AtmoRep Large Scale Representation Learning of Atmospheric Dynamics

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Example applications





Forecasting

Impact analysis