Karlsruhe Institute of Technology

Generative ML methods for multivariate ensemble post-processing

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Sebastian Lerch, based on joint work with Jieyu Chen and Tim Janke | September 2022



Motivation

Ensemble forecasts typically show systematic biases and lack calibration.

Post-processing can successfully correct errors and has become a standard practice in research and operations.

Overview of the state of the art: Vannitsem et al. (2021)

Statistical Postprocessing for Weather Forecasts – Review, Challenges and Avenues in a Big Data World

Stéphane Vannitsem; John Bjørnar Bremnes; Jonathan Demaeyer; Gavin R. Evans; Jonathan Flowerdew; Stephan Hemri; Sebastian Lerch; Nigel Roberts; Susanne Theis; Aitor Atencia ... Show more

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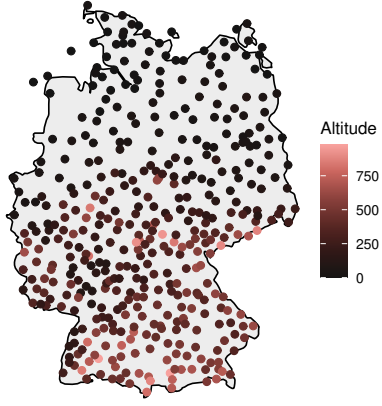
While various methods have been developed for univariate post-processing for single locations, lead times or weather variables, many applications require accurate models of multivariate dependencies.

Key examples include hydrological applications, air traffic management and energy forecasting.

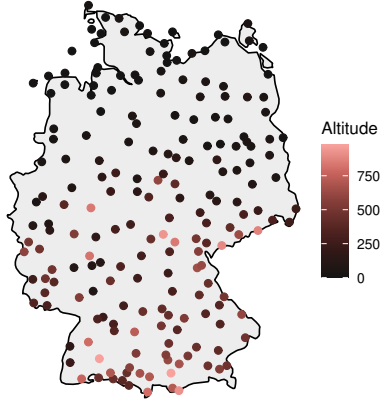
Data

- ECMWF 2-day ahead 50-member ensemble forecasts (temperature & wind speed at 00 UTC)
- 16 auxiliary variables available as additional predictors + station information
- 2007–2015 for training, 2016 for evaluation
- focus: spatial dependencies across stations

(a) Stations with temperature data



(b) Stations with wind speed data



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1. Univariate post-processing: Distributional regression models correct systematic biases and lack of calibration. A sample is generated from the post-processed distributions.
   - simple standard approach: ensemble model output statistics (EMOS, Gneiting et al., 2005, MWR)
   - state of the art: ML methods allow for incorporating additional predictors (e.g., NN-based methods, Rasp and Lerch, 2018, MWR)

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2. Multivariate dependencies are restored by applying copula-based methods to re-order the sample values. Prominent examples:
   - ensemble copula coupling (ECC): based on dependence structure in the raw ensemble
   - Schaake shuffle (SSh): as ECC, but based on past observations
   - Gaussian copula approach (GCA): parametric approach based on Gaussian copulas

   Comparative studies indicate that there is no consistently best approach and differences in performance are generally small.

Limitations of state of the art approaches

All state of the art methods for multivariate post-processing share common key limitations.

Most importantly, there is no straightforward way to include additional predictors beyond the target variable in the second step of restoring multivariate dependencies.

Further, the number of samples from the multivariate forecast distribution is limited by the size of the ensemble (ECC) or the historical dataset (SSh).

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We propose a novel nonparametric multivariate post-processing method based on generative ML.

Samples are directly obtained as output of a generative deep neural network which allows for

- incorporating arbitrary input predictors
- circumventing the two-step structure of traditional methods to simultaneously model distributions and multivariate dependencies
- generating an arbitrary number of samples.

Generative ML



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Artificial, GAN-generated images of human faces,
Source: `https://thispersondoesnotexist.com/`

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Generative ML aims at learning properties underlying a training dataset to generate realistic new data.

Implicit generative models aim to provide a representation of the probability distribution of a target variable by defining a stochastic procedure to generate samples.

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Impressive results have been achieved by GANs for image processing tasks, but GAN training tends to be challenging.

