Bayesian hierarchical modeling and analysis of spatial-temporal data
Project IV (MATH4072)

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Description

The focus of this project is the study of statistical methods, and related computational tools that can be used for the analysis of spatial, or spatial-temporal data-sets, mainly in the Bayesian framework.

Data-sets with the colorful adjectives 'spatial' or 'temporal' contain data with labels indicating where or when (respectively) have been collected. Such data exist in problems in environmental, climatology, weather forecasting, epidemics, engineering, biology, etc... Spatial-temporal statistical methodologies utilizing such data-sets to build probabilistic models in order to perform predictions and inferences. Bayesian hierarchical modelling allows one to express and quantify uncertainties at different levels, as well as to perform more accurate predictions.

Project specific intended learning outcomes

By the end of this project, students will be able to design suitable Bayesian hierarchical models over space-time-stochastic domains, and apply these models for the analysis of real spatial-temporal data, as well as implement Bayesian computational tools for training these models. You will be exposed to the use of suitable software required to the practical implementation of the methodology.

Potential project directions

By the end of term 1, students will be able to choose a specific direction on which the project focuses, some examples:

Temporal data methods: In many cases the spatial data are time-dependent. The challenge is to capture the dynamic behaviours.

Multivariate data methods: Often when we collect data, (e.g., weather data), we collect several characteristics/variables (e.g., precipitation, pressure, etc...). Here, a challenge is how to model their dependencies.

Large data methods: A satellite picture of a region may contain several 'pixels' (aka data), or be contaminated by noise. Processing all this information bears serious computational challenges.

Downscaling/upscaling methods What if we get data on one scale and we need to make inference on another one? Spatial data at different scales e.g. global, regional, local, etc.. are associated with different variabilities/dependencies.

Multi-resolution data methods: Often data from different sources are available. We may have weather data collected from different satellites (an old and an new); or from different sources a satellites and field stations.

Analysis of real data: Possible data-sets you can analyze as part of your projects can be: disease (like SARS, H1N1, COVID-19, etc...), CO2 concentration, remote sensing satellite data, etc ...

or any other...

Mode of Operation and Evidence of Learning:

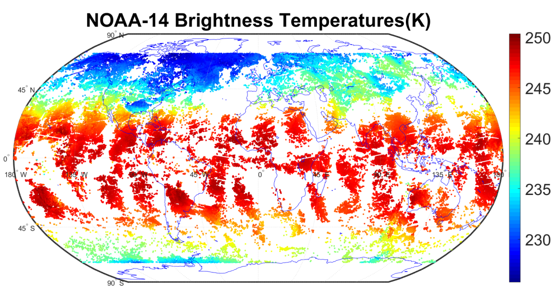
- The individual project will involve independent reading, sustained critical investigation, and a substantial piece of statistical work on a focused topic. Depending on the topic selected, this may include methodological comparison, simulation design, real-data analysis, algorithmic implementation, or a structured review of the literature. Evidence of learning will be demonstrated through a coherent written report, supported where appropriate by figures, tables, code, and critical discussion of modelling choices, assumptions, limitations, and conclusions.

An example

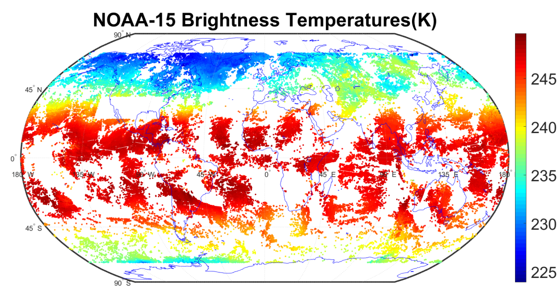
Fig 1 presents temperature data collected from an old, a-little-a-bit-rusty, satellite N-14 a long time ago. Fig 2 presents data collected from a new satellite N-15 which is in a better shape and hence more accurate.

A statistical challenge here is how to build a model properly combining big data sets from different sources at different accuracy, in order to learn what is going on at locations where measurements from the accurate source are not available (e.g. U.S.A, Oceania, etc...), as well as learn discrepancies between the different data sources, over time.

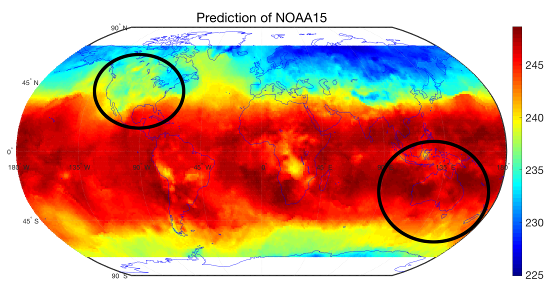
Fig 3 presents the predicted temperatures, at a specific time-step and over the whole area, produced by a Spatial-Temporal Statistics approach properly combining information available from different sources of different accuracy.



(1)



(2)



(3)

Borrowed from: Cheng, S., Konomi, B. A., Matthews, J. L., Karagianis, G., & Kang, E. L. (2020). Hierarchical Bayesian Nearest Neighbor Co-Kriging Gaussian Process Models; An Application to Intersatellite Calibration. arXiv preprint arXiv:2004.01341.

Requirements

- Bayesian Computation and Modelling III, or Advanced Statistical Modelling III

References

- Wikle, C. K. (2015). Modern perspectives on statistics for spatio-temporal data. Wiley Interdisciplinary Reviews: Computational Statistics, 7(1), 86-98. [LINK]
- Cressie, N., & Wikle, C. K. (2015). Statistics for spatio-temporal data. John Wiley & Sons. [https://spacetimewithr.org/]
- Banerjee, S., Carlin, B. P., & Gelfand, A. E. (2014). Hierarchical modeling and analysis for spatial data. CRC press.

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