

# **DeepRain**

## - Improving local scale rainfall prediction through deep learning

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# **DeepRain motivation and objectives**

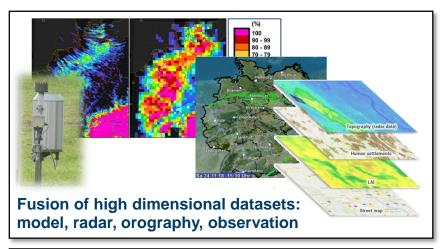


- (1) Current regional (and future global) operational regional weather forecast models (will) operate at grid sizes around 2 km permitting the **simulation of deep, heavy convection** which can have severe economic and environmental consequences
- (2) Due to numerical reasons the spatial localization is accurate to about 3-5 times the grid size leaving room to exploit further downscaling and to increase the pointwise forecast skill

We want to explore to what extent deep learning methods can help to improve precipitation forecasts by including fine scale orography and radar observations which are not yet used to their full potential.

### Novel data use, ML application, validation, and technology

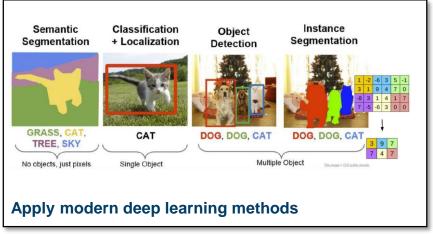


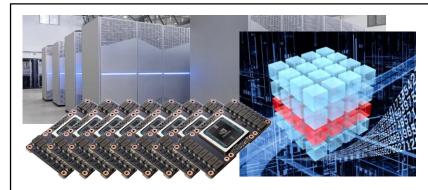


Partial correlation:

$$\rho_{12\cdot 3} = \frac{\rho_{12} - \rho_{13}\rho_{23}}{\sqrt{1 - \rho_{13}^2}\sqrt{1 - \rho_{23}^2}}$$

Develop validation methods, added value of ML compared to alternatives





**Operability: Develop high-performance workflows** 

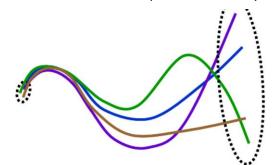
### "Big" Datasets: DWD COSMO-DE-EPS data archive and radar data



Data management established: so far ~30 TB copied from DWD to Jülich

# **DWD NWP Data Archive** COSMO-DE-EPS (COSMO-D2-EPS)

- Archive range 2011-2018 (2017-2019)
- Archive size 440 TB (200 TB) total: ~2 mio. files
- Grid size 2.8 km (2km)
- 8 model runs (starts) per day (00, 03, 06,... 21 UTC)
- Hourly Lead times: +00, +01, +02,... +21 (27, 45) hours
- 20 Ensemble (Monte Carlo) members

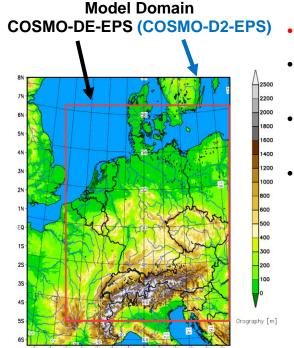


#### **DWD RADOLAN Radar Data**

- Radar based quantitative precipitation estimation product
- Rain gauge adjusted quantitative radar composite with hourly precipitation amounts (0.1 mm resolution) and a spatial resolution of 1 km<sup>2</sup>
- Covers Germany in real-time (with 30 min. delay) every 10 min.

#### **RADOLAN DWD Radar Network + Rain Gauge Data**



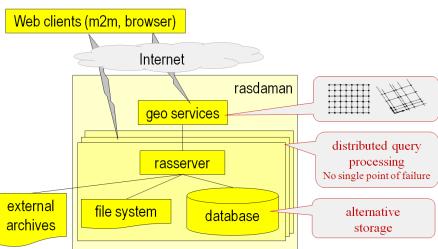


# Data and work flow, the RASDAMAN array DB



- Problem: for smooth data analysis, analysis-ready data are needed
  - "Big Data" part in the project: (regular & irregular) x / y / z / t<sub>cal</sub> / t<sub>lead</sub> / MC grids = spatio-temporal datacubes
- Approach: Provide datacube view and functionality
  - instead of large number of files in specialized formats
- Tool used: rasdaman array DBMS
  - SQL-style querying on massive n-D arrays
  - Standardized as Part 15 of ISO SQL
  - Variety of clients supported through open OGC standards