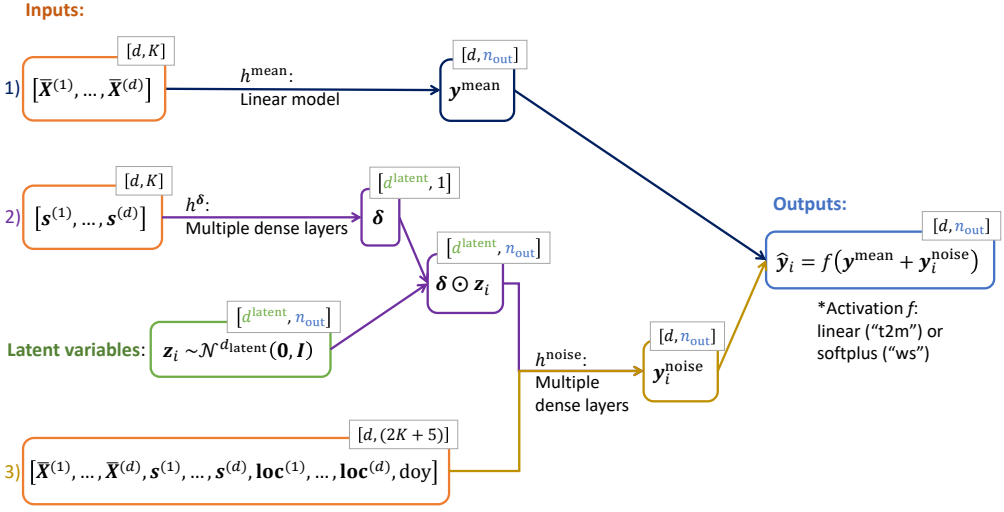
We aim for a conditional generative model of the form

$$\boldsymbol{Y}_i = g_{\boldsymbol{\theta}}(\boldsymbol{X}, \boldsymbol{Z}_i), \tag{1}$$

where the discriminator part of a GAN is replaced by a suitable multivariate evaluation metric (the energy distance).

Multivariate samples $\boldsymbol{Y}_i$ are generated as the output of a NN, conditional on ensemble forecasts $\boldsymbol{X}$ and random noise $\boldsymbol{Z}_i$.

Conditional generative model for multivariate post-processing



Experimental setup

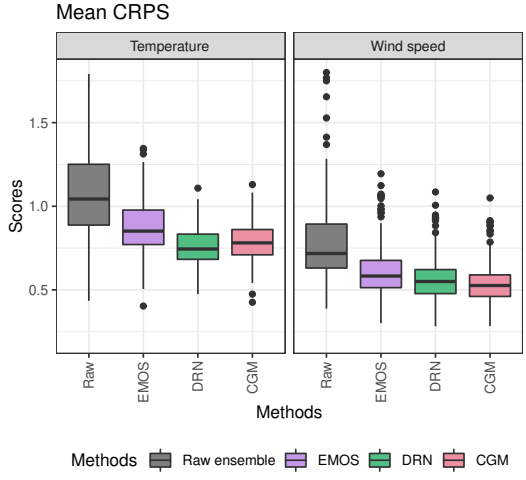
Independently for both temperature and wind speed:

- Randomly pick a station location
- Select the $d - 1$ closest stations (with $d = 5, 10, 20$)
- Generate multivariate probabilistic forecasts with benchmark and CGM approaches.

The above procedure is repeated 100 times, the results in the following summarize the variability across repetitions via boxplots.

Benchmark methods: EMOS + ECC; EMOS + GCA; DRN + ECC; DRN + GCA

Results: Univariate performance



Results: Multivariate performance

Variable	Score	d	Raw ens.	EMOS+ ECC	EMOS+ GCA	DRN+ ECC	DRN+ GCA	CGM
Temperature	ES	5	2.81	2.27	2.27	**1.97**	**1.97**	**1.97**
		10	4.22	3.37	3.37	2.91	**2.90**	2.91
		20	6.09	4.87	4.87	**4.21**	4.22	4.26
	VS	5	8.22	4.81	4.36	4.12	3.74	**3.50**
		10	39.0	22.6	21.0	19.5	18.0	**16.9**
		20	153	96.7	92.8	85.0	80.7	**77.8**
Wind speed	ES	5	2.44	1.69	1.68	1.56	1.55	**1.44**
		10	3.67	2.55	2.53	2.31	2.30	**2.16**
		20	5.04	3.52	3.51	3.23	3.22	**3.04**
	VS	5	9.49	4.37	4.00	4.01	3.66	**3.31**
		10	39.7	20.2	19.0	18.0	16.9	**15.4**
		20	153	82.5	78.9	75.6	72.3	**67.0**

