Ozone concentration in Lombardy

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- 1 The problem
- Explorative analysis of the data
- A model of interest
- Selection of the covariates
- Model Comparison
- Open Predictions obtained with the trained model
- Conclusion



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The problem

Ozone: a threat to the environment and health

Respiratory illness:

- Asthma
- Lung issues
- Stroke

Around 20,000 people die prematurely in Europe each year.

Plant absorption:

- Impact on crops
- Food supply and economical loss



The problem

Mapping the Ozone levels in Lombardy

Known elevation factors:

- High temperatures
- Solar radiation

Known reduction factors:

- Rain
- Humidity

Still hard to predict the area of contamination :

- Wind-driven
- Dependent on elevation



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The location of interest for our study: Lombardy

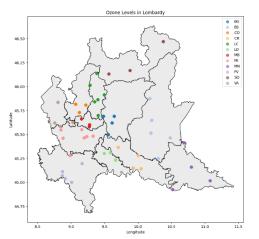
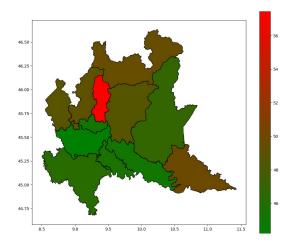


Figure: Ozone sensors in Lombardy

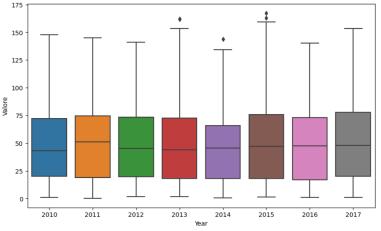


Overview of mean ozone levels in Lombardy (2010-2017)



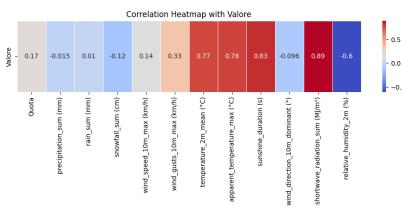


Boxplot of ozone levels over years (2010-2017)



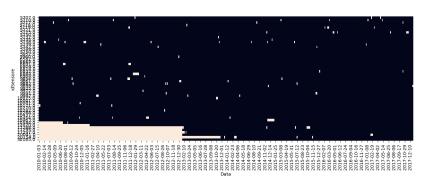


Exploration of meteorological effects





Missing data by sensor and time





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A model of interest

The variables and their meaning

Main variables:

- $O_l(s_i, w)$: True Ozone level during year l at place s_i , for week w.
- $Z_l(s_i, w)$: Measured Ozone level.
- $x_{lj}(s_i, w)$: Measured meteorological variable j in the p of interest.
- $\bullet \ \delta_{lj}(s_i, w) = x_{lj}(s_i, w) x_{lj}(s_i, w 1)$

First assumptions:

- $\overline{\bullet Z_l(s_i, w) = O_l(s_i, w) + \epsilon_l(s_i, w)}$
- $\{\epsilon_l(s_i, w), \forall (l, i, w)\} | \sigma_{\epsilon} \stackrel{iid}{\sim} N(0, \sigma_{\epsilon}^2)$
- ullet $\delta_{lj}(s_i,w)$: spatially correlated, temporally independent.

We also assume a correlation due to the weather parameters.



A model of interest

An autoregressive model[3]

$$O_l(\mathbf{s}, w) = \rho O_l(\mathbf{s}, w - 1) + \xi_l \mathbf{1} + \delta_l(\mathbf{s}, w) \boldsymbol{\beta} + \eta_l(\mathbf{s}, w)$$

- ullet 0<
 ho<1 is the autoregressive factor.
- ξ_l is the global annual intercept of year l.
- $\delta_l(\mathbf{s}, w)\boldsymbol{\beta}$ is the weather adjustment term.
- $\eta_l(\mathbf{s}, w)$ is a spatially correlated error term.

The initial condition

$$O_l(\mathbf{s},1) = \mu_l \mathbf{1} + \gamma_l(\mathbf{s})$$

• $\gamma_l(\mathbf{s})$ is the regional effect in year l for all sites s_i .



A model of interest

Priors for the different terms of the model

- $\rho \sim N(0,1)$
- $\xi_1, ..., \xi_L \stackrel{iid}{\sim} N(0, 1)$
- $\eta_1(\mathbf{s}, 1), ..., \eta_L(\mathbf{s}, 1), ..., \eta_1(\mathbf{s}, W), ..., \eta_L(\mathbf{s}, W) | \sigma_{\eta}, \phi_{\eta} \stackrel{iid}{\sim} N(0, \Sigma_{\eta}),$ with $\Sigma_{\eta}(i, j) = \sigma_{\eta}^2 exp(-\phi_{\eta} d_{ij})$
- $\mu_1, ..., \mu_L \stackrel{iid}{\sim} N(0, 1)$
- $\gamma_1(\mathbf{s}), ..., \gamma_L(\mathbf{s}) | \sigma_{\gamma}, \phi_{\gamma} \stackrel{iid}{\sim} N(0, \Sigma_{\gamma}),$ with $\Sigma_{\gamma}(i, j) = \sigma_{\gamma}^2 exp(-\phi_{\gamma} d_{ij})$
- $\boldsymbol{\beta} \sim N(0, I_p)$
- $\forall (l, w) \in [1, L] \times [1, W], \delta_l(\mathbf{s}, w) | A, \boldsymbol{\phi} \stackrel{iid}{\sim} N(0, \Sigma_{\delta})$ with $A = (\mathbf{a}_1, ..., \mathbf{a}_p), \Sigma_{\delta}(i, j) = \sum_{k=1}^p \exp(-\phi_k d_{ij}) \mathbf{a}_k^T \mathbf{a}_k$
- $\phi_1, ..., \phi_p \stackrel{iid}{\sim} U(0.001, 0.1)$
- $\forall (i,j) \in [1,p]^2, a_{i,j} \stackrel{iid}{\sim} N(0,1)$
- $\frac{1}{\sigma_{\star}^2}, \frac{1}{\sigma_{\star}^2}, \frac{1}{\sigma_{\star}^2} \stackrel{iid}{\sim} Gamma(a, b)$



