

# Seminar Statistical Forecasting and Classification

## WS 2025/26

Prof. Dr. Tilmann Gneiting  
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Tuesday 14:00–15:30, building 20.30, room 0.016

Initial meeting: Tuesday, 8 July 2025, 14:45–15:30, building 20.30, room 0.016

### Overview

A common desire of all humankind is to make predictions for an uncertain future. Clearly then, forecasts ought to be probabilistic, i.e., they ought to take the form of probability distributions over future quantities or events. In this seminar, we will study advanced facets of the probabilistic and statistical foundations of forecasting and classification problems.

The seminar will be offered within the Master Program. Each seminar presentation will be based on a research paper, as follows.

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<i>Scoring rules and related topics</i>	
1	The role of the information set (Holzmann and Eulert, 2014)
2	Generic conditions for forecast dominance (Krüger and Ziegel, 2021)
3	Asymmetries in proper scoring rules (Buchweitz et al., 2025)
4	Local scale invariance and robustness of proper scoring rules (Bolin and Wallin, 2023)
5	Extreme events and forecast verification (Lerch et al., 2017)
6	Locally tail-scale invariant scoring rules (Olafsdottir et al., 2024)
7	Elicitability of probabilistic top list predictions (Resin, 2023)
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<i>Calibration and recalibration of probabilistic forecasts</i>	
8	Calibration of probabilistic multi-category classifiers (Vaicenavicius et al., 2019)
9	Stable reliability diagrams for probabilistic classifiers (Dimitriadis et al., 2021)
10	Calibration of point and probabilistic forecasts (Gneiting and Resin, 2023)
11	Isotonic recalibration (Wüthrich and Ziegel, 2023)
12	Recalibrating multivariate ensemble predictions (Scheffzik et al., 2013)
13	Calibration of multivariate ensemble forecasts (Allen et al., 2024)
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<i>Distributional regression</i>	
14	Extrapolation through distributional regression (Shen and Meinshausen, 2024)

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### Requirements for successful participation

Students are expected

- to present a 60 minute talk in English (we strongly recommend the use of  $\text{\LaTeX}$  for the slides);
- to provide a handout (two to four pages) in either English or German, with the contents of the presentation summarized in their own words, and with all references and supporting tools used properly cited;
- to replicate (or develop) data and/or simulation studies in (or related to) the assigned paper.

A description of the code used needs to be included in the presentation. While you are free to use supporting tools such as ChatGPT for coding and other purposes, you need to acknowledge any such use, and you need be able to show and properly explain every single line in newly developed code, both in the presentation and (if requested) thereafter. Importantly, you need to familiarize yourself with the guidelines for the use of generative AI in teaching posted at [https://www.informatik.kit.edu/downloads/studium/Guidelines\\_Generative\\_AI\\_Informatics.pdf](https://www.informatik.kit.edu/downloads/studium/Guidelines_Generative_AI_Informatics.pdf), and you need to follow these rules in all detail. If any questions remain, contact us.

## Prerequisites

Prerequisites include an introductory course in probability and statistics (“Einführung in die Stochastik” or equivalent) and an advanced course in probability and measure (“Wahrscheinlichkeitstheorie” or equivalent). Successful completion of the course sequence “Forecasting: Theory and Practice I and II” is expected and strongly recommended. In particular, participants need to be familiar and confident with the contents of the papers by Gneiting and Ranjan (2013) and Gneiting and Katzfuss (2014).

## References

- Allen, S., Ziegel, J. and Ginsbourger, D. (2024). Assessing the calibration of multivariate probabilistic forecasts. *Quarterly Journal of the Royal Meteorological Society*, **150**, 1315–1335.
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- Dimitriadis, T., Gneiting, T. and Jordan, A. I. (2021). Stable reliability diagrams for probabilistic classifiers. *Proceedings of the National Academy of Sciences*, **118**, e2016191118.
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- Gneiting, T. and Ranjan, R. (2013). Combining predictive distributions. *Electronic Journal of Statistics*, **7**, 1747–1782.
- Gneiting, T. and Resin, J. (2023). Regression diagnostics meets forecast evaluation: conditional calibration, reliability diagrams, and coefficient of determination. *Electronic Journal of Statistics*, **17**, 3226–3286.
- Holzmann, H. and Eulert, M. (2014). The role of the information set for forecasting—with applications to risk management. *Annals of Applied Statistics*, **8**, 595–621.
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- Resin, J. (2023). From classification accuracy to proper scoring rules: Elicitability of probabilistic top list predictions. *Journal of Machine Learning Research*, **24**, 1–21.
- Schefzik, R., Thorarinsdottir, T. L. and Gneiting, T. (2013). Uncertainty quantification in complex simulation models using ensemble copula coupling. *Statistical Science*, **28**, 616–640.
- Shen, X. and Meinshausen, N. (2024). Engression: Extrapolation through the lens of distributional regression. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, in press, <https://doi.org/10.1093/jrsss/b/qlae108>.
- Vaicenavicius, J., Widmann, D., Andersson, C., Lindsten, F., Roll, J. and Schön, T. B. (2019). Evaluating model calibration in classification. In: *Proceedings of the 22<sup>nd</sup> International Conference on Artificial Intelligence and Statistics*.
- Wüthrich, M. V. and Ziegel, J. (2024). Isotonic recalibration under a low signal-to-noise ratio. *Scandinavian Actuarial Journal*, **2024**, 279–299.