Monitoring Short Term Changes of Malaria Incidence in Uganda with Gaussian Processes

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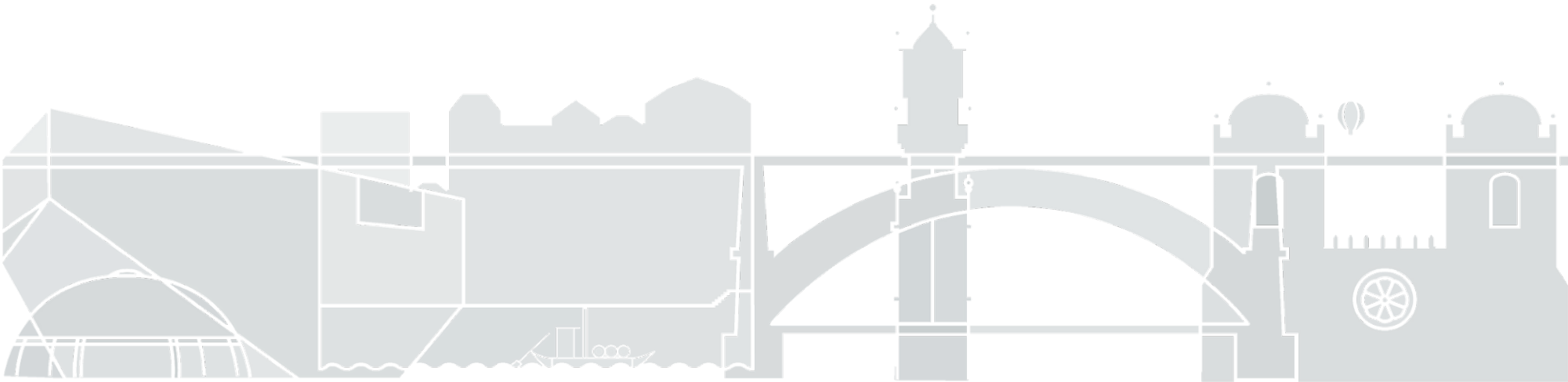
John Quinn, Neil Lawrence

ECML/PKDD 2015, Workshop on
Advanced Analytics and Learning on Temporal Data

11 September 2015

Outline

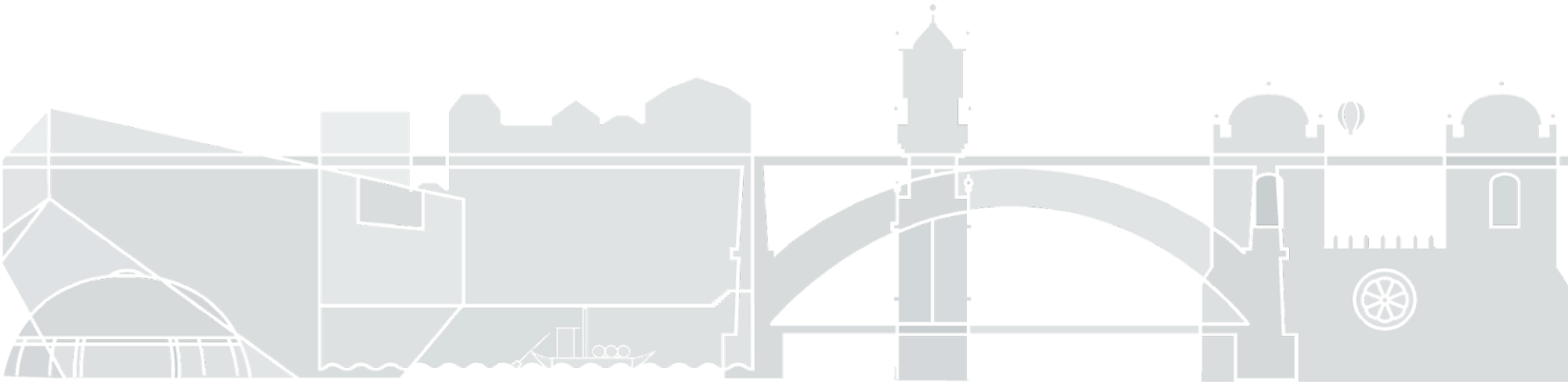
- The problem we are working on
- The challenges we have found in our way
- The solution proposed



About Malaria

Why we care?

- Endemic in 100 countries.
- A threat for 3.3 billion people approximately.
- Among the leading causes of morbidity and mortality in Uganda.



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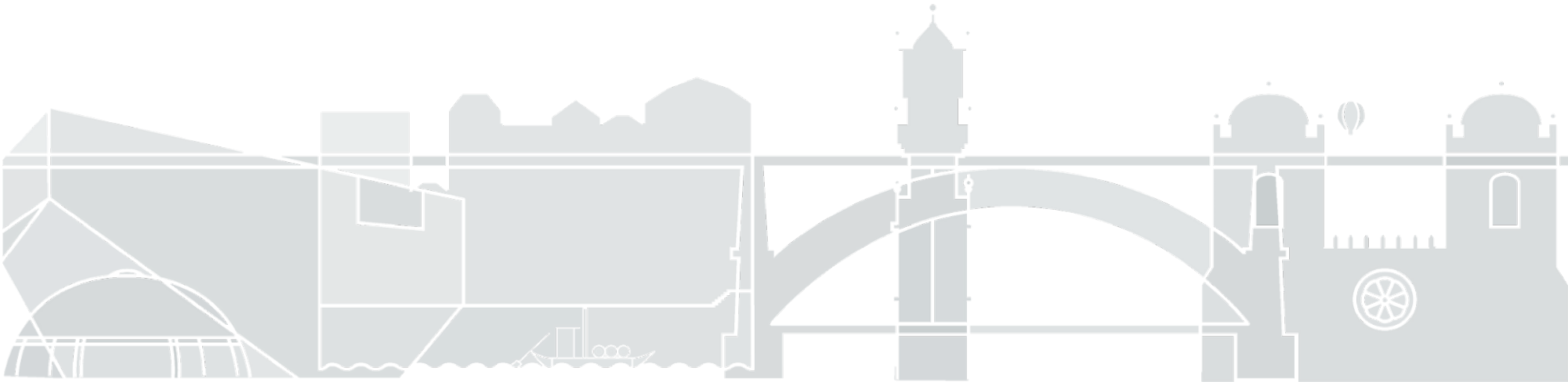

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Reaction mechanisms available

- Diagnostic testing
- Treatment

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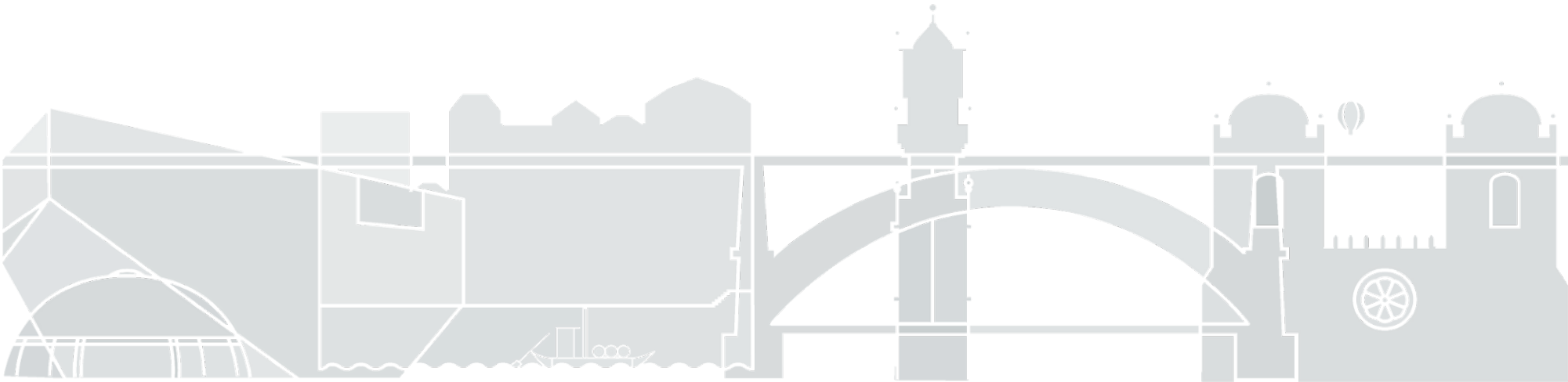
We need information to anticipate the disease and respond.

Health Management Information System (HMIS)

The Ministry of Health shared some of its information with us.

Data provided:

- Health facilities records across the whole country
- Number of individuals treated for malaria
- Weekly data aggregated by district



Challenges

Noise and errors

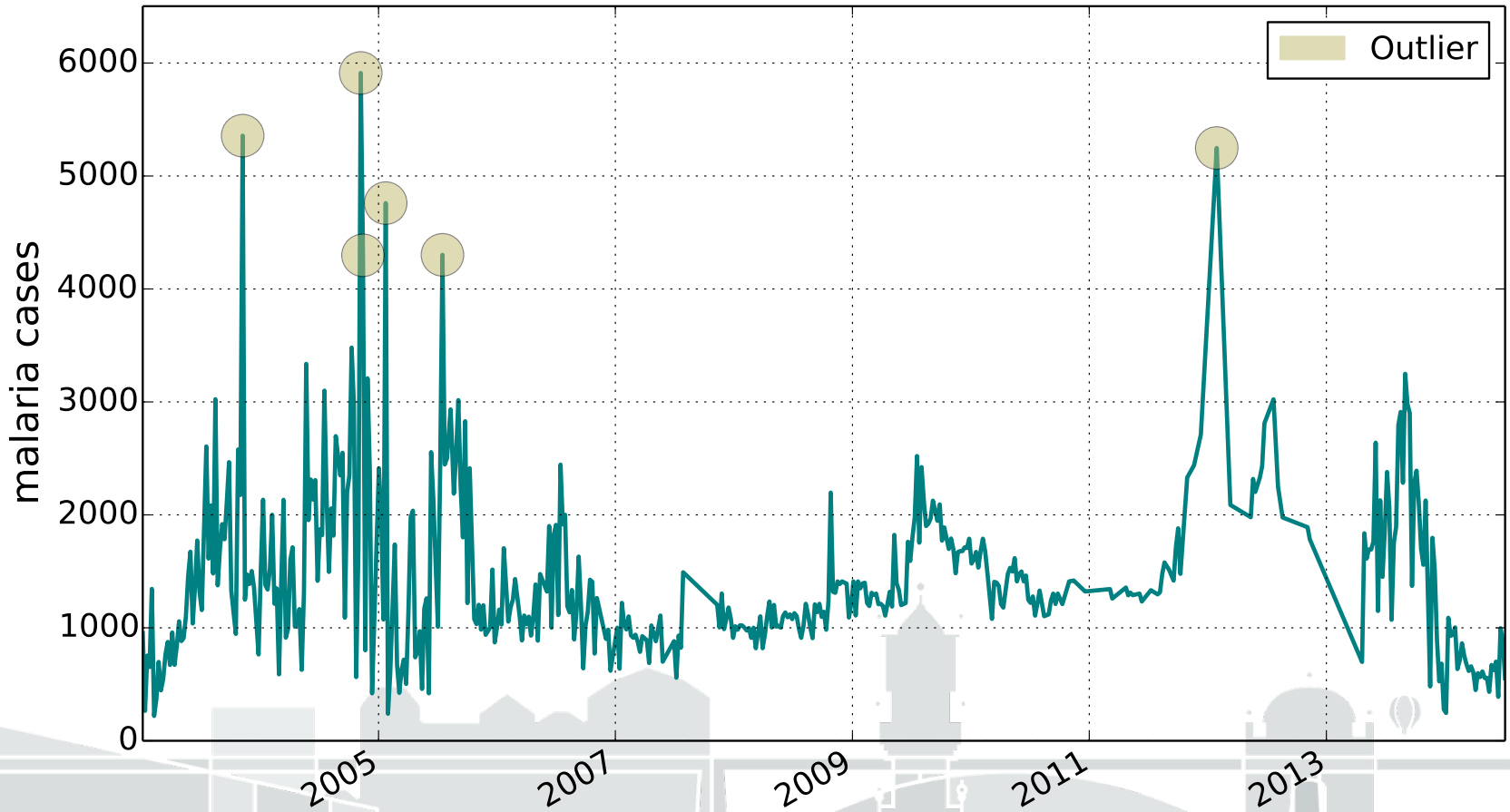


Figure : Kotido district

Challenges

Variation in the number of reporting facilities.

