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Generative machine learning methods for multivariate ensemble post-processing - display material

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Motivation and background

- PROBLEM: univariate post-processing fails to preserve the spatial, temporal, or inter-variable dependence structures.
- GOAL: preserving the **spatial** dependence in multivariate post-processing.
- STANDARD APPROACH: combining *univariate post-processing* (e.g. **EMOS**[1] or **NN**[2]) and *copula-based reordering* to restore multivariate dependencies (e.g. **ECC**[3] or **GCA**[4]).

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[1] [Gneiting et al. 2005]

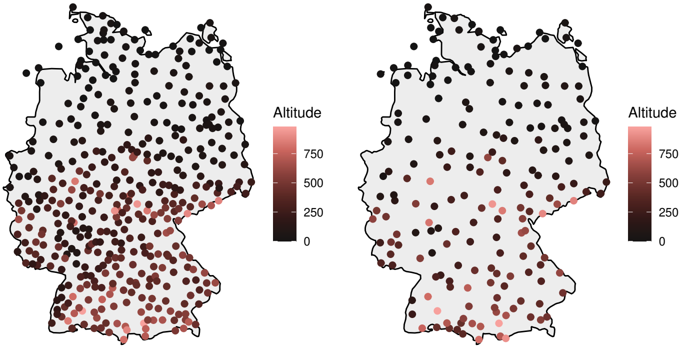
[2] [Rasp and Lerch 2018]

[3] [Schefzik, Thorarinsdottir, and Gneiting 2013]

[4] [Möller, Lenkoski, and Thorarinsdottir 2013]

Data

- ECMWF 2-day ahead **50**-member ensemble forecasts and observations for **temperature** and **wind speed**, at German official weather stations.
- Data of 16 auxiliary weather variables: ‘d2m’, ‘gh_pl500’, ‘sp’, ‘tcc’, etc.
- 10 years data available: training set (**2007–2014**), validation set (**2015**), and test set (**2016**).



(a) Stations with temperature data (b) Stations with wind speed data

- Location information: ‘lat’, ‘lon’, ‘alt’.

Generative machine learning approach for multivariate post-processing

- Conditional generative model (**CGM**):
  learning the patterns in the input data to generate new data from the noise, which looks like been drawn from the original data.

1. Bypassing the copula-based two-step approaches;
2. Generating unlimited number of post-processed samples;
3. Incorporating additional predictors into the multivariate post-processing straightforwardly.

The conditional generative model (CGM) structure

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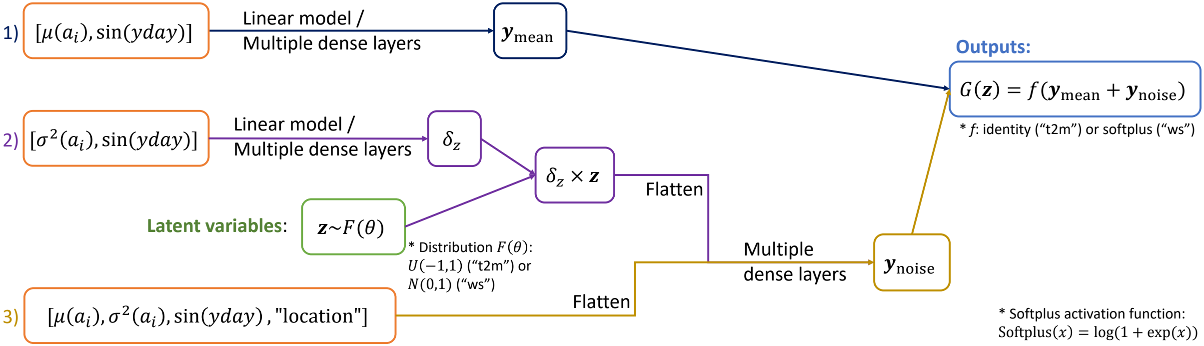
- Training loss: **Energy score**;
- Optimizer: **Adam**.

Inputs:
$a_i (i = 1,2,\ldots)$: weather variables



Model settings and tests

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- The model is trained to minimize the energy score using ‘Adam’ optimizer.
- Drawing 50 samples to compute loss (energy score) during training and testing the model, as a fair comparison with raw ensemble forecasts and other post-processing methods.
- Generating **10** post-processed samples each time and run **5** times to get 50 ensemble members, in order to reduce the uncertainty effects in the generative model.
- Repeating 100 tests for each dimension case ($d = 5, 10, 20$):
  1. Picking a random station (altitude $\leq$ 1000 m);
  2. Selecting the ($d - 1$) closest stations (altitude $\leq$ 1000 m);
  3. Considering multivariate forecasts from the d stations.
- Comparison with: **EMOS** / **NN** **+** **ECC** / **GCA**
- Evaluating using skill scores, with ‘EMOS + ECC’ as the reference forecast: energy score, variogram score of order 0.5.

