

Estimation of non-stationary Processes : Part II (31.10.2008)

Illia Horenko



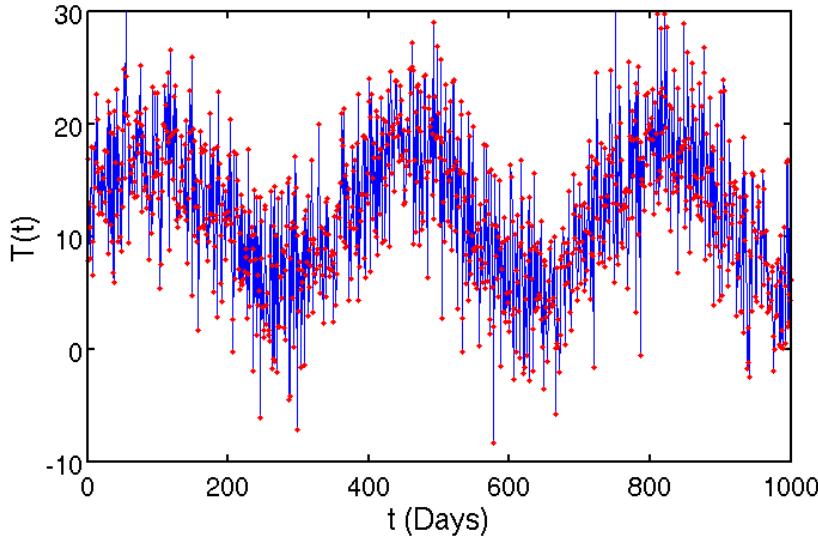
Research Group “***Computational Time
Series Analysis***“
Institute of Mathematics
Freie Universität Berlin (FU)

DFG Research Center ***MATHEON***
„Mathematics in key technologies“





Memo III: Data-Interpolation



Hypothesys:

$$T(t) = C_0 + \sin\left(\frac{2\pi}{365.4}t\right) * (C_1t + C_2) + C_3\epsilon_t$$

$$\epsilon_t \sim \mathcal{N}(0, 1)$$

$$\{C_0, C_1, C_2, C_3\} - ?$$

In General:

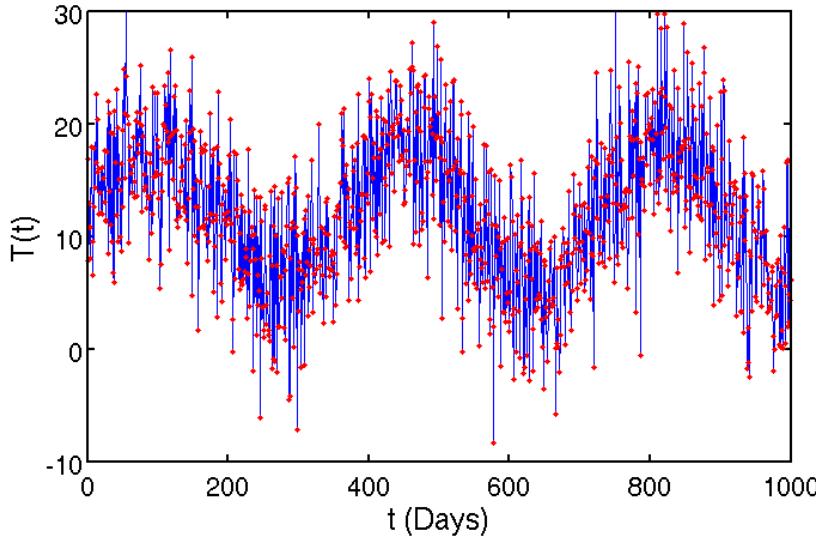
given $(x_i, y_i) \quad i = 1, 2, \dots, N$, *identify the “optimal” parameters of a*

certain function $y = F(x, \theta)$ *such that:*

$$\sum_{i=1}^N \|y_i - F(x_i, \theta)\| \rightarrow \min_{\theta}$$
$$\theta \in \Theta$$



