships between sequential time steps, a reduced LSTM module was used to. Secondly, to deal with the transfer effect between different places, a convolutional model with learned local-variant kernel was used to redistribute the pollutant concentrations between the data point and its neighborhood.

4.1 ReducedLSTM

Hochreiter & Schmidhuber (1997) proposed the Long Short-Term Memory (LSTM) model to alleviate the gradient vanishing problem, which successfully applied in the field of natural language processes. In order to optimize the algorithm's performance in the field ofair quality forecasting, we modified the model of LSTM to fit in the air pollutant change. The modification is demonstrated below.

The original LSTM model is:

$$\begin{aligned} f_t &= \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right) \\ i_t &= \sigma_g\left(W_i x_t + U_i h_{t-1} + b_i\right) \\ o_t &= \sigma_g\left(W_o x_t + U_o h_{t-1} + b_o\right) \\ c_t &= f_t \circ c_{t-1} + i_t \circ \sigma_h\left(W_c x_t + U_c h_{t-1} + b_c\right) \\ h_t &= o_t \circ \sigma_h\left(c_t\right) \end{aligned} \tag{6}$$

We modified this formula as follow[4]:

$$\begin{aligned} f_t &= \sigma_{hg}\left(W_f x_t + U_f h_{t-1} + b_f\right) \\ i_t &= W_i x_t + U_i h_{t-1} + b_i \\ c_t &= f_t \circ Relu\left(c_{t-1} + i_t\right) \\ h_t &= c_t - mean_t \end{aligned} \tag{7}$$

The input and output gate were removed, as suggested in Jozefowicz et al. (2015). In the above formulas, x_t represents the meteorological conditions, and we regard i_t, as the accumulation of air pollutants induced by adverse weather conditions like higher tempratur , no wind etc.. By adding this accumulation term into c_{t-1},we tried to simulate the air pollutant concentration changing under static stability weather, while using the forget gate to simulate the removal factors like wind, rainfall, and high humidity.

After this process, we stored the air pollutant concentration for every time steps in c_t and the subtracted the mean value which was calculated in advance to render h_t as the fluctuation value at every time step, then feeding h_t and c_t to the next time step. After substituting LSTM with the ReducedLSTM, we achieved a better result.

4.2 WipeNet

In the above LSTM and ReducedLSTM method, we predicted the future air pollutant concentration without considering the data from nearby places. In the real physical environment, however, the flow in atmosphere would definitely transport pollutant from one place to another. The pollutant concentration would also change by different meteorological conditions.

We considered this pollutant transport as a redistribution around a place regionally and used a local convolutional operation to encode such processes. A softmax layer is also added after the convolutional operation to characterize the redistribution phenomenon .

To better featurizing the different places, the covolutional knernel should be different for each regional wind fields, which was learnt from the local wind field by another standard convolutional operation.

Our final formula is defined as:

$$\begin{aligned} f_{i,j,t} &= \sigma_{hg}\left(W_f^{ij} x_{i,j,t} + U_f^{ij} h_{i,j,t-1} + b_f^{ij}\right) \\ i_{i,j,t} &= W_i^{ij} x_{i,j,t} + U_i^{ij} h_{i,j,t-1} + b_i^{ij} \\ \widehat{c}_{i,j,t} &= f_{i,j,t} \circ Relu\left(c_{i,j,t-1} + i_{i,j,t}\right) \\ \gamma_{p,q,t} &= softmax(cnn(wind_{p,q,t})) \\ c_{i,j,t} &= \sum_{i-k \le p \le i+k; j-k \le q \le j+k} \gamma_{p,q,t} \widehat{C}_{p,q,t} \\ h_{i,j,t} &= c_{i,j,t} - mean_{i,j,t} \end{aligned} \tag{8}$$

In brief, we used $\widehat{c}$ to denote the pollutant change caused by its own meteorological condition, and then used a learned convolutional kernel to redistribute the pollutant concentration within the neighborhood.