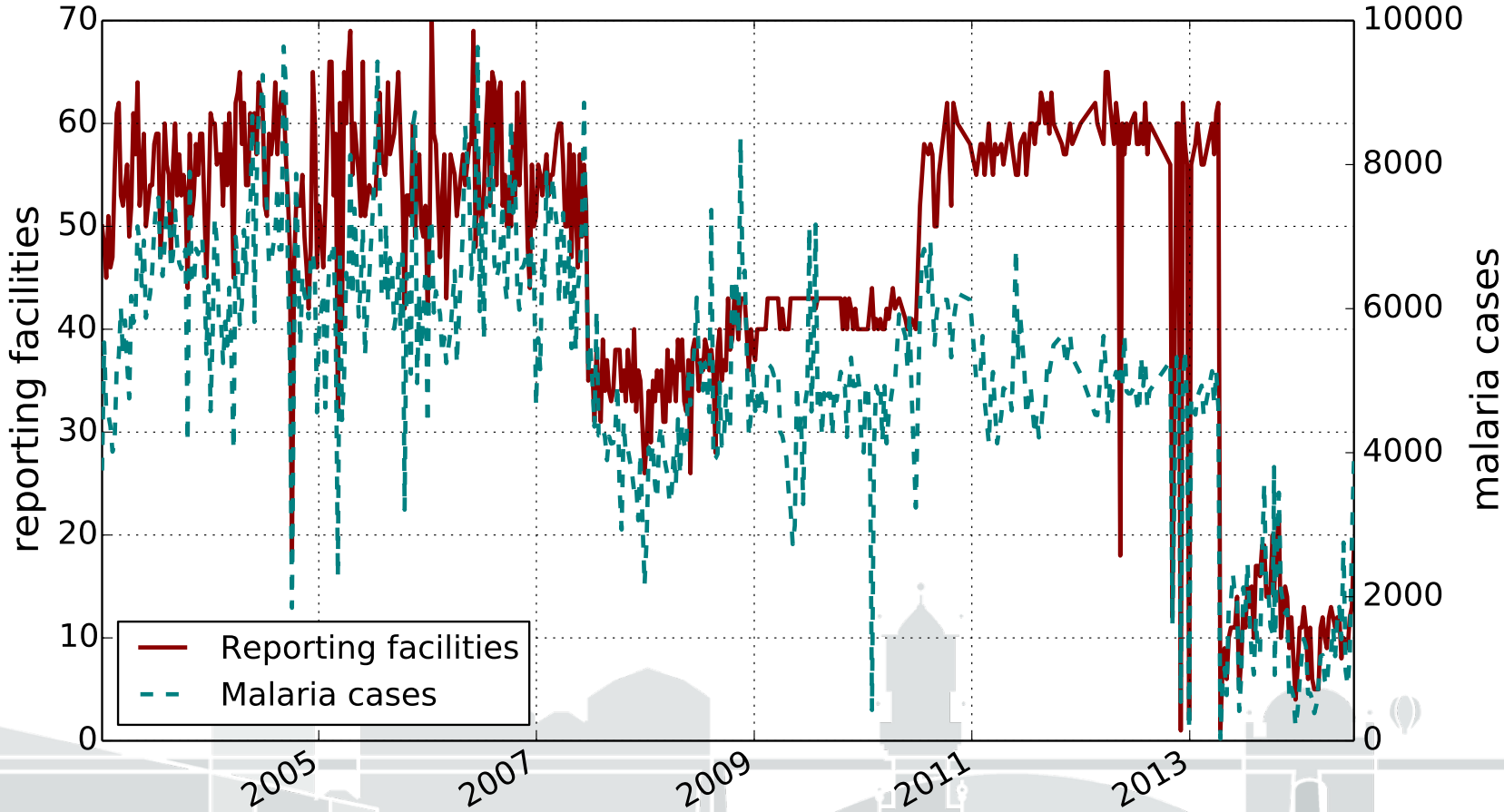


Figure : Arua district

Challenges

Change in districts boundaries definition.

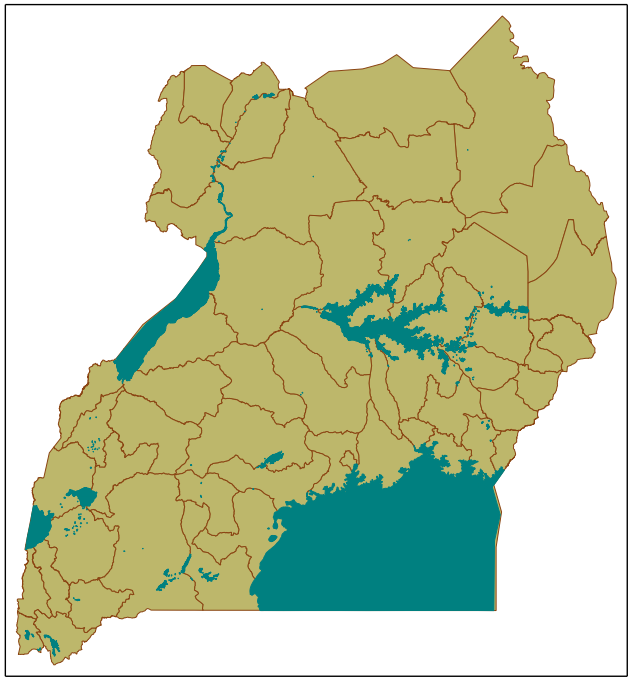


Figure : 2003 (56 districts)

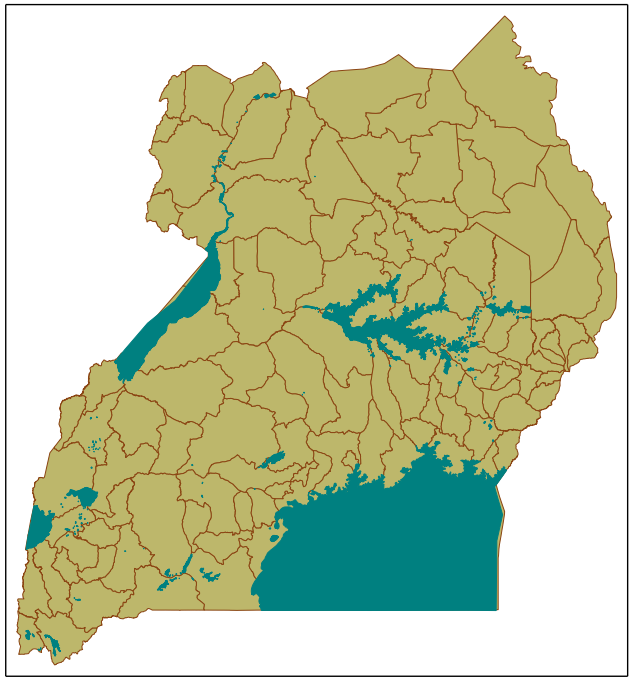
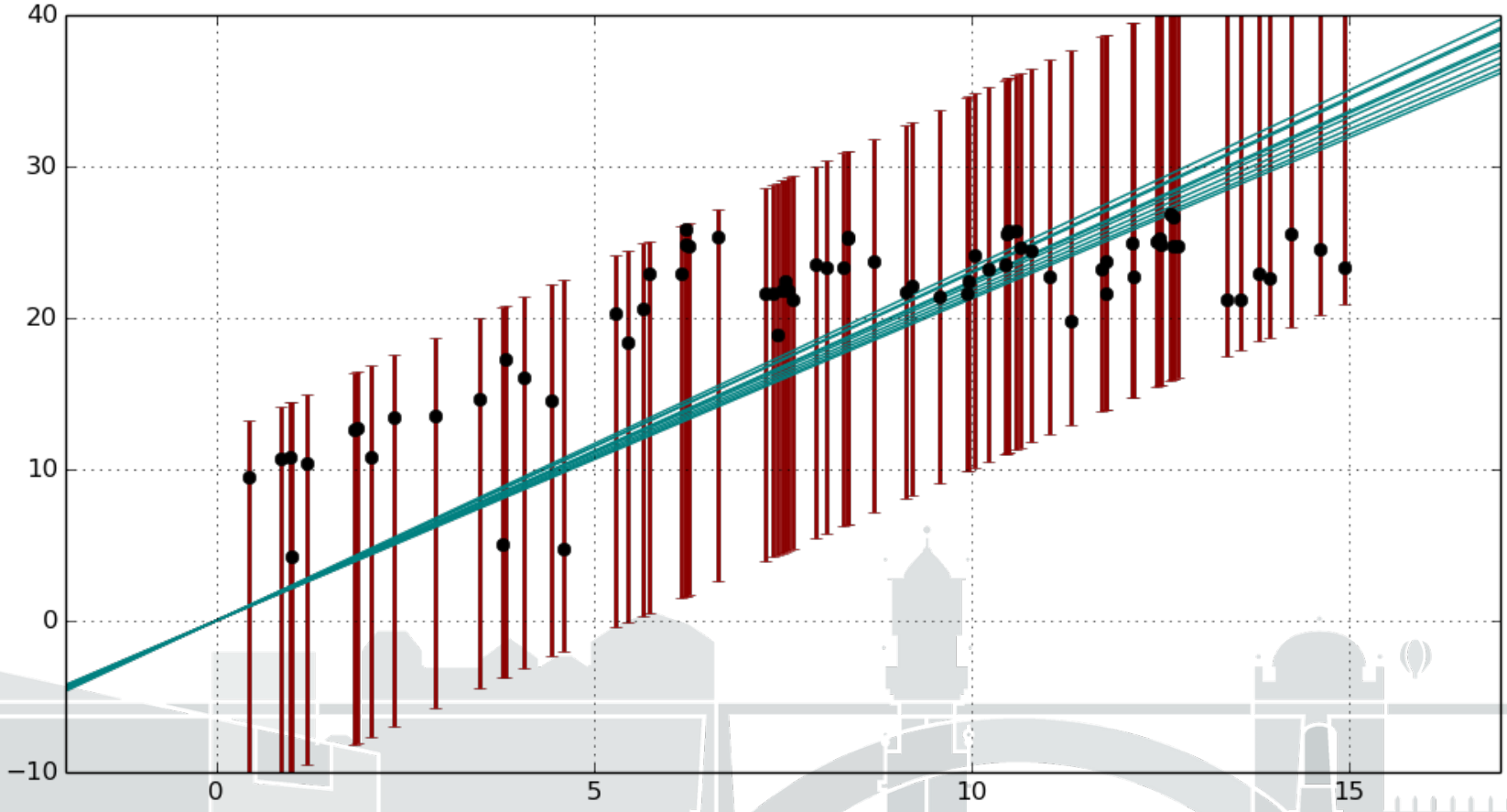


Figure : 2015 (112 districts)

Gaussian processes

A wide range of functions can be learnt through the use of different covariance functions and noise assumptions.