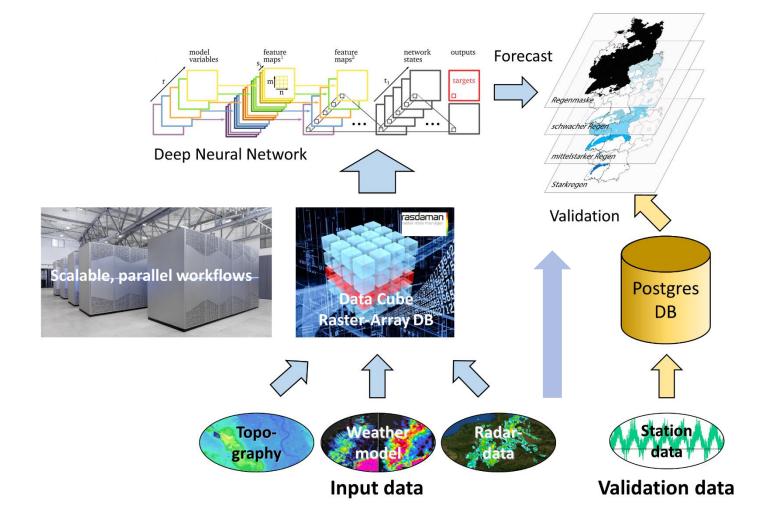
Research question: How can Array Databases make ML on Big Datacubes easier, faster, more scalable?



Data import functioning; first extraction queries ready

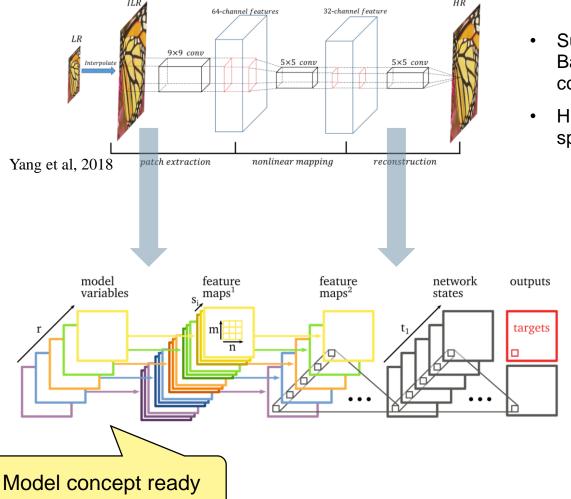
## **Data system architecture**





### Adapt deep learning (convolutional) networks to meteorological data





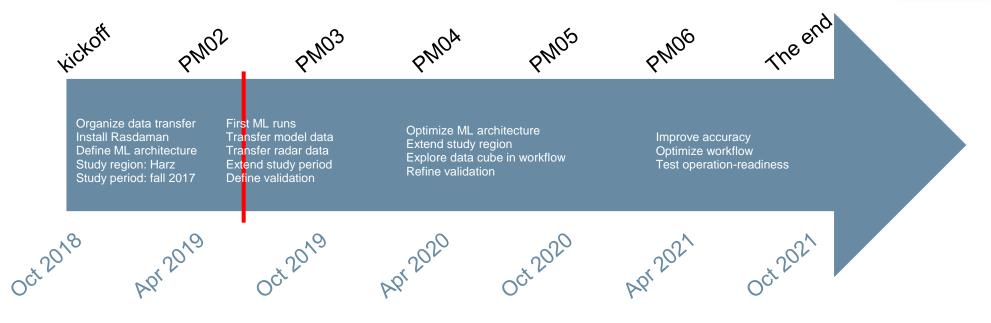
- Super-Resolution in Deep Learning: Bad interpolation, then learn the correction.
- High dimensional RGB inputs and spatially invariant mapping

#### For meteorological data:

- Much higher feature depth r
- Input: Model | Target: Radar
- Spatial invariance only if geographical features in the input
- High-dim. data but fewer data-points for models with big #parameters
- Constraints dictated by Physics (?)
- Evaluation vs alternative approaches
  - Specify the (ML) Added Value

### **Project roadmap and status**





- Project is generally on schedule; slight delays due to data management issues and hiring
- Data organisation and access to storage and compute resources in place
- Highly motivated team