Presentation

Application

OBJECTIVE: Forecasting the levels of air pollution for the

TableView station in Cape Town.

RESPONSE: Nitrogen dioxide

COVARIATES: Particulate matter, Sulfur dioxide, and Wind speed

Time series plot

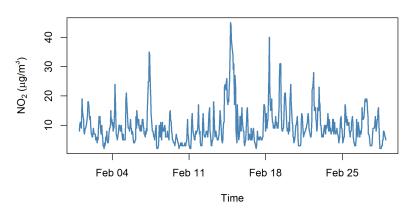


Figure 1: Time series of \boldsymbol{X}_t

Components of the time series

TREND COMPONENT: Using the ndiffs() function in the forecast package, we obtain 1, suggesting that there is a linear trend in the time series.

SEASONAL COMPONENT: Using the nsdiffs() function in the forecast package, we obtain 0, suggesting that no seasonality is present in the time series.

CYCLICAL COMPONENT: There is no clear indication of a cyclical component in the time series.

RANDOM COMPONENT: Random variation is present in the time series.

Heteroscedasticity

$$X_t \nsim \mathcal{N}(\mu, \sigma^2)$$
.

Using the BoxCox.lambda() function in the forecast package, we get that $\lambda \approx 0$, suggesting a natural log transformation.

$$\mathrm{Let}\,Y_t=\ln(X_t),$$

$$Y_t \overset{approx}{\sim} \mathcal{N}(\mu,\,\sigma^2).$$

Fitted models

AVERAGE: The prediction is the average value.

NAIVE: The prediction is the last observed value.

DRIFT: The prediction is the last observed value adjusted for the average trend.

AR(1): The prediction is based on a constant, plus a fraction of the previous value.

Gaussian process models

$$\begin{split} f_1(x) \sim &\operatorname{GP}(0,\,\sigma^2\delta_{ij}),\, \delta_{ij} = 1 \operatorname{for} i = j, \operatorname{and} \delta_{ij} = 0 \operatorname{for} i \neq j. \\ f_2(x) \sim &\operatorname{GP}(\mathbf{X}\beta,\,\sigma^2\delta_{ij}),\, \delta_{ij} = 1 \operatorname{for} i = j, \operatorname{and} \delta_{ij} = 0 \operatorname{for} i \neq j. \\ f_3(x) \sim &\operatorname{GP}(0,\,\alpha^2 \mathrm{exp}[(\frac{x_i - x_j}{\rho})^2]). \\ f_4(x) \sim &\operatorname{GP}(\mathbf{X}\beta,\,\alpha^2 \mathrm{exp}[(\frac{x_i - x_j}{\rho})^2]). \end{split}$$

Results

Model	RMSE			MAE		
Model	Forecasts			Forecasts		
	(h day time horizon)			(h day time horizon)		
	24	168	744	24	168	744
Average	7.731	5.397	7.439	6.042	4.254	5.385
Naive	10.553	7.864	10.040	7.708	6.071	7.308
Drift	10.606	8.128	11.358	7.764	6.391	8.809
AR(1)	8.662	5.912	8.044	6.029	4.422	5.616
GP-0-WN	13.756	11.141	13.169	11.719	9.786	11.081
GP-0-SE						
GP-MLR-WN	7.692	6.134	7.225	6.119	4.490	5.136
$\operatorname{GP-MLR-SE}$						

Figure 2: OOS performance of the fitted models.