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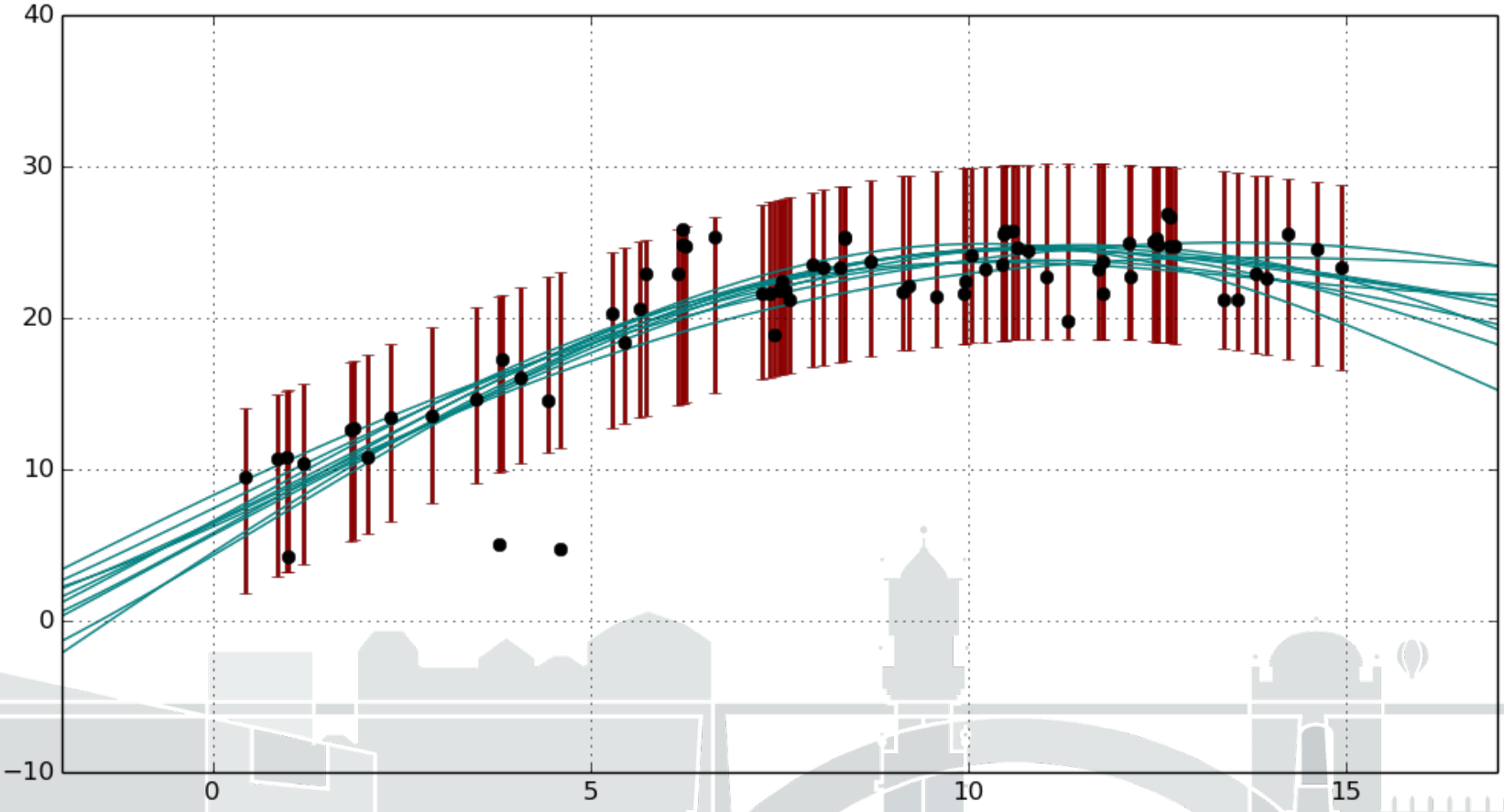

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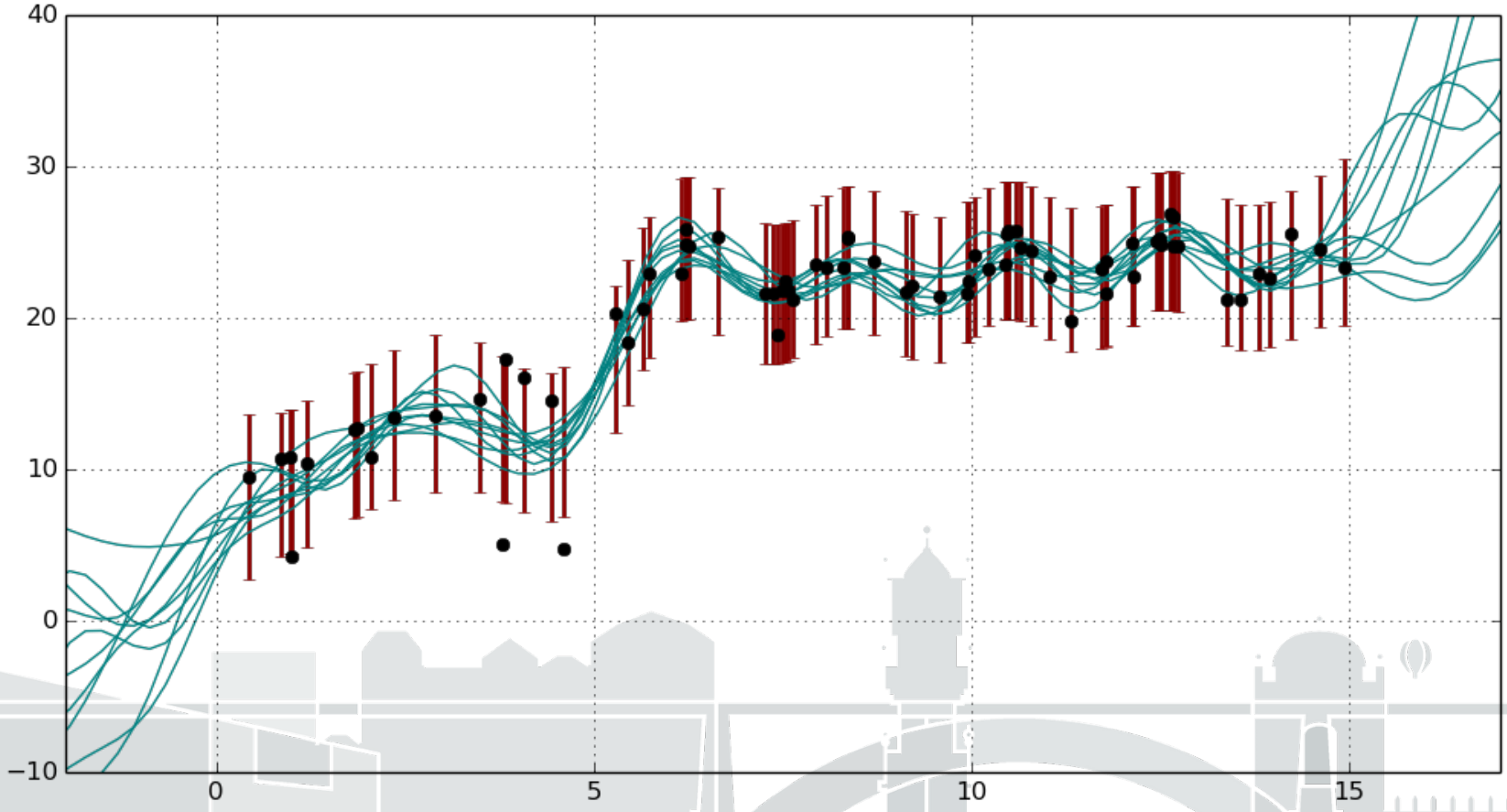

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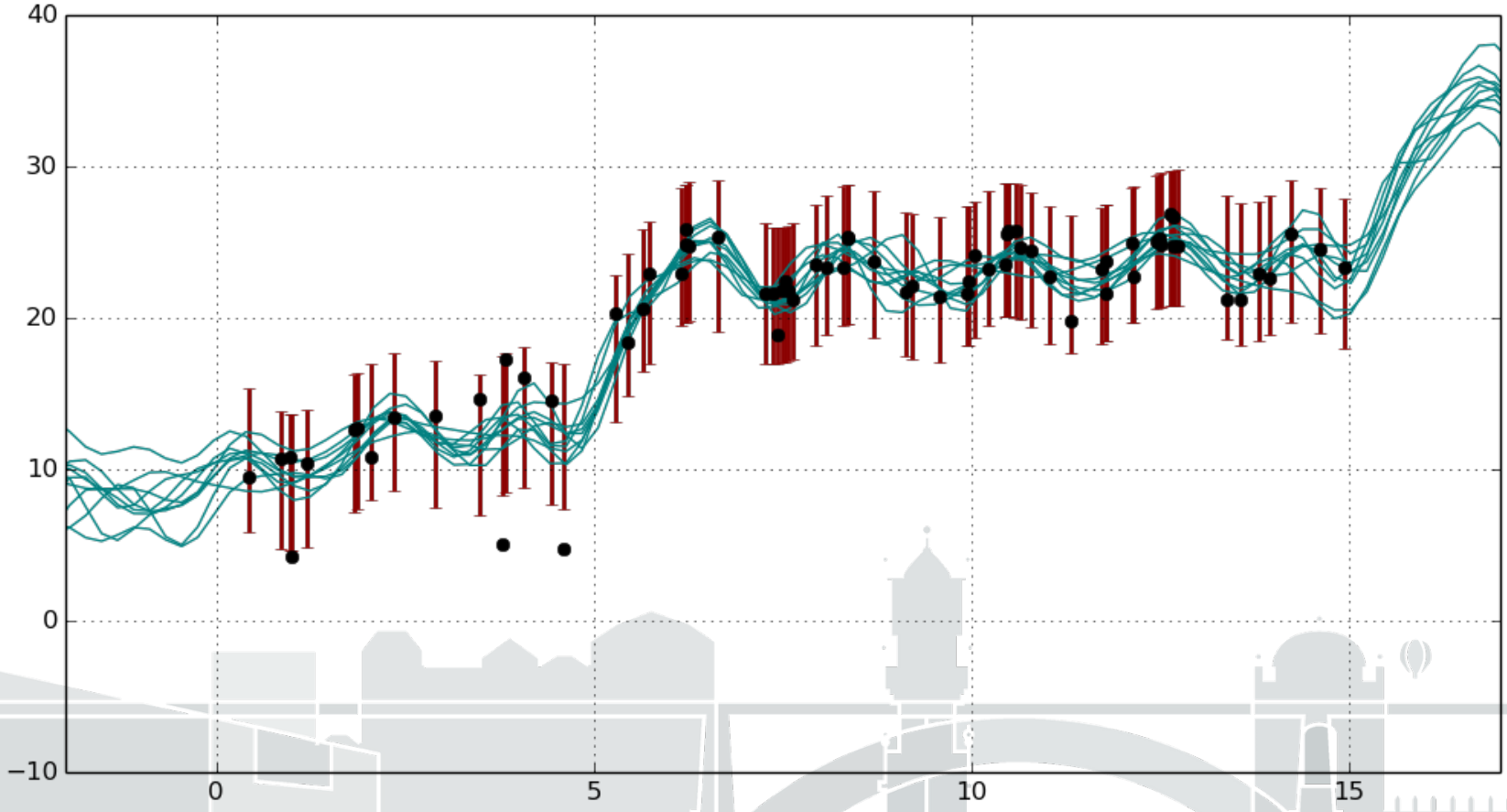