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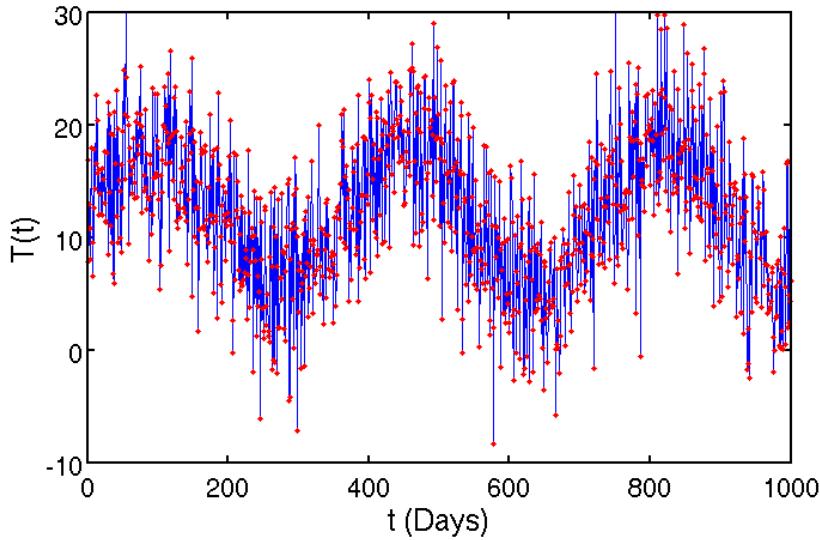
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$$\|\theta_k\| < C_i$$



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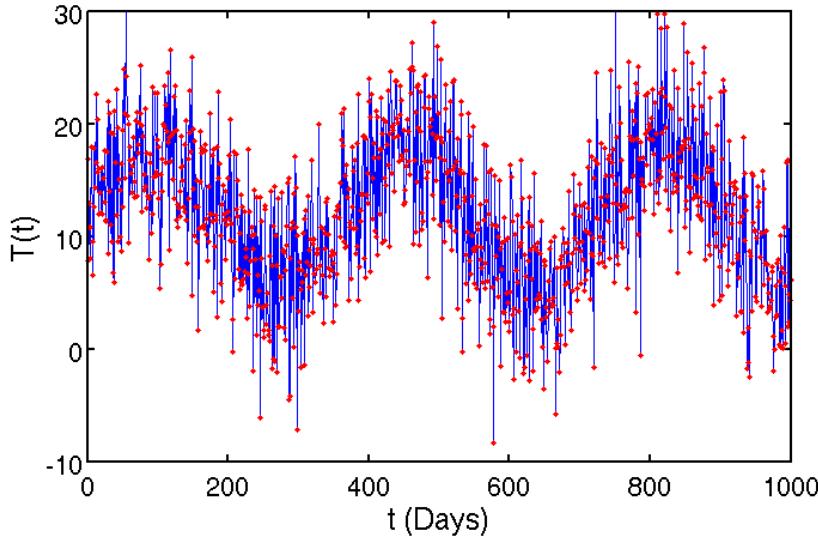
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Tykhonov-Regularization:

$$\mathcal{L}(\theta) = \sum_{i=1}^N \|y_i - F(x_i, \theta)\| + \epsilon \sum_k \|\theta_k\| \rightarrow \min_{\theta}$$



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Tikhonov-Regularization:

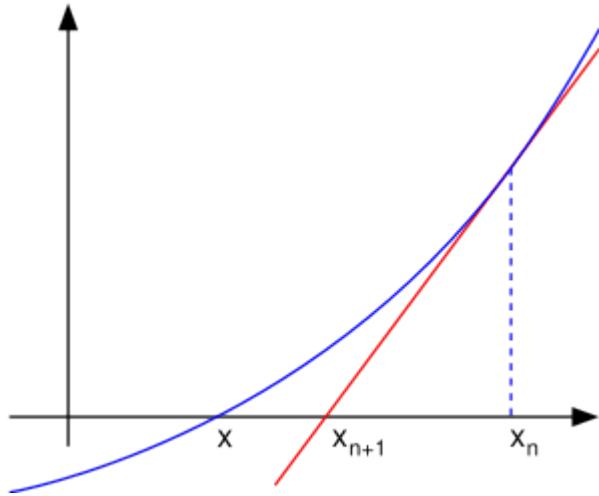
$$\mathcal{L}(\theta) = \sum_{i=1}^N \|y_i - F(x_i, \theta)\| + \epsilon \sum_k \|\theta_k\| \rightarrow \min_{\theta}$$

Numerical Minimisation: Newton's-Method

$$\frac{\partial}{\partial \theta} \mathcal{L}(\theta) = 0$$



Memo IV: Newton's-Method



$$f'(x_n) = \frac{\text{rise}}{\text{run}} = \frac{\Delta y}{\Delta x} = \frac{f(x_n) - 0}{x_n - x_{n+1}}$$