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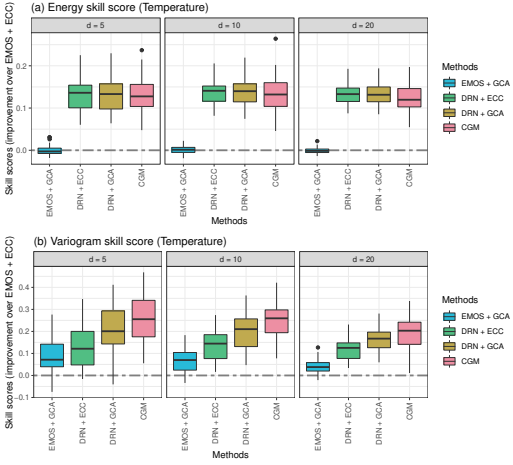

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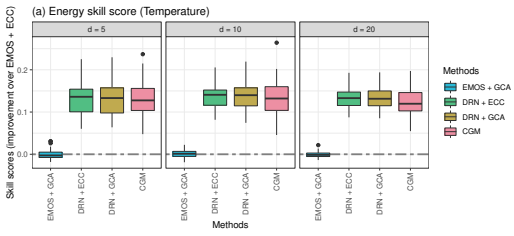
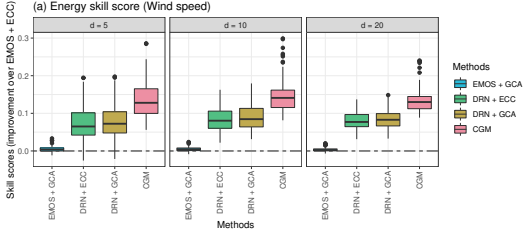
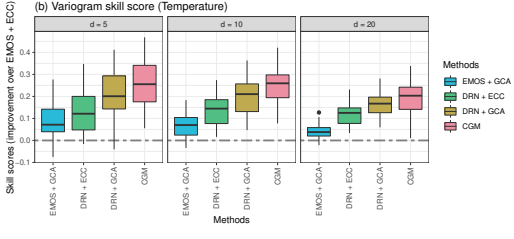
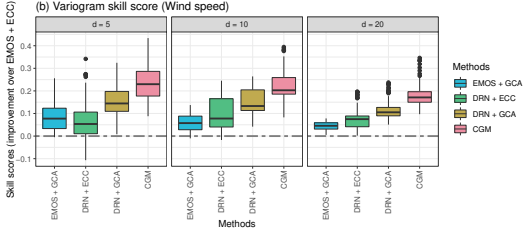
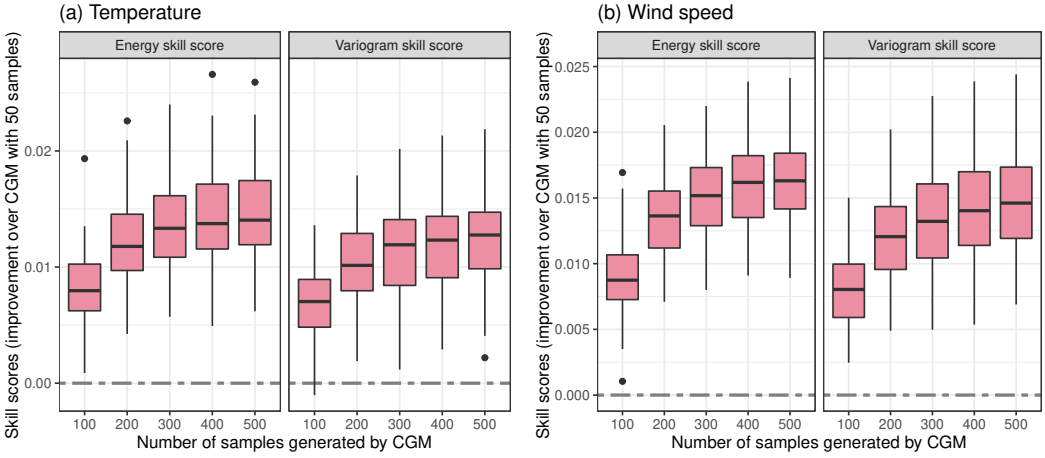








Results: Sample size



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Main challenges and opportunities for future work include multivariate evaluation for extremes, and applications to spatial forecast fields.

A preprint will be available on arXiv within the next weeks.

On the effects of including additional predictors