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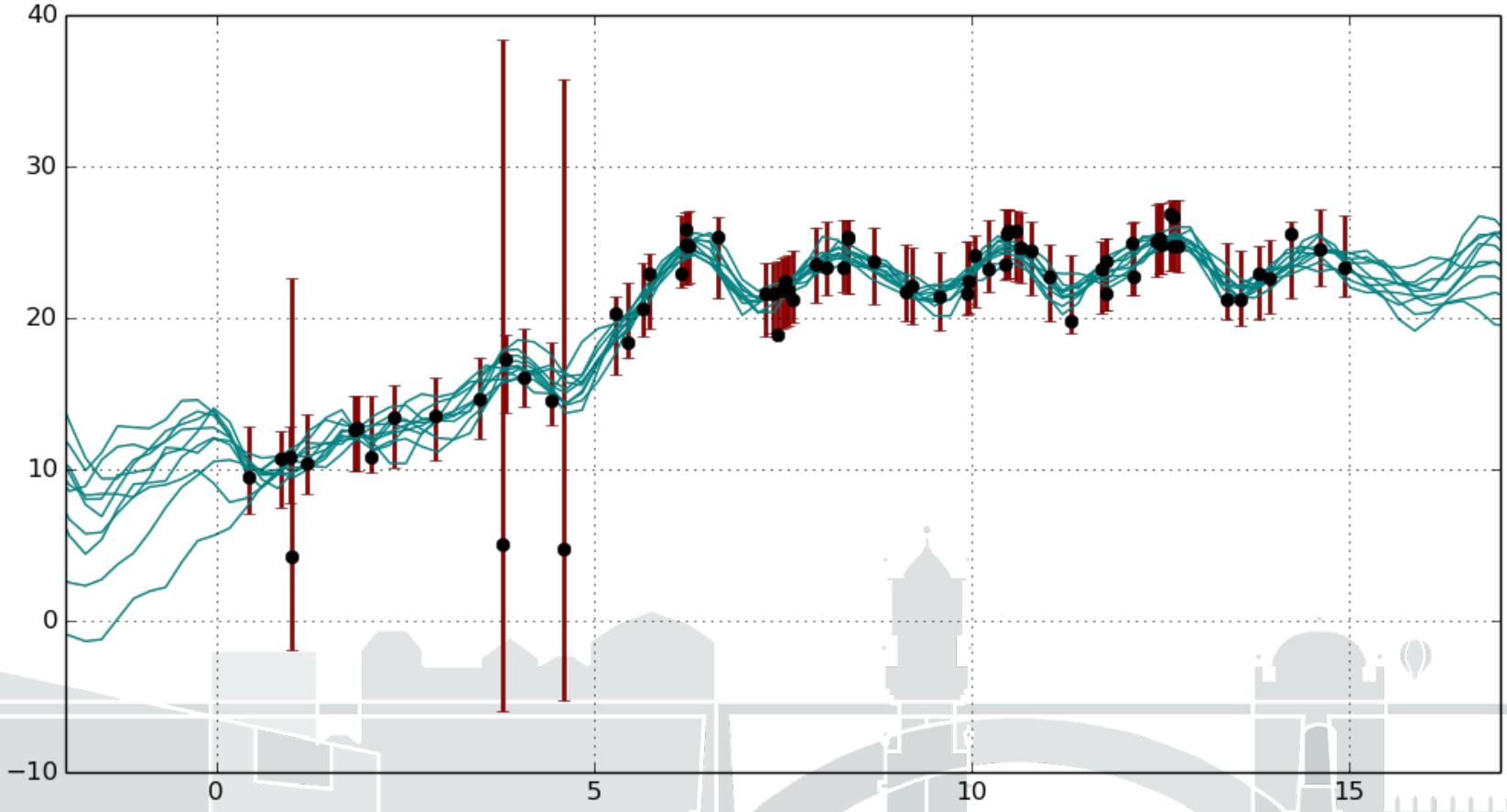

Gaussian processes

We can achieve a less noisy and consistent time series.

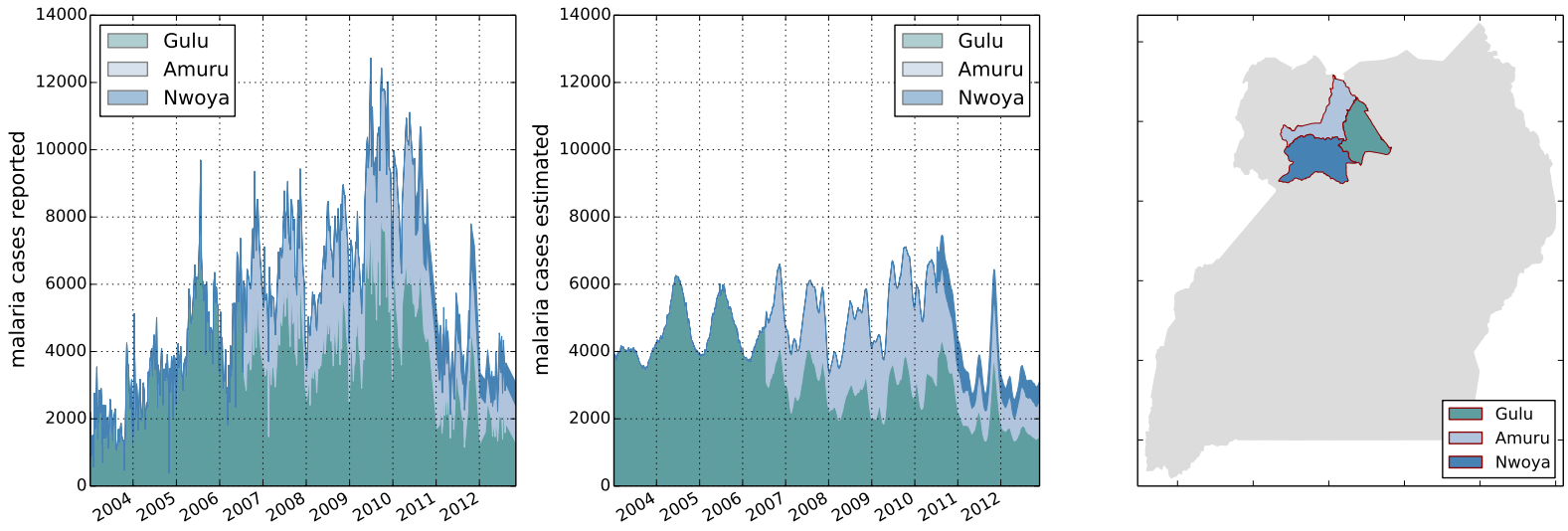

Figure : Signals estimated using a composed kernel

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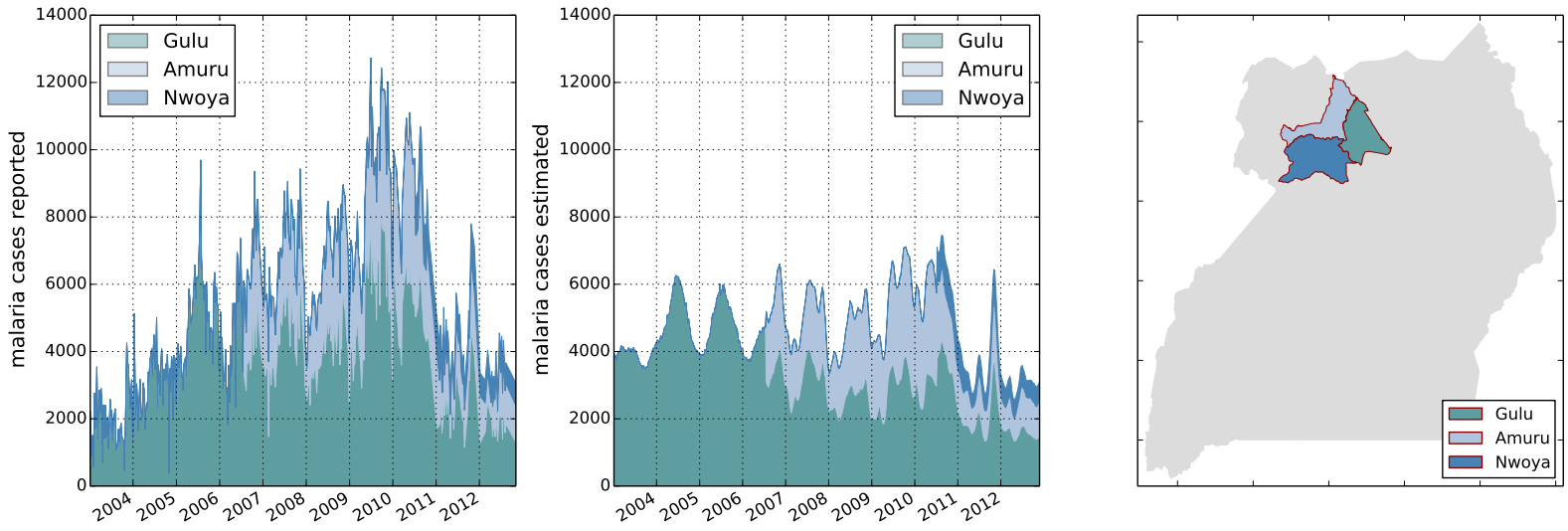

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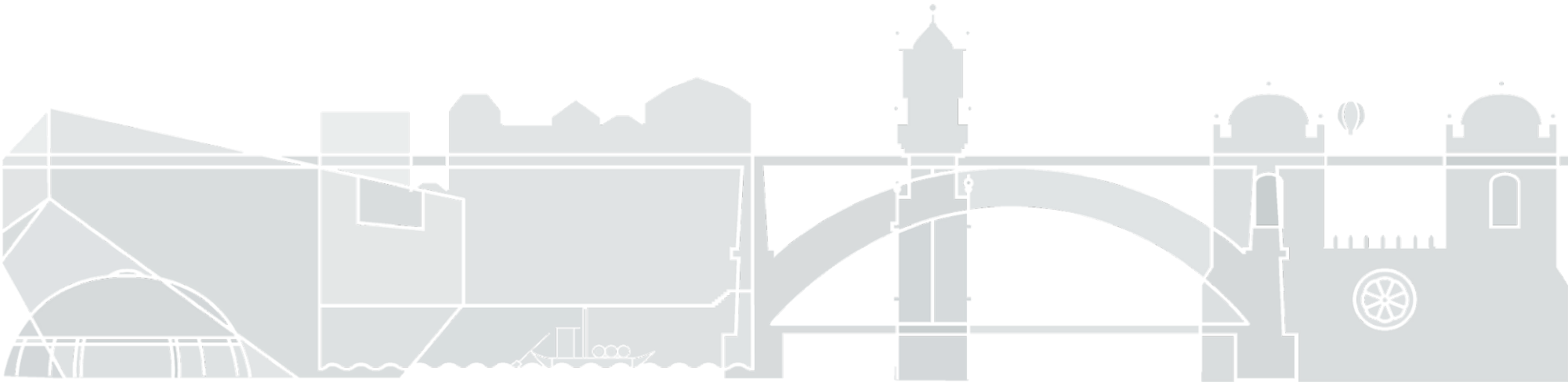
... but there is a smallprint.

Important considerations

- Unknown coverage of HMIS data against total population
- Total number of health facilities is not clear
- Being treated for malaria $\neq$ having malaria



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... so, we do not have means to assess the accuracy of our estimates.

- How to contribute given the current circumstances?

Gaussian process basics

Say we have an observed output y, we can model it as

$$y = f_{\mathbf{x}} + \epsilon$$

where $f_{\mathbf{x}} \sim \mathcal{GP}(\mathcal{M}, K)$.

The kernel function K defines the dependence structure of the process.

