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Deep learning for weather prediction

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Weather and air pollution have much in common and if it is possible to forecast weather with deep neural networks, it should also be possible to forecast air pollution. This is why, in the IntelliAQ project, we have focused on weather forecasting to explore deep learning methods from video prediction. The presentation will cover results from IntelliAQ as well as from the European MAELSTROM project.

Accurate weather predictions are essential for many aspects of social society. Nowadays, weather prediction highly relies on numerical weather prediction (NWP) models, which require huge computational resources. Recently, the potential of deep neural networks to generate bespoken weather forecasts has been explored in a couple of scientific studies inspired by the successful applications in the computer vision domain. The super-resolution task aiming to project low resolution to a high-resolution field is somewhat analogous to downscaling, and video prediction is similar to weather forecasting in the meteorological domain. Inspired by this, we explore three case studies by exploring the state-of-the-art deep learning approaches for short-term weather forecasting and downscaling for 2 m temperature and precipitation.

In the first study, we focus on the predictability of the diurnal cycle of near-surface temperatures. A ConvLSTM, and an advanced generative network, the Stochastic Adversarial Video Prediction (SAVP), are applied to forecast the 2 m temperature for the next 12 hours over Europe. Results show that SAVP is significantly superior to the ConvLSTM model in terms of several evaluation metrics. Our study also investigates the sensitivity to the input data in terms of selected predictors, domain size, and the number of training samples. The results demonstrate that additional predictors, i.e., in our case the total cloud cover and the 850 hPa temperature, enhance the forecast quality. The model can also benefit from a larger spatial domain. By contrast, the effect of reducing the training dataset length from 11 to 8 years is rather small. Furthermore, we reveal a small trade-off between the MSE and the spatial variability of the forecasts when tuning the weight of the krenL1-loss component in the SAVP model.

In the second study, we explore a custom-tailored GAN-based architecture for precipitation nowcasting. The prediction of precipitation patterns at a high spatiotemporal resolution up to two hours ahead, also known as precipitation nowcasting, is of great relevance in weather-dependent decision-making and early warning systems. We developed a novel method named Convolutional Long-short term memory Generative Adversarial Network (CLGAN) to improve the nowcasting skills of heavy rain events with deep neural networks. The model constitutes a GAN architecture whose generator is built upon an u-shaped encoder-decoder network (U-Net) equipped with recurrent LSTM cells to capture spatiotemporal features. A comprehensive comparison between CLGAN, another advanced video prediction model PredRNN-v2 and the optical flow model DenseRotation is performed. We show that CLGAN outperforms in terms of point-by-point metrics as well as scores for dichotomous events and object-based diagnostics. The results encourage future work based on the proposed CLGAN architecture to improve the accuracy of precipitation nowcasting systems further.

In the last case study, we make use of deep neural networks with a super-resolution approach for statistical precipitation downscaling. We apply the Swin transformer architecture (SwinIR) as well as convolutional neural network (U-Net) with a Generative Adversarial Network (GAN) and a diffusion component for probabilistic downscaling. We use short-range forecasts from the Integrated Forecast System (IFS) on a regular spherical grid with xIFS=0.1° and map to the high-resolution observation radar data RADKLIM (xRK=0.01°). The neural networks are fed with nine static and dynamic predictors similar to the study by Harris et al., 2022. All the models are comprehensively evaluated by grid point-level errors as well as error metrics for spatial variability and the generated probability distribution. Our results demonstrate that the Swin Transformer model can improve accuracy with lower computation cost compared to the U-Net architecture. The GAN and diffusion models both further help the model to capture the strong spatial variability from the observed data. Our results encourage further development of DNNs that can be potentially leveraged to downscale other challenging Earth system data, such as cloud cover or wind.

In our study, we investigate the performance of the state-of-art deep learning models with a focus on the generative models for weather forecasting and downscaling task. Our results We analyzed the model performance of the deep learning model in-depth on various evaluation metrics. The results demonstrate that deep learning from computer vision attains some predictive skills in weather forecasting and downscaling. Particularly, the generative models can help to reserve small-scale details of the prediction.

Beyond the generative models, the success of vision transformer models (ViT) and graph neural networks (GNN) in image generation have gained tremendous attention recently. They also spark a huge performance revolution in weather forecasting. The models such as Pangu-Weather (Bi et al., 2022, Pathak et al., 2022, Lam, 2022), show the potential capability to surpass the NWP model. In future work, we will explore the tailored ViT models to better address meteorological problems.

ML method

GAN

Main air pollutant of interest

Other

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Track Classification: Machine learning applications