Advanced Topics in Time Series, Spatiotemporal Modeling, and Prediction with uncertainty quantification

This 3 ECTS PhD course is modular, coordinated by Prof. Anotnietta Mira, with guest lecturers. It will take place during the week of 23.2.2026

Names of the lecturers, titles and abstracts of the modules are listed below (with time)

Students are welcome to also take single modules.
To signup please send an email to Katie Mue katia.mue@usi.ch with an approval letter (or email) from your advisor who agrees on you taking the course.

Module by Luca Danese requires to have a background in Bayesian statistics which is provided in the module by Anish Mukherjee.

The lectures will take place in Lugano, Via Buffi, room PC-04 (Blue Building).
For motivated reasons a TEAMS link could be provided.

Module 1: Dr. Anish Mukherjee
Monday: 10.30-12.00 and 13.00-17.00
Tuesday: 9.00-12.00

Foundations of Bayesian Inference and Spatial/Temporal Dependence

Abstract: This module provides a comprehensive introduction to **Bayesian spatiotemporal models** with a particular focus on applications in **macroeconomics and finance**. The module begins with the foundations of Bayesian inference and modern computational techniques, including Markov Chain Monte Carlo methods, and introduces the key challenges posed by spatial and temporal dependence in economic and financial data. Participants will learn how to model spatial heterogeneity, spillovers, and dynamic interactions using Bayesian spatial regression models, state-space formulations, and time-varying parameter models.
Building on these foundations, the module covers advanced topics such as Bayesian Vector Autoregressions (BVARs) and their spatiotemporal extensions, hierarchical models for multi-scale data, and approaches to handling high-dimensional parameter spaces through informative priors. The final sessions focus on real-world applications, including monetary policy transmission, regional housing markets, and financial contagion, as well as model comparison, Bayesian model averaging, and forecasting. The module concludes with a discussion of frontier research directions, including nonlinear models, machine learning integration, and open research questions.
The module combines **theoretical lectures with hands-on sessions** using making it suitable for graduate students, researchers, and practitioners with a background in econometrics or applied statistics who wish to apply Bayesian methods to complex spatiotemporal data.

Main references:

- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2013). Bayesian data analysis (3rd ed.). CRC Press.
- LeSage, J. P., & Pace, R. K. (2009). Introduction to spatial econometrics. CRC Press.
- Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. The Review of Economic Studies, 72(3), 821–852.
- Clark, T., & Mertens, E. (2023, September 20). Stochastic Volatility in Bayesian Vector Autoregressions. Oxford Research Encyclopedia of Economics and Finance.
- Sahu, S. K. (2022). Bayesian Modeling of Spatio-Temporal Data with R. CRC Press.

Module 2: Prof. Luiza Piancastelli
Tuesday 13.00-16.00
Wednesday 9.00-12.00 and 13.00-16.00
Statistical analysis of integer-valued time series

Abstract: This module approaches statistical analysis of integer-valued time series with the INGARCH (Integer-valued Generalized Autoregressive Conditional Heteroskedasticity) models, the integer-valued counterpart of GARCH models. These are general time series models in which the conditional mean may depend on past observations, its own lagged values and covariates. INGARCH models based on the Poisson and Negative-Binomial distributions are addressed, alongside their linear and log-linear stipulations. Methods for estimation, inference, and model diagnostics are discussed, with practical implementation illustrated using the **tscount** package in R. Extensions to multivariate series and dynamic variance modeling are also discussed.

Main references:

Handbook of Discrete-Valued Time Series is: Davis, R. A., Holan, S. H., Lund, R., & Ravishanker, N. (Eds.). (2016). Chapman & Hall/CRC.

Fokianos K, Tjøstheim D (2011). "Log-Linear Poisson Autoregression." *Journal of Multivariate Analysis*, **102**(3), 563–578

Fokianos, K., Støve, B., Tjøstheim, D., Doukhan, P., 2020. Multivariate count autoregression. Bernoulli 26, 471–499.

Barreto-Souza, W., Piancastelli, L. S., Fokianos, K., & Ombao, H. (2025). Time-Varying Dispersion Integer-Valued GARCH Models. *Journal of Time Series Analysis*.

Module 3: Dr. Matteo Gasparin
Thursday 9.00-12.00 and 13.00-16.00

Conformal Prediction

Abstract: Conformal prediction is a statistical framework designed to provide reliable, distribution-free measures of uncertainty for predictive models. By wrapping around any underlying machine learning or statistical algorithm, conformal prediction produces prediction sets that are guaranteed to achieve a desired coverage level under minimal assumptions. We will introduce the theoretical foundations of conformal prediction and discuss its main variants, including split conformal, full conformal, and cross-conformal methods, along with recent extensions and developments. Practical implementations of conformal prediction methods will be carried out using **R**. A basic knowledge of standard prediction algorithms (e.g., regularized linear regression, CART, random forest) is recommended.

Main references:

- Angelopoulos, A. N., Barber, R. F., & Bates, S. (2024). Theoretical foundations of conformal prediction. *arXiv preprint arXiv:2411.11824*
- Lei, J., G'Sell, M., Rinaldo, A., Tibshirani, R. J., & Wasserman, L. (2018). Distribution-free predictive inference for regression. *Journal of the American Statistical Association*, *113*(523), 1094-1111
- Vovk, V., Gammerman, A., & Shafer, G. (2005). *Algorithmic learning in a random world*. Boston, MA: Springer US
- Barber, R. F., Candes, E. J., Ramdas, A., & Tibshirani, R. J. (2021). Predictive inference with the jackknife+. *The Annals of Statistics*, *49*(1), 486-507

Module 4: Dr. Luca Danese
Friday 9.30-13.00

Bayesian nonparametric statistics for change point detection

Abstract: This module provides an introduction to Bayesian nonparametric (BNP) statistics and its application to change point detection problems. Change point detection concerns the identification of time points at which the probabilistic structure of a data-generating process-such as its mean or variance-undergoes an abrupt change. Bayesian nonparametric models offer a flexible framework for this task by allowing model complexity, including the number

of regimes or clusters, to be inferred directly from the data rather than fixed in advance.
The module begins with the core concepts of Bayesian nonparametric statistics, with particular emphasis on mixture models and the clustering structures induced by random probability measures. Building on this foundation, the module presents modern change point detection methodologies based on random partitions and Bayesian nonparametric priors, with a focus on recent methodological developments. Applications to financial time series are used throughout to illustrate the practical relevance of the methods. Alongside the theoretical foundations, the module includes hands-on tutorials using real-world data, enabling participants to implement Bayesian nonparametric change point models in R.

Main references:

1. Corradin, R., Danese, L., & Ongaro, A. (2022). Bayesian nonparametric change point detection for multivariate time series with missing observations. *International Journal of Approximate Reasoning*, *143*, 26–43. https://doi.org/10.1016/j.ijar.2021.12.019

2. Asael Fabian Martínez. Ramsés H. Mena. "On a Nonparametric Change Point Detection Model in Markovian Regimes." Bayesian Anal. 9 (4) 823 - 858, December 2014. https://doi.org/10.1214/14-BA878

3. Danese, L., Corradin, R., & Ongaro, A. (2025). *BayesChange: An R package for Bayesian change point analysis*. arXiv. https://doi.org/10.48550/arXiv.2511.04785

4. Corradin, R., Danese, L., KhudaBukhsh, W.R. *et al.* Model-based clustering of time-dependent observations with common structural changes. *Stat Comput* 36, 7 (2026). https://doi.org/10.1007/s11222-025-10756-x