Signal decomposition with Gaussian processes

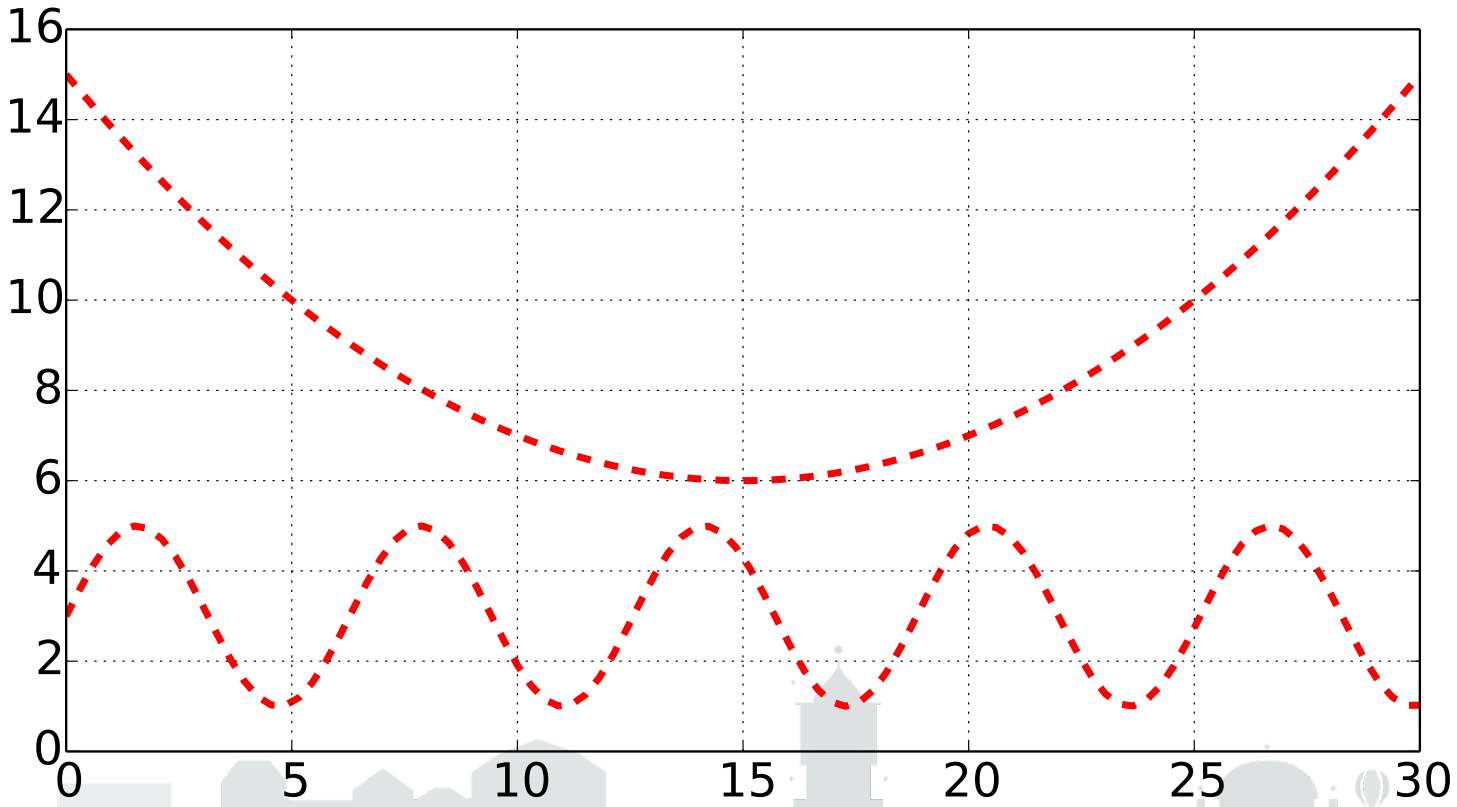


Figure : Two independent signals

Signal decomposition with Gaussian processes

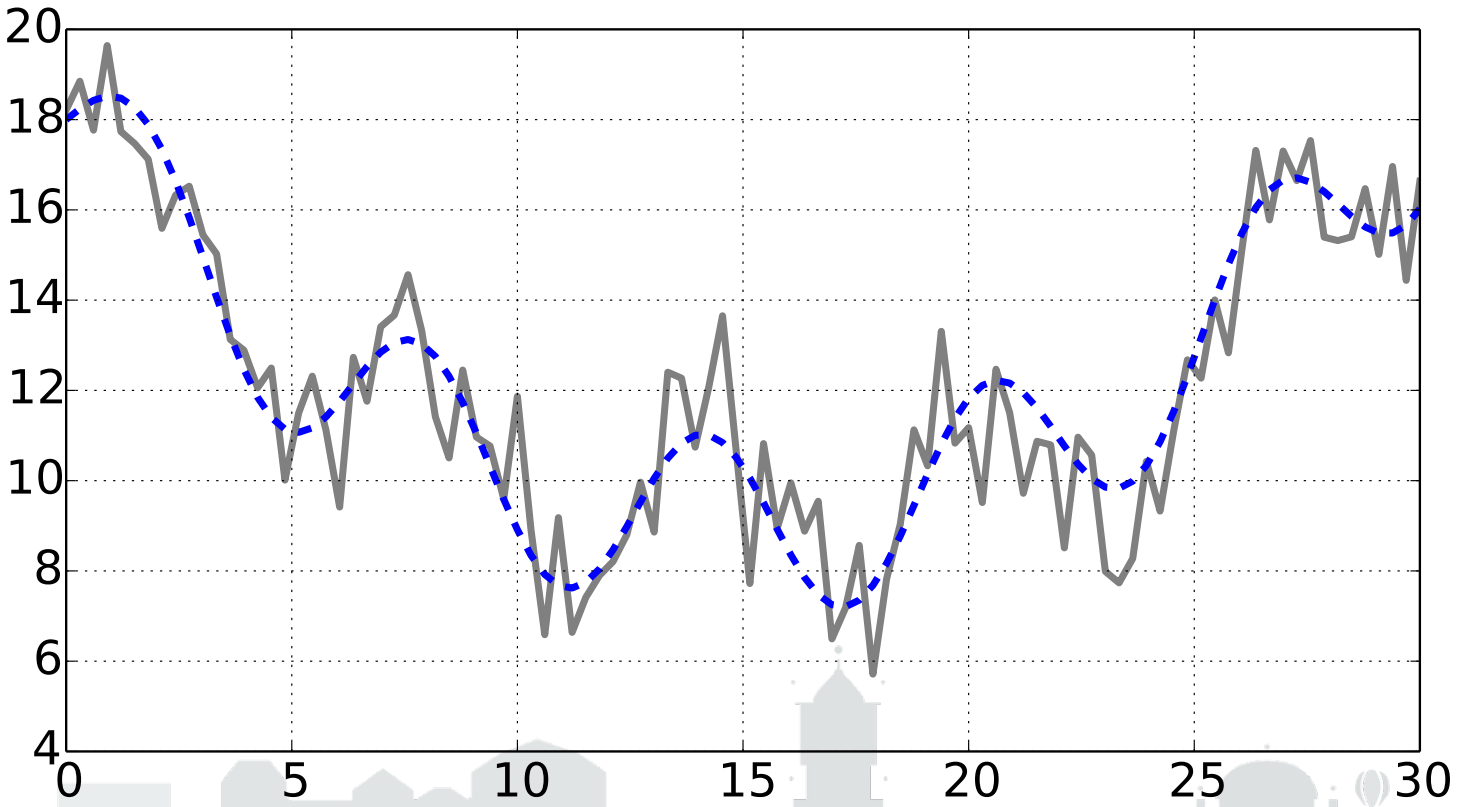


Figure : Combined signal with noise

Signal decomposition with Gaussian processes

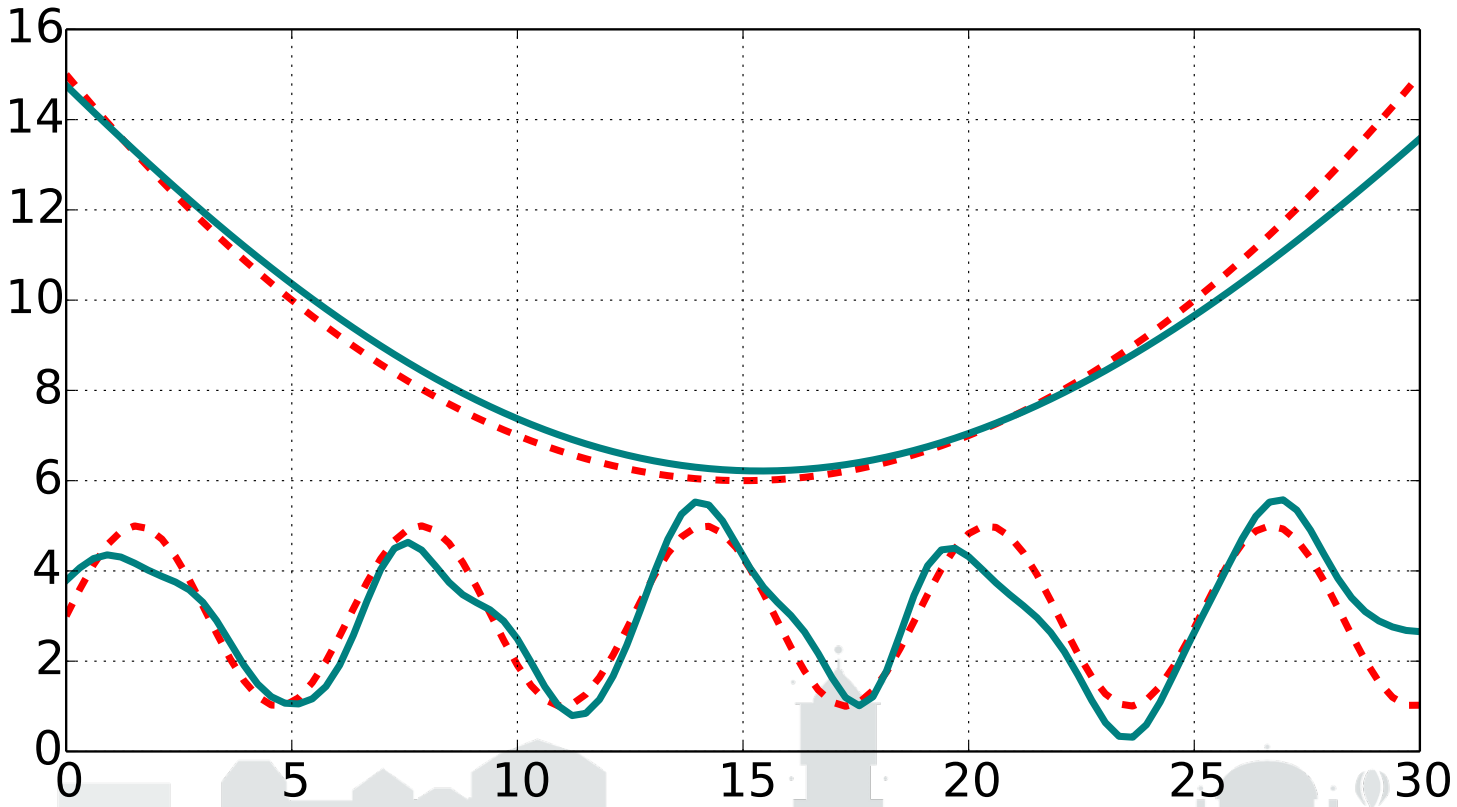
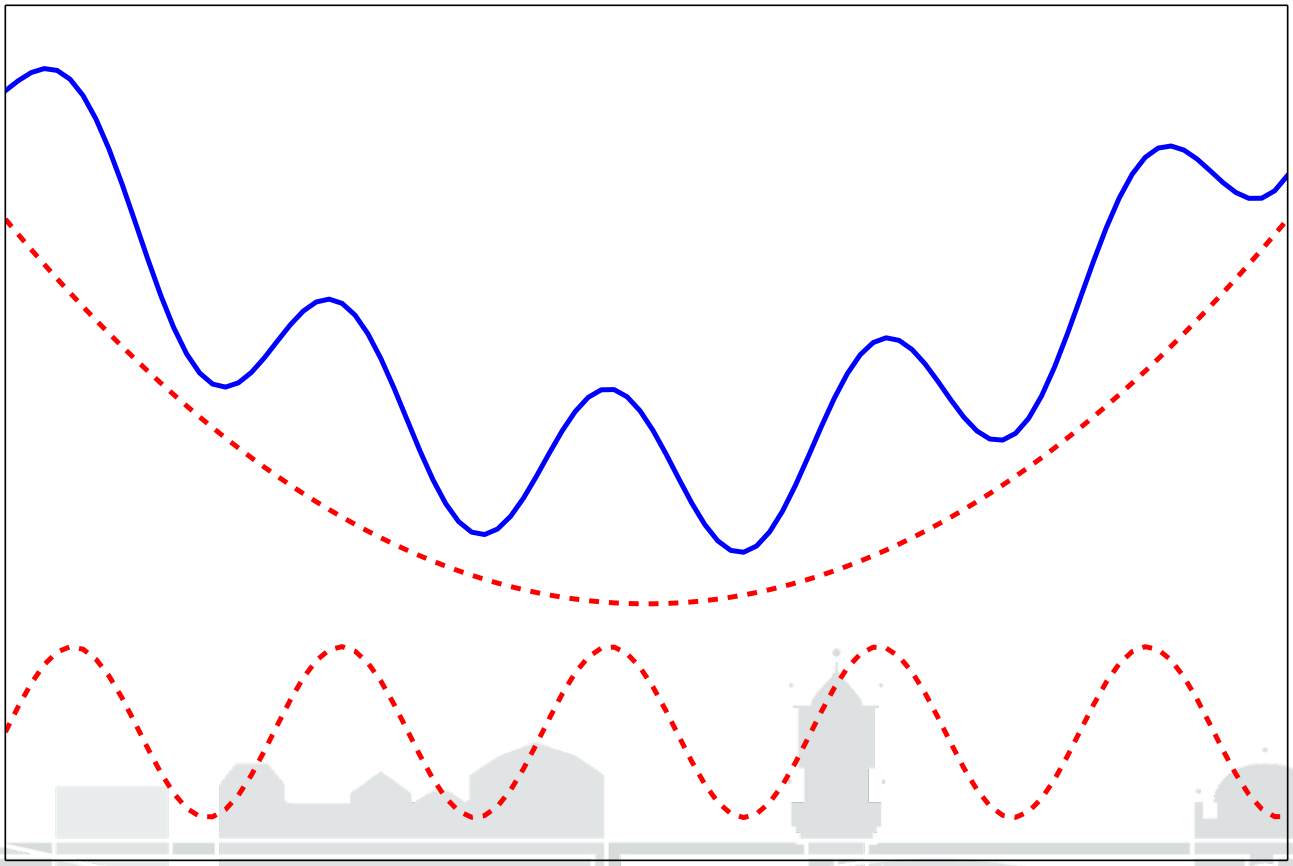