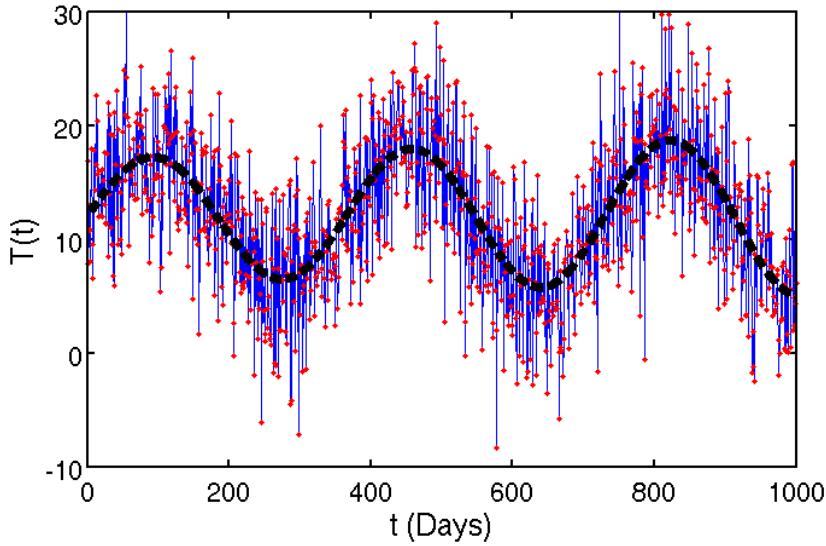
$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}.$$

In case of many variables:

$$J_F(x_n)(x_{n+1} - x_n) = -F(x_n)$$



Memo III: Data-Interpolation



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$$\epsilon_t \sim \mathcal{N}(0, 1)$$

$$\{C_0, C_1, C_2, C_3\} - ?$$

Fitted Trend Model:

$$T(t) = 12 + \sin\left(\frac{2\pi}{365.4}t\right) * (0.002t + 5) + 5\epsilon_t$$



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Parametric Estimation

H., submitted to Journal of Atmos. Sci. (2008)

Markovian Trend Model:

$$P(t) = P^{(0)} + P^{(1)}\phi(t), \quad \phi : [1, T] \rightarrow (-\infty, +\infty)$$



Parametric Estimation

Markovian Trend Model:

$$P(t) = P^{(0)} + P^{(1)}\phi(t), \quad \phi : [1, T] \rightarrow (-\infty, +\infty)$$

Log-Likelihood:

$$\sum_{j=1}^m \sum_{t \in \{t_{ij}\}} \log \left(P_{ij}^{(0)} + P_{ij}^{(1)}\phi(t) \right) \rightarrow \max_{P^{(0)}, P^{(1)}},$$

$$\sum_{j=1}^m P_{ij}^{(0)} = 1,$$

$$\sum_{j=1}^m P_{ij}^{(1)} = 0,$$

$$P_{ij}^{(0)} + P_{ij}^{(1)} \sup_{t \in [1, T]} \phi(t) \geq 0, \quad \text{for all } j,$$

$$P_{ij}^{(0)} + P_{ij}^{(1)} \inf_{t \in [1, T]} \phi(t) \geq 0, \quad \text{for all } j.$$

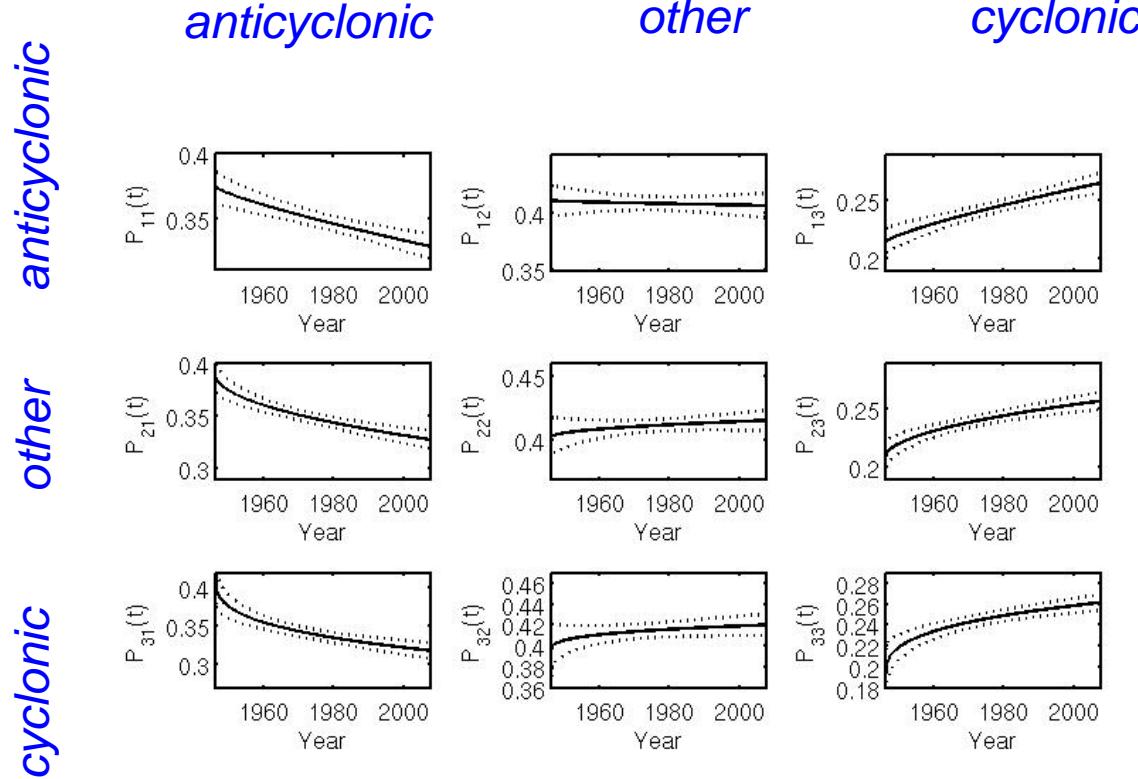
Numerics: Nelder-Mead Optimization Algorithm