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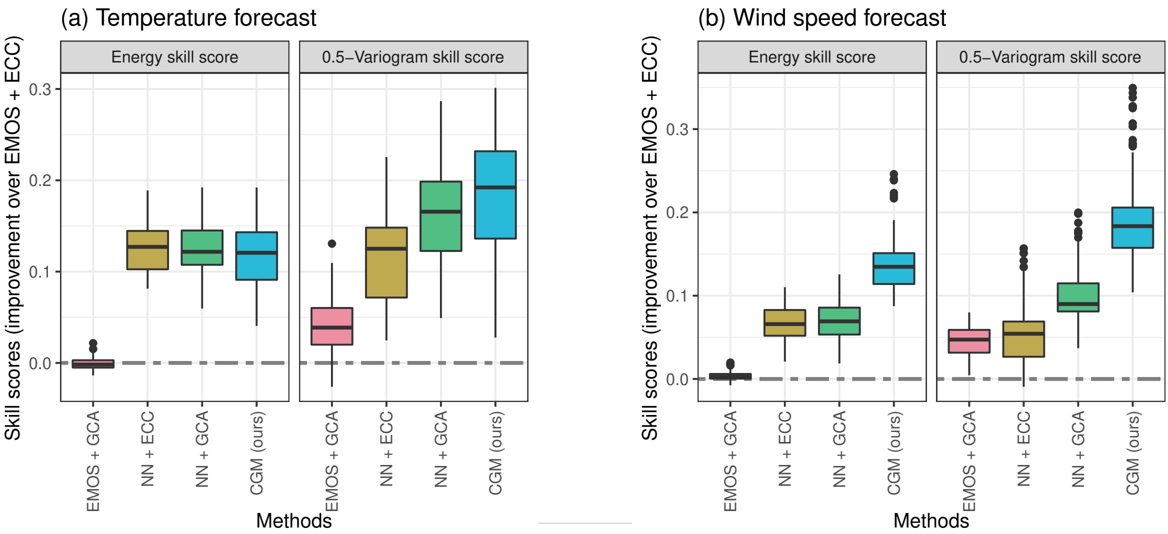
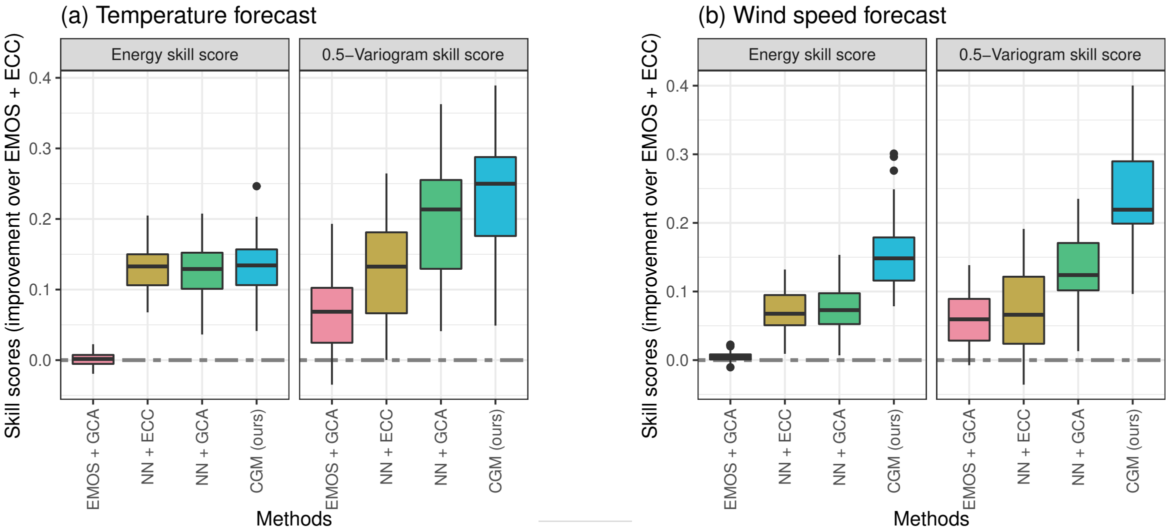
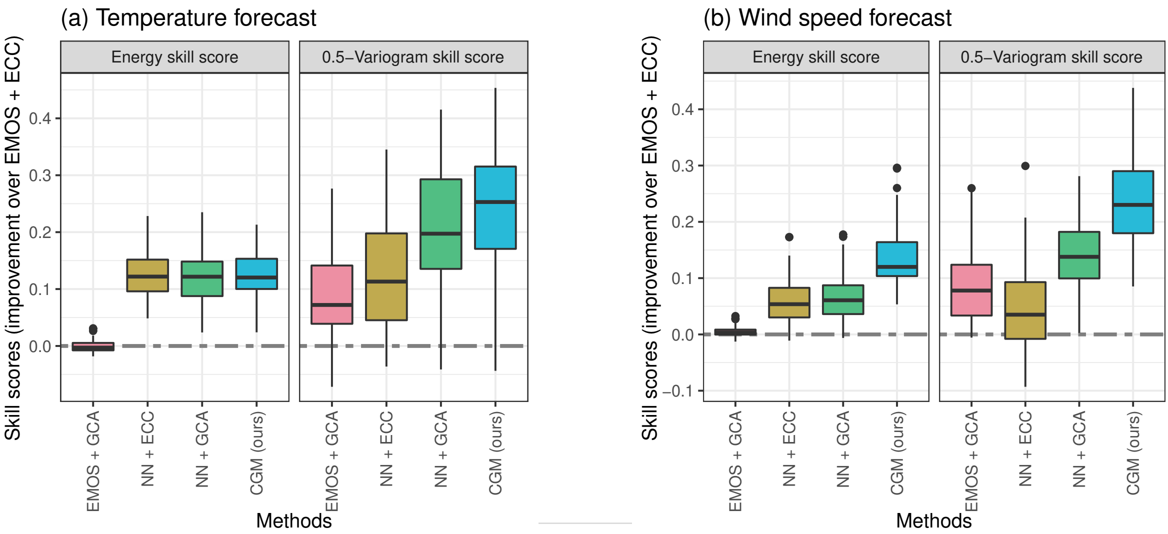
Performances evaluation for 20-dimensional tests