Figure : Signal estimation with a composed kernel

Signal decomposition with Gaussian processes



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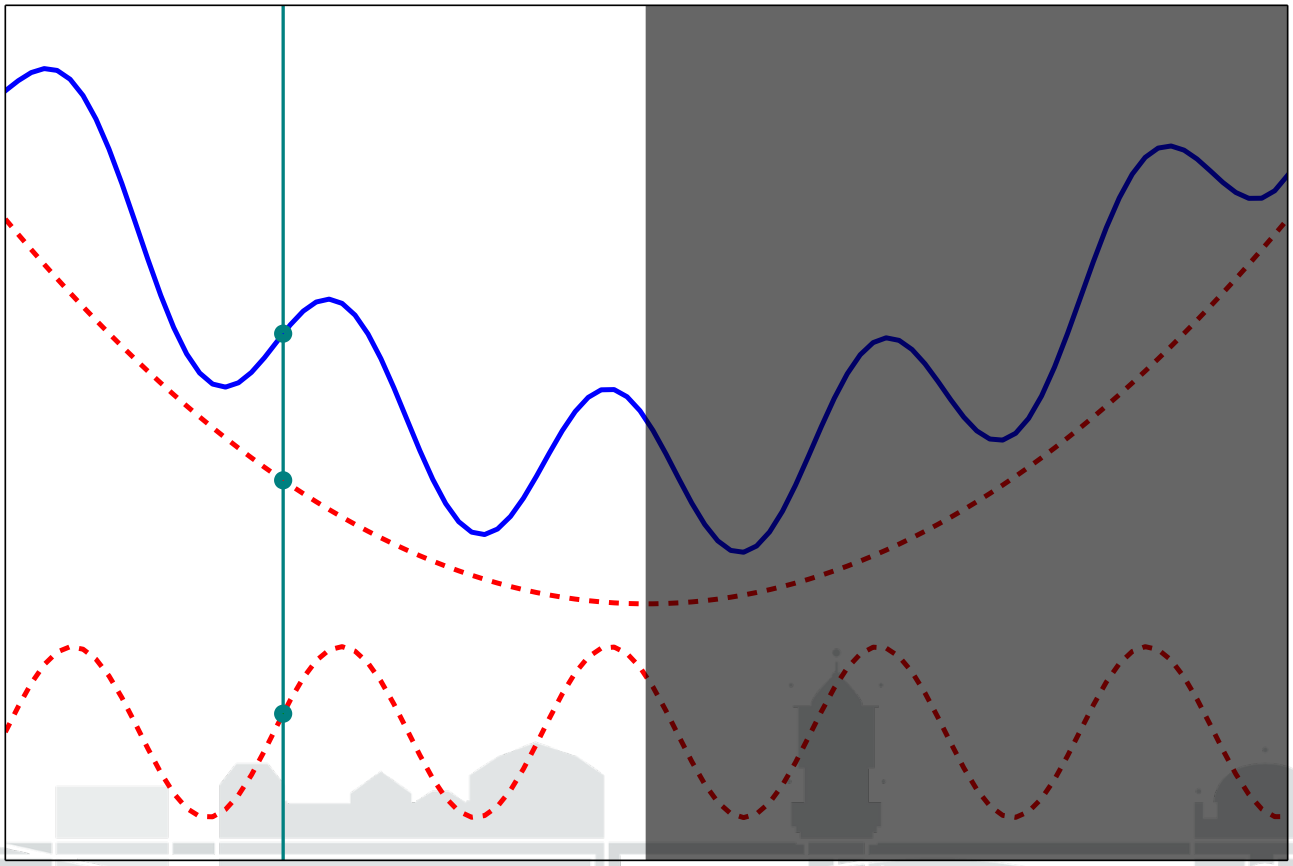


Simple computation of the derivative of each signal

If $f_{\mathbf{x}} \sim \mathcal{GP}(0, K)$, then

$$\begin{bmatrix} f_{\mathbf{x}} \\ \frac{\partial f_{\mathbf{x}}}{\partial \mathbf{x}} \end{bmatrix} \sim \mathcal{GP}(\mathbf{0}, \Gamma)$$

where

$$\Gamma = \begin{bmatrix} K & \frac{\partial}{\partial \mathbf{x}} K \\ \frac{\partial}{\partial \mathbf{x}} K & \frac{\partial^2}{\partial \mathbf{x}^2} K \end{bmatrix}$$