Circulation Patterns for UK(1945-2007)

Historical Circulation Data: weather regimes
(Data from the Univ. of East Anglia)
3 atmospherical states considered

Polynomial Trend Model



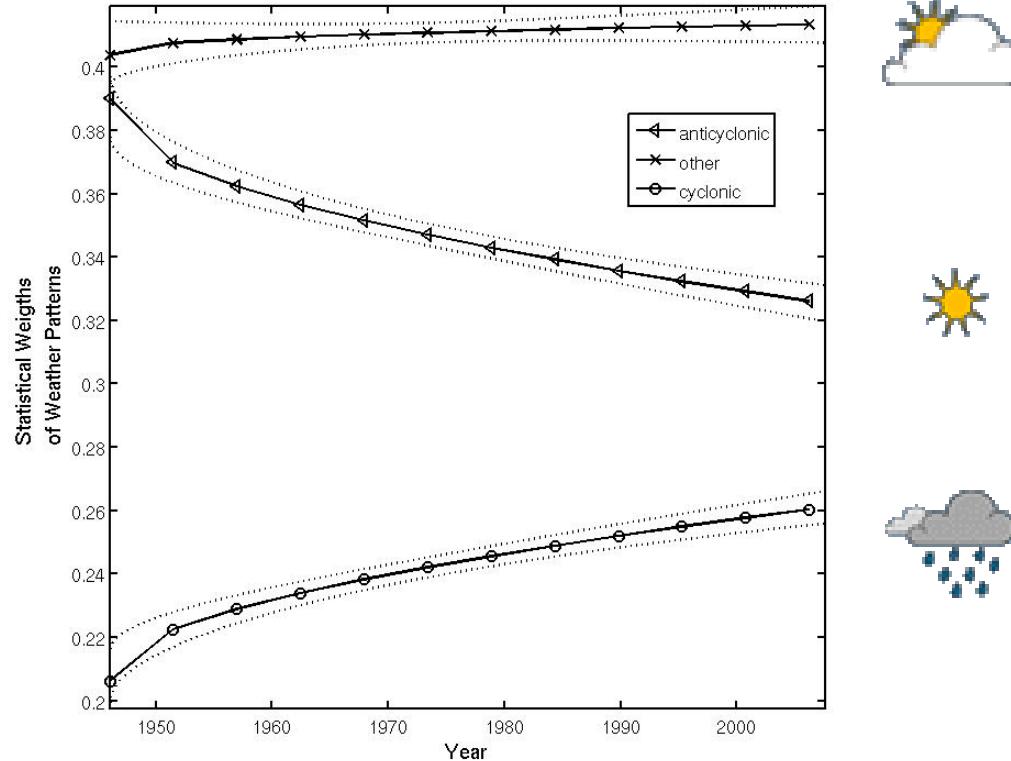


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Circulation Patterns for UK(1945-2007)

$$\pi(t) P(t) = \pi(t)$$



Conclusion:

What kinds of Markov estimators do we know now?

- Stationary Estimator (standart)
- Locally Stationary Estimator (Gaussian window, non-parametric)
- Non-Stationary Single Trend Estimator (regression, parametric)



Thank you for attention!