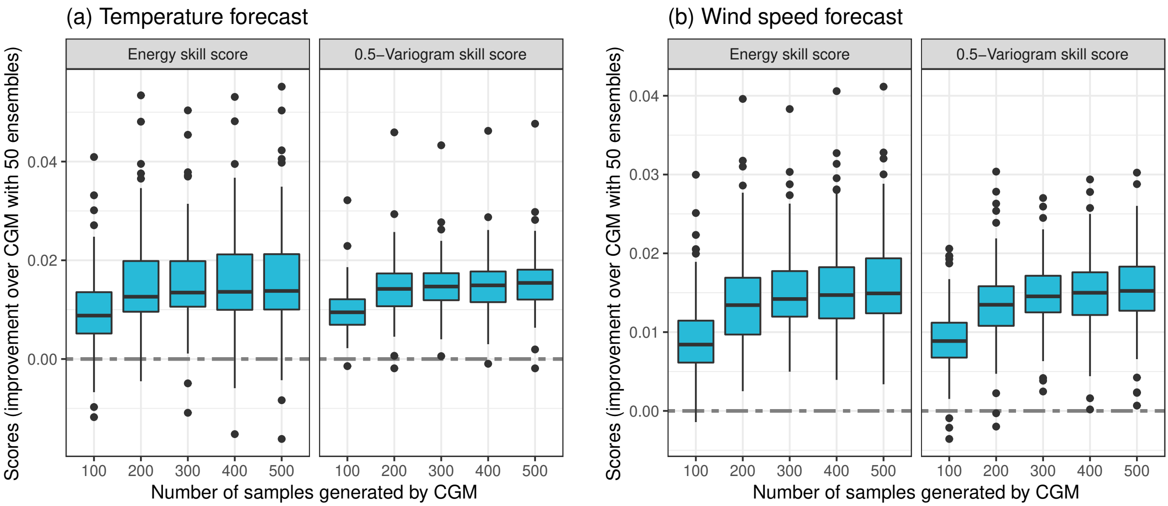
Performances evaluation for 10-dimensional tests



Performances evaluation for 5-dimensional tests



CGM generating more samples further improves performance, in 20-dimensional tests



Summary and conclusions

- The conditional generative model (CGM) shows very promising outcomes on multivariate ensemble post-processing, outperforming the state-of-the-art copula-based approaches, particularly powerful in restoring dependencies;
- A new class of data-driven multivariate distributional regression models;
- Incorporating additional predictors improves the post-processing performance;
- Generating a larger number of post-processed ensemble members further improves calibration.

References I

[1] Tilmann Gneiting et al. "Calibrated probabilistic forecasting using ensemble model output statistics and minimum CRPS estimation". In: *Monthly Weather Review* 133.5 (2005), pp. 1098–1118.

[2] Annette Möller, Alex Lenkoski, and Thordis L Thorarinsdottir. "Multivariate probabilistic forecasting using ensemble Bayesian model averaging and copulas". In: *Quarterly Journal of the Royal Meteorological Society* 139.673 (2013), pp. 982–991.

[3] Stephan Rasp and Sebastian Lerch. "Neural networks for postprocessing ensemble weather forecasts". In: *Monthly Weather Review* 146.11 (2018), pp. 3885–3900.

[4] Roman Schefzik, Thordis L Thorarinsdottir, and Tilmann Gneiting. "Uncertainty quantification in complex simulation models using ensemble copula coupling". In: *Statistical science* 28.4 (2013), pp. 616–640.