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Selection of the covariates

A reduced model

$$O_l(\mathbf{s}, w) = \rho O_l(\mathbf{s}, w - 1) + \xi_l \mathbf{1} + \delta_l(\mathbf{s}, w) \boldsymbol{\beta} + \eta_l(\mathbf{s}, w)$$

The initial condition is:

$$O_l(\mathbf{s},1) = \mu_l \mathbf{1} + \gamma_l(\mathbf{s})$$

The priors are :

- $\rho \sim N(0,1)I(0 < \rho < 1)$
- $\xi_1, ..., \xi_L \stackrel{iid}{\sim} N(0,1)$
- $\eta_1(\mathbf{s}, 1), ..., \eta_L(\mathbf{s}, 1), ..., \eta_1(\mathbf{s}, W), ..., \eta_L(\mathbf{s}, W) | \sigma_{\eta}, \phi_{\eta} \stackrel{iid}{\sim} N(0, \Sigma_{\eta}), \text{ with } \Sigma_{\eta}(i, j) = \sigma_{\eta}^2 exp(-\phi_{\eta}d_{ij})$
- $\mu_1, ..., \mu_L \stackrel{iid}{\sim} N(0,1)$
- $\gamma_1(\mathbf{s}), ..., \gamma_L(\mathbf{s}) | \sigma_{\gamma}, \phi_{\gamma} \stackrel{iid}{\sim} N(0, \Sigma_{\gamma}), \text{ with } \Sigma_{\gamma}(i, j) = \sigma_{\gamma}^2 exp(-\phi_{\gamma} d_{ij})$
- $\boldsymbol{\beta} \sim N(0, I_p)$
- $\frac{1}{\sigma_{\epsilon}^2}, \frac{1}{\sigma_{n}^2}, \frac{1}{\sigma_{n}^2} \stackrel{iid}{\sim} Gamma(a, b)$, where a = 2 and b = 1



Selection of the covariates

The steps of the method

- Split the data in a training/verification part on a shorter time period.
- Train a model with all the covariates.
- Look at the posterior distribution of β .
- ullet Remove the covariates whose coefficient contains 0 in its 95% confidence interval.
- Retrain a reduced model with the remaining covariates
- Compare the results of both models on the verification part of the data.



Selection of the covariates

Precipitation_sum (mm)	(-0.599079, 1.17779)
Rain_sum (mm)	(-1.14169, 0.609446)
Snowfall_sum (cm)	(-0.240372, 0.14824)
Wind_speed_10m_max (km/h)	(-0.0158849, 0.0385158)
Temperature_2m_mean (°C)	(-0.0573153, 0.413884)
Apparent_temperature_max (°C)	(-1.13284, -0.622585)
Sunshine_duration (s)	(0.0111516, 0.177066)
Wind_gusts_10m_max (km/h)	(0.0147535, 0.0742081)
Wind_direction_10m_dominant (°)	(-0.0230213, 0.00380585)
Shortwave_radiation_sum (MJ/m²)	(-0.313512, 0.0424594)
Relative_humidity_2m (%)	(-0.170991, -0.0886358)

Table: Confidence intervals



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Model Comparison

Comparison between 3 models

Model 1

- Apparent_temperature_max, Sunshine_duration, Wind_gusts_10m_max, Relative_humidity_2m.
- VMSE: 50169.4225.

Model 2

- Temperature_2m_mean, Apparent_temperature_max, Sunshine_duration, Shortwave_radiation_sum.
- VMSE : 167018.2634.

Model 3

- Apparent_temperature_max, Wind_speed_10m_max, Relative_humidity_2m
- VMSE: 20.2133.

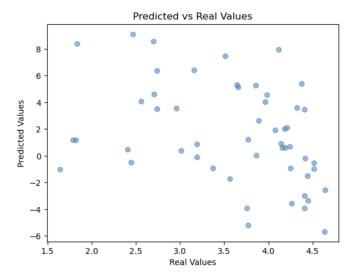


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Predictions obtained with the third trained model

Comparison with some known ground truth





Predictions obtained with the third trained model

Ozone levels predicted at a new location over a year

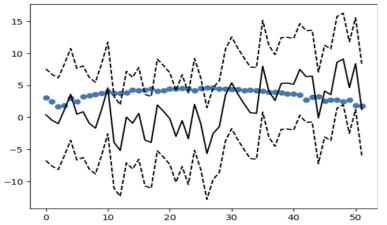


Figure: Prediction for a location in the validation set



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Conclusion

• Importance of the covariates

Computational issues

Possible improvements



Thank you for your attention!



References

- [1] Hussein A Al-Amery and Osama T Al-Taai. "The ozone effect on shortwave solar radiation in the atmosphere over Iraq". In: *AIP Conference Proceedings*. Vol. 2290. 1. AIP Publishing. 2020.
- [2] Amandine Chevalier et al. "Influence of altitude on ozone levels and variability in the lower troposphere: a ground-based study for western Europe over the period 2001–2004". In: *Atmospheric Chemistry and Physics* 7.16 (2007), pp. 4311–4326.
- [3] Sujit K Sahu, Alan E Gelfand, and David M Holland. "High-resolution space—time ozone modeling for assessing trends". In: Journal of the American Statistical Association 102.480 (2007), pp. 1221–1234.