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WeatherBench: A benchmark dataset for data-driven weather forecasting

Stephan Rasp¹, Peter D. Dueben², Sebastian Scher³, Jonathan A. Weyn⁴, Soukayna Mouatadid⁵, and Nils Thuerey¹

¹Technical University of Munich, Germany

²European Centre for Medium-range Weather Forecasts, Reading, UK

³Department of Meteorology and Bolin Centre for Climate Research, Stockholm University, Sweden

⁴Department of Atmospheric Sciences, University of Washington, Seattle, USA

⁵Department of Computer Science, University of Toronto, Canada



Context

- DL is a family of algorithms driving the recent revolution in many fields (computer vision, language understanding, etc)
- Data is a big part of the success of DL. Physical sciences lack training/benchmark datasets
- First effort to create a community dataset for medium-range weather forecasting, basic metrics and baseline algorithms



Methods: data

- Variables from ERA5 archive, preprocessed for the direct application of ML (3.81 TB in total)
 - 40 years of 1hourly data
 - 3 spatial resolutions: 5.625° (32×64 grid points), 2.8125° (64×128 grid points) and 1.40525° (128×256 grid points)
 - 3D fields with 11 selected vertical levels (1, 10, 100, 200, 300, 400, 500, 600, 700, 850 and 1000 hPa)



Methods: data

1y NetCDF file











Methods: metric and baselines

• Metric: mean latitude-averaged RMSE over all forecasts. The anomaly correlation coefficient might be more adequate for other variables

$$\mathbf{RMSE} = \frac{1}{N_{\text{forecasts}}} \sum_{i}^{N_{\text{forecasts}}} \sqrt{\frac{1}{N_{\text{lat}}N_{\text{lon}}} \sum_{j}^{N_{\text{lat}}} \sum_{k}^{N_{\text{lon}}} L(j)(f_{i,j,k} - t_{i,j,k})^2}} \qquad L(j) = \frac{\cos(\operatorname{lat}(j))}{\frac{1}{N_{\text{lat}}} \sum_{j}^{N_{\text{lat}}} \cos(\operatorname{lat}(j))}}$$

- Comparison of baselines, wrt a persistence and a climatological forecast and the gold standard of medium-range NWP (IFS, 2017/2018 forecasts from TIGGE)
 - Operational forecasting: ~12k cores and 1h (10 day forecast at 10km)
 - Coarser resolution NWP much faster, only a few minutes. This should be the target to beat



Methods: baselines and dd models

- Two variables chosen for the tests: Z500 and T850
- Persistence forecast: fields at initialization time are used as forecasts (tomorrows weather is todays weather)
- Climatology: two were computed for the training data (1979-2016): a mean over all data, and a weekly one
 - A useful forecast must beat the weekly climatology and the persistence forecast
- Linear Regression: data flattened and concatenated. Iterative forecasts (single model takes its previous output as input for the next step)
- CNN: simple model exploiting the translational invariances in images/fields (two channels t850 and z500). 5 Conv layers, with 64 channels, ksize=5, ELU activations, Adam optimizer, MSE loss, 313k trainable params, periodic convolutions in longitude



Results





Results



Conclusions

- State-to-state weather prediction similar to image-to-image translation, lots of recent developments in CV
- 3D structure needs to be exploited, data is extremely rich/complex
- More complex networks could be used, but few data points (overfitting)
 Augmentation not easy
 - U-Nets, Resnets, CGANs, etc
- Technical challenges: GPU memory!
- Interesting venues:
 - Extreme events
 - Climate simulations



Critique

- Data in an standardized format
- Pangeo data repo as a communication platform (better a challenge platform?)
- Good comparison of the relevant literature
- Baseline implementations provided (simple algorithms)
 - 3D structure not taken into account
- Metric is convenient and simple (maybe too basic?)