5 Expriments

In the previous study, Liang et al. (2015) demonstrated that pollutant concentration is significantly affected by meteorological conditions, hence we feed the meteorological condition at every time steps as the control information. Preliminarily, we found the Reduced LSTM

[4] σ_{hg} mean hard sigmoid activate function

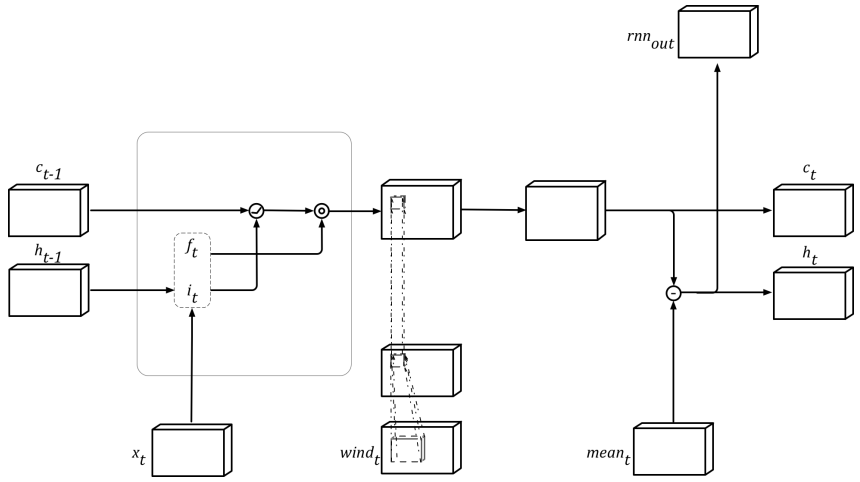

Figure 3: Use a learned convolutional kernel to redistribute air pollutant in neighbour place

Table 4: The effect of ReducedLSTM, LSTM* and ReducedLSTM* means we just use past air pulltant to prediction.

	DEV			TEST		
	POD	FAR	CSI	POD	FAR	CSI
GRU	0.62	0.36	0.43	0.43	0.47	0.31
LSTM	0.82	0.37	0.53	0.75	0.43	0.48
ReducedLSTM	0.87	0.37	0.56	0.63	0.43	0.44
LSTM*	0.65	0.58	0.32	0.38	0.53	0.23
ReducedLSTM*	0.73	0.57	0.35	0.49	0.54	0.27
WipeNET	0.87	0.28	0.67	0.76	0.30	0.56

outperformed the LSTM and Gated Recurrent Unit (GRU). We chose PM2.5 as the forecasting object of the air pollutant, and selected October 5, 2016, to January 3, 2017 data, as the training dataset, and January 3, 2017, to February 2, 2017,data as the validation dataset. As there is one data point every three hours, and we predict air pollutant concentration for 5 days, we sliced each dataset into 40 timesteps length segment, allowing overlaying segments. In total, 680(90 * 8 - 40) matrix samples in the training dataset, and 200(30 * 8 - 40) matrix samples in the validation dataset were obtained, respectively. Because the methods of LSTM and ReducedLSTM did not use the spatial relationship, we shuffle our on the locational dimension. For better precision, we chose the datapoints logged at monitor station in the HuaBei area and got 91120(for every matrix we got 134 stations) samples for training and 26800 samples for validation. The test dataset was set from October 5, 2015, to January 3, 2016.

We implemented all code through Keras(Chollet et al. (2015)), and chose TheanoBergstra et al. (2011) as backend, using the built-in LSTM and GRU modules. For simplification, we trained and predicted using subtracted PM25 data between two consecutive time steps. We preprocessed the meteorological condition information through two multiple perceptrons (MLP), as each dimension of MLP is 20. We set the batchsize to 32 and the dropout rate to 0.2, we ran 30 epoch with the patience option of 10. After every 10 experiments, the average value was calculated and the results are displayed in Table 4.

The results demonstrated that, without the meteorological condition into consideration, the accuracy of the prediction results dramatically deteriorated. Furthermore, reduced LSTM is improved than LSTM, we assumed this is because our equation considered air pollutant dynamics, thus we gave more information to model than LSTM while keeping LSTM's advantage.

Finally, we implemented the WipeNeT, with kernel size of (5, 5), and init weight with the Glorot Uniform Distribution, the dataset and the other settings are not changed .

We could see that the WipeNeT achieved best accuracy on all of our three criterions. We could see that the WipeNeT achieved best accuracy on all of our three criterions.

6 Conclusion

In this paper, we publicized a new dataset, AirNet, for researchers who want to use deep learning method to analyze air quality. Compared to previous studies in the field, it contains 7 indices of air quality from 1498 monitoring stations, which is at least 40 times larger than most previous datasets. In addition, we set up a baseline method WipeNet, for 5-day air quality prediction using AirNet dataset, and received a CSI score of 0.56, which achieved a 16% point improvement compared to classic LSTM methods.

6.1 Future work

In the future, we plan to add more data types into AirNet, for example, we only used ground meteorological data in this paper, but data from multiple heightscan reveal the change of inversion temperature layer which is a crucial factor for air quality forecast.

We wish AirNet would not only be applied to air quality forecast but also be utilized to reveal the critical factors in the causality of air pollution. For example, if we combine land-cover data with air pollution change, we may find some interactions between them. Perhaps we could even find new methods to reduce air pollution.

References

James Bergstra, Olivier Breuleux, Pascal Lamblin, Razvan Pascanu, Olivier Delalleau, Guillaume Desjardins, Ian Goodfellow, Arnaud Bergeron, Yoshua Bengio, and Pack Kaelbling. Theano: Deep learning on gpus with python. 2011.

François Chollet et al. Keras, 2015.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on, pp. 248–255. IEEE, 2009.

Irina Djalalova, Luca Delle Monache, and James Wilczak. Corrigendum to" PM2. 5 analog forecast and Kalman filter post-processing for the Community Multiscale Air Quality (CMAQ) model"[Atmos. Environ. 108 (2015) 76-87]. Atmospheric Environment, 119: 430–430, 2015.

Geoffrey Hinton, Li Deng, Dong Yu, George Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara Sainath, and Brian Kingsbury. Deep Neural Networks for Acoustic Modeling in Speech Recognition - The Shared Views of Four Research Groups. IEEE Signal Process. Mag., 29(6):82–97, 2012.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

Rafal Jozefowicz, Wojciech Zaremba, and Ilya Sutskever. An empirical exploration of recurrent network architectures. pp. 2342–2350, 2015.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. pp. 1097–1105, 2012.

Atakan Kurt and Ayşe Betül Oktay. Forecasting air pollutant indicator levels with geographic models 3days in advance using neural networks. Expert Systems with Applications, 37(12):7986–7992, 2010.

Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. Nature, 521(7553): 436–444.

Xuan Liang, Tao Zou, Bin Guo, Shuo Li, Haozhe Zhang, Shuyi Zhang, Hui Huang, and Song Xi Chen. Assessing Beijing's PM2.5 pollution: severity, weather impact, APEC and winter heating. Proc. R. Soc. A, 471(2182):20150257, October 2015.

Xuan Liang, Shuo Li, Shuyi Zhang, Hui Huang, and Song Xi Chen. PM2.5 data reliability, consistency, and air quality assessment in five Chinese cities. Journal of Geophysical Research: Atmospheres, 121(17):10,220–10,236, September 2016.

Fan Liu, Feng Xu, and Sai Yang. A Flood Forecasting Model Based on Deep Learning Algorithm via Integrating Stacked Autoencoders with BP Neural Network. pp. 58–61, 2017.

Baolei Lv, Yu Liu, Peng Yu, Bin Zhang, and Yuqi Bai. Characterizations of PM2. 5 pollution pathways and sources analysis in four large cities in China. Aerosol Air Qual. Res, 15: 1836–1843, 2015.

Baolei Lv, Bin Zhang, and Yuqi Bai. A systematic analysis of PM 2.5 in Beijing and its sources from 2000 to 2012. Atmospheric Environment, 124:98–108, 2016.

Bun Theang Ong, Komei Sugiura, and Koji Zettsu. Dynamically pre-trained deep recurrent neural networks using environmental monitoring data for predicting PM2. 5. Neural Computing and Applications, 27(6):1553–1566, 2016.

Vivian Chit Pun, Ignatius Tak-Sun Yu, Hong Qiu, Kin-Fai Ho, Zhiwei Sun, Peter KK Louie, Tze Wai Wong, and Linwei Tian. Short-term associations of cause-specific emergency hospitalizations and particulate matter chemical components in Hong Kong. American journal of epidemiology, 179(9):1086–1095, 2014.

Guo Shangzan, Xiao Da, and Yuan Xingyuan. A short-term rainfall prediction method based on neural networks and model ensemble. Advances in Meteorological Science and Technology, 7(1):107–113, 2017.

Xingjian Shi, Zhourong Chen, Hao Wang, Dit-Yan Yeung, Wai-kin Wong, and Wang-chun WOO. Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting. June 2015.

Wei Sun, Hao Zhang, Ahmet Palazoglu, Angadh Singh, Weidong Zhang, and Shiwei Liu. Prediction of 24-hour-average PM 2.5 concentrations using a hidden Markov model with different emission distributions in Northern California. Science of the total environment, 443:93–103, 2013.

Kaan Yetilmezsoy and Sabah Ahmed Abdul-Wahab. A prognostic approach based on fuzzy-logic methodology to forecast PM10 levels in Khaldiya residential area, Kuwait. Aerosol and Air Quality Research, 12(6):1217–1236, 2012.

Xiang Zhang and Yann LeCun. Text Understanding from Scratch. arXiv.org, February 2015.