Large-scale signal derivative

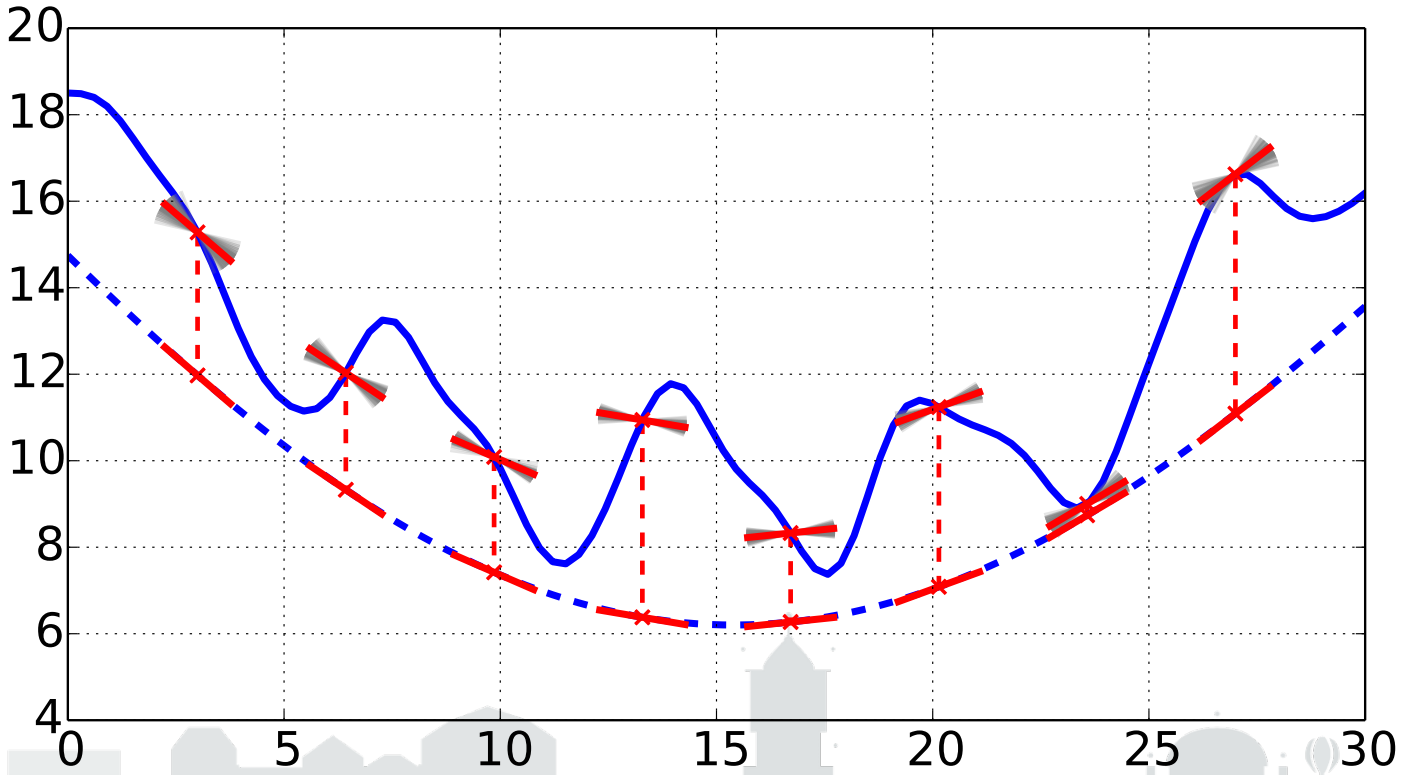


Figure : Signals estimated using a composed kernel

Short-scale signal derivative

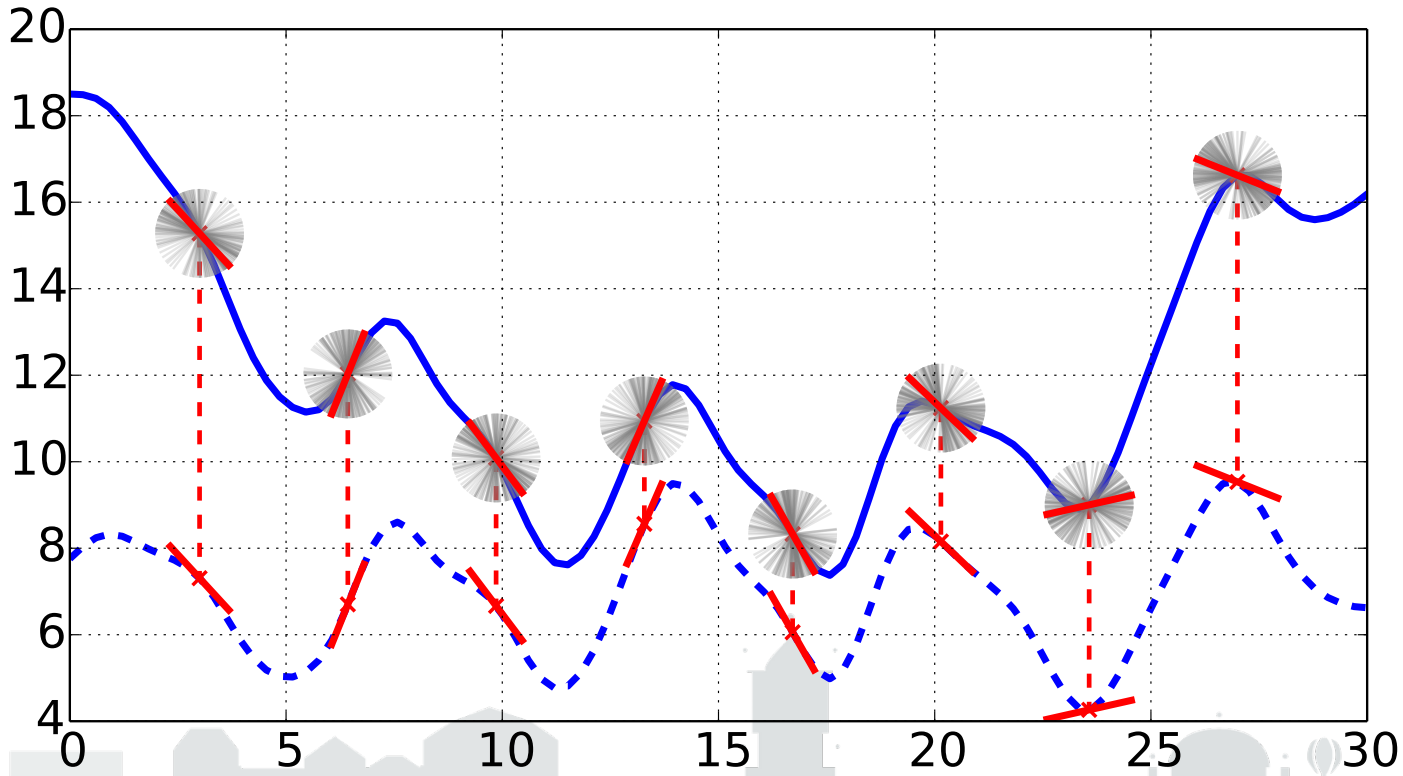


Figure : Signals estimated using a composed kernel

Back to our problem

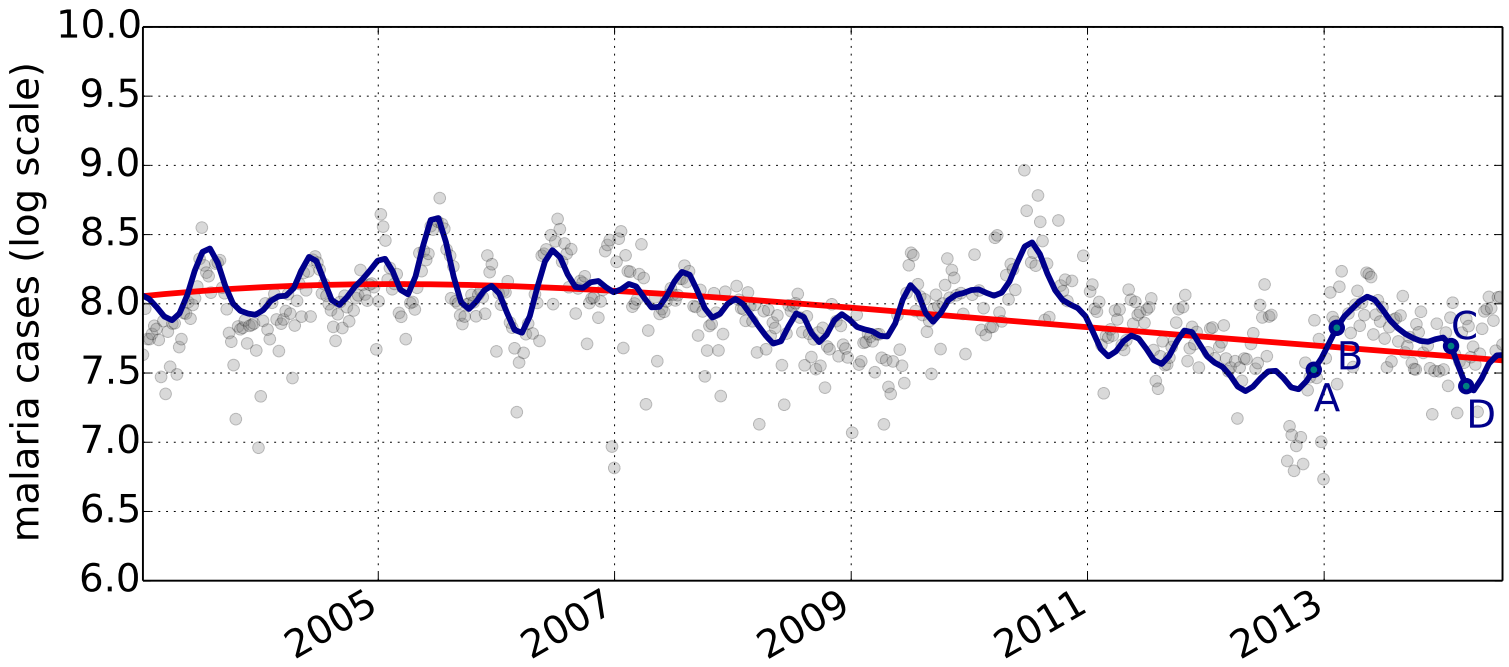


Figure : Short and long-scale variations in HMIS data

Warning system

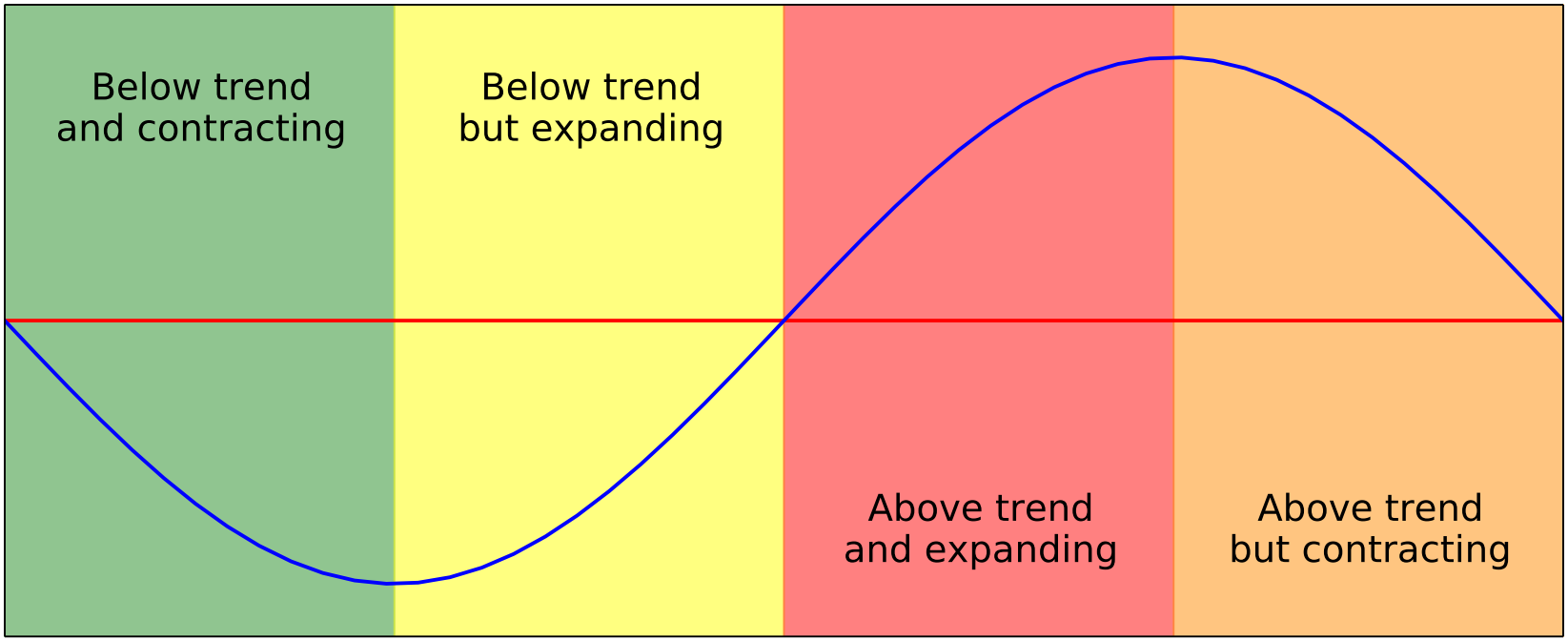
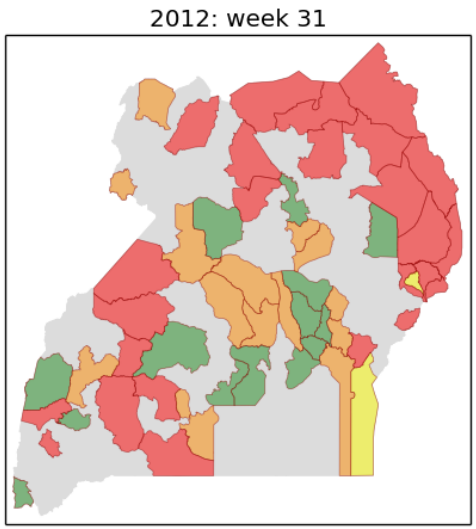
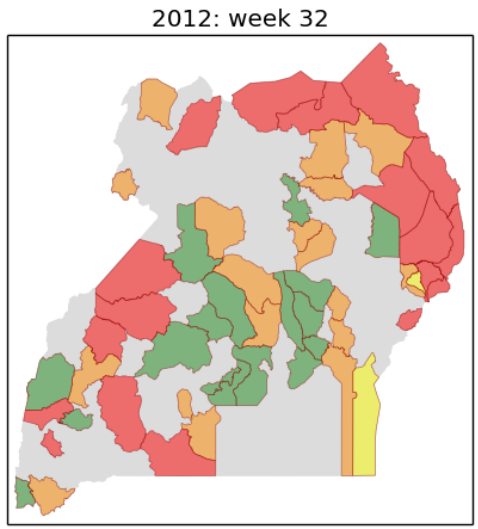


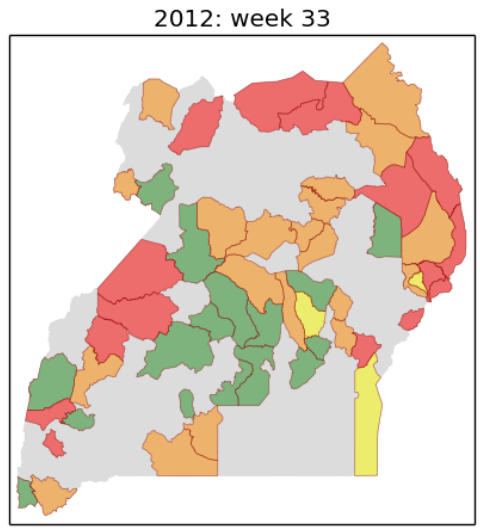
Figure : Classification of variations around the long-term trend

Uganda's monitor

http://ric70x7.github.io/research.html

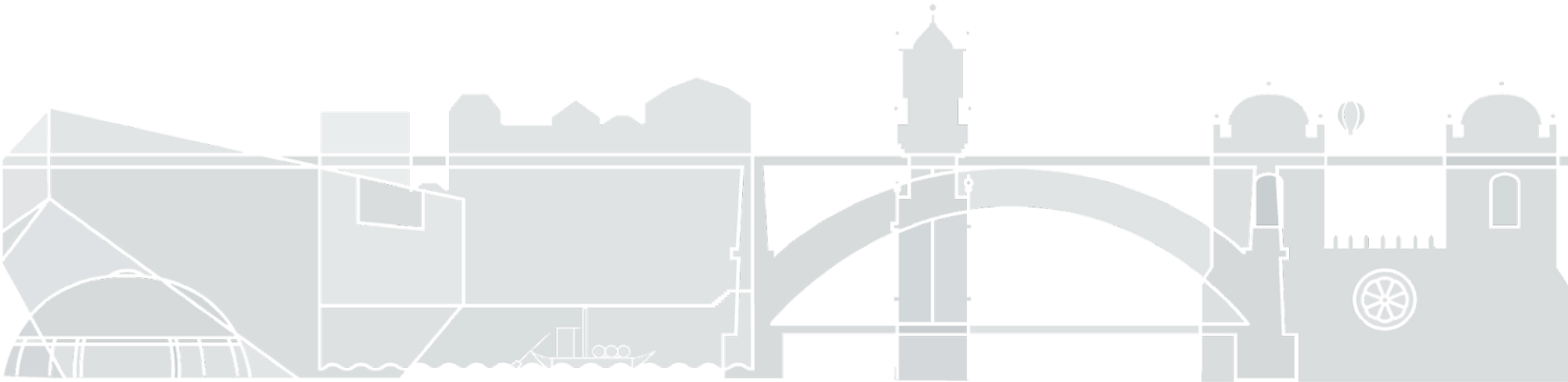






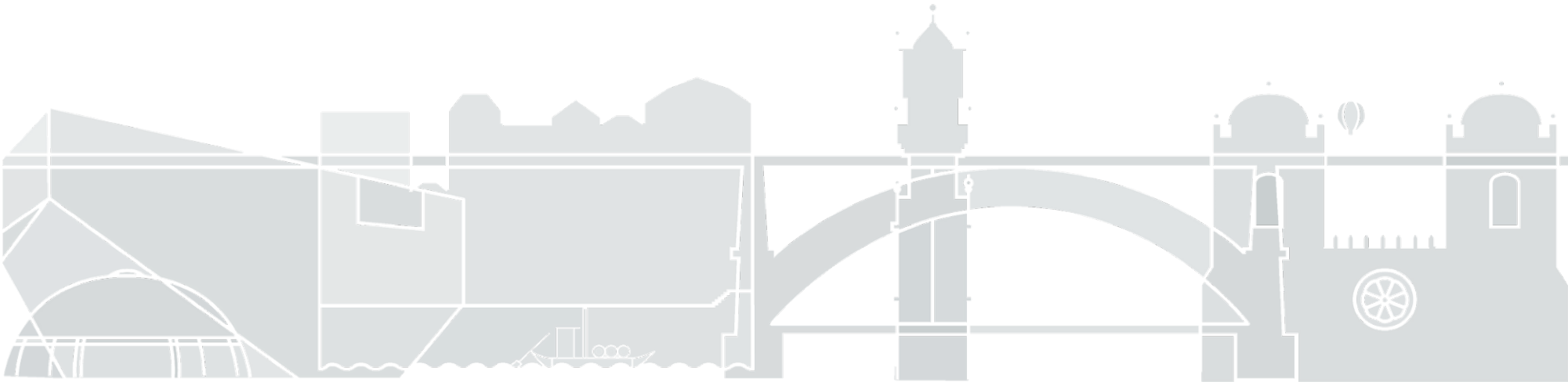
Next steps

- Further research is needed to explore the benefits of this model in practice.
- Future plans to implement it with other diseases.



Final remark

- Perhaps one of the most important challenges of statistics will always be to communicate with domain-oriented sciences and planners from different sectors.



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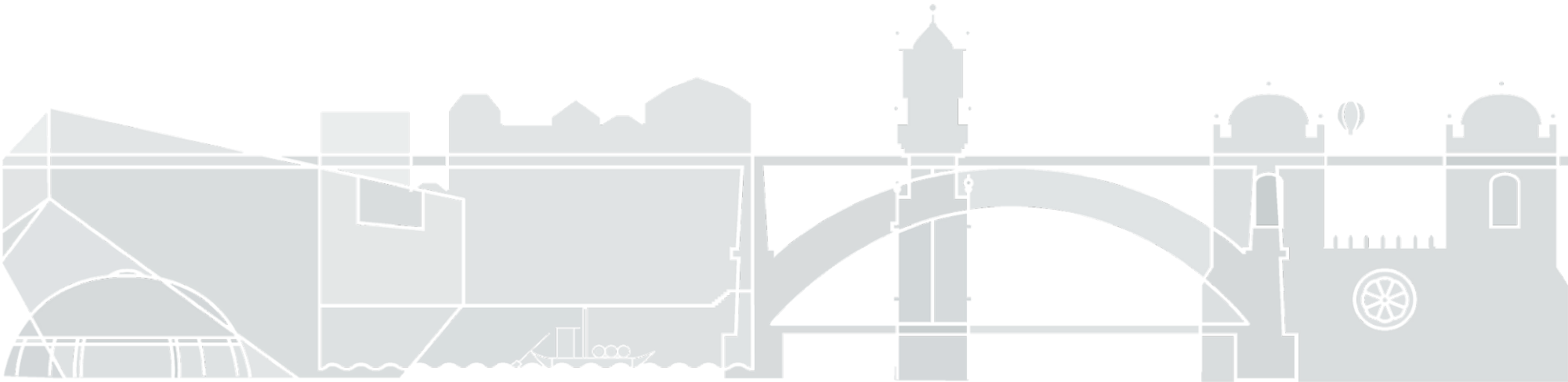
- We have passed the stage where we were able to provide just a mean and variance estimate, and now are able to provide density functions estimates.



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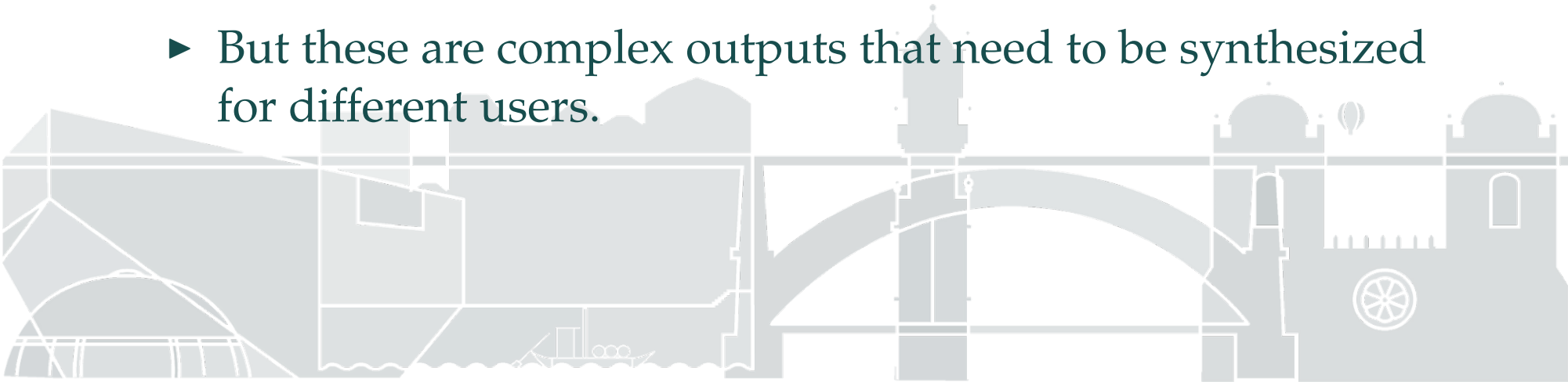
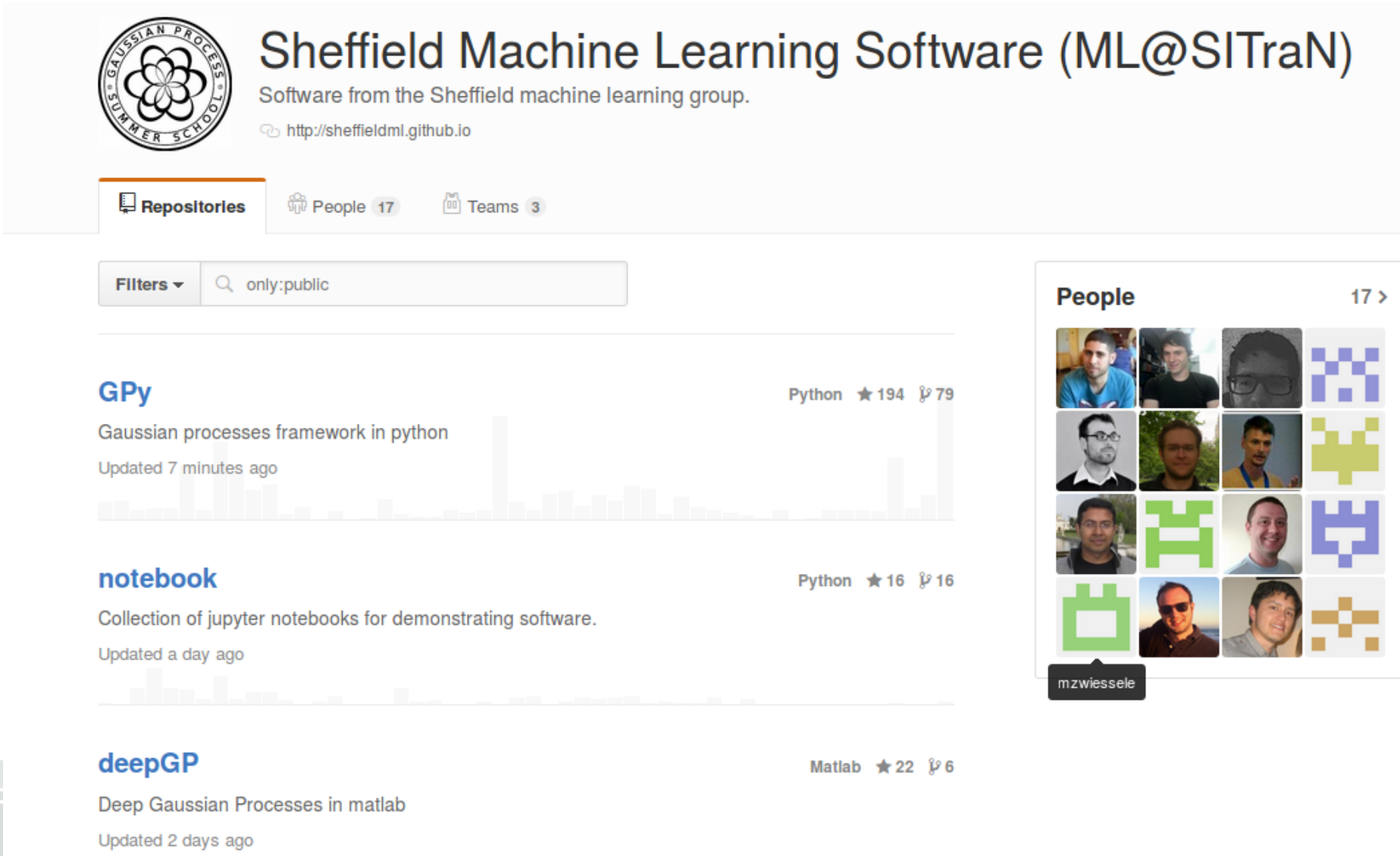
- We have passed the stage where we were able to provide just a mean and variance estimate, and now are able to provide density functions estimates.
- But these are complex outputs that need to be synthesized for different users.



All our models were implemented using GPy



- https://github.com/SheffieldML/GPy

Collaborators

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References I

[1] Luca Baldassarre, Lorenzo Rosasco, Annalisa Barla, and Alessandro Verri. Multi-output learning via spectral filtering. *Machine Learning*, 87(3):259–301, 2012.

[2] Marianne Baxter and Robert G King. Measuring business cycles: approximate band-pass filters for economic time series. *Review of economics and statistics*, 81(4):575–593, 1999.

[3] William P Cleveland and George C Tiao. Decomposition of seasonal time series: A model for the census X-11 program. *Journal of the American statistical Association*, 71(355):581–587, 1976.

[4] Nicolas Durrande, James Hensman, Magnus Rattray, and Neil D Lawrence. Gaussian process models for periodicity detection. *arXiv preprint arXiv:1303.7090*, 2013.

[5] Simon I. Hay, Robert W. Snow, and David J. Rogers. From predicting mosquito habitat to malaria seasons using remotely sensed data: practice, problems and perspectives. *Parasitology Today*, 14(8):306–313, 1998.

[6] Aapo Hyvärinen and Erkki Oja. Independent component analysis: algorithms and applications. *Neural networks*, 13(4):411–430, 2000.

[7] Georges Matheron. Pour une analyse krigeante de donnés régionalisées. Technical report, École des Mines de Paris, Fontainebleau, France, 1982.

[8] Charles A. Micchelli and Massimiliano Pontil. Kernels for multi-task learning. In *Advances in Neural Information Processing Systems (NIPS)*. MIT Press, 2004.

References II

[9] Charles A. Micchelli and Massimiliano Pontil. On learning vector–valued functions. *Neural Computation*, 17:177–204, 2005.

[10] Donald E. Myers. Matrix formulation of co-Kriging. *Journal of the International Association for Mathematical Geology*, 14(3):249–257, 1982.

[11] H. Quenouille. *The analysis of multiple time-series*. Griffin's statistical monographs & courses. Griffin, 1957.

[12] Simo Särkkä. Linear operators and stochastic partial differential equations in Gaussian process regression. In *Artificial Neural Networks and Machine Learning–ICANN 2011*, pages 151–158. Springer, 2011.

[13] John Shawe-Taylor and Nello Cristianini. *Kernel Methods for Pattern Analysis*. Cambridge University Press, Cambridge, U.K., 2004.

[14] Floris van Ruth, Barry Schouten, and Roberto Wekker. The statistics Netherlands business cycle tracer. Methodological aspects; concept, cycle computation and indicator selection. Technical report, Statistics Netherlands, 2005.

[15] Christopher K. I. Williams and Carl Edward Rasmussen. *Gaussian processes for Machine Learning*. MIT Press, 2006.

[16] World Health Organization. World health statistics 2015. Technical report, WHO Press, Geneva, 2015.

[17] World Health Organization and others. World malaria report 2014. Technical report, WHO Press, Geneva, 2014.

[18] Akira Moiseevich Yaglom. *Correlation theory of stationary and related random functions I: Basic results*. Springer-Verlang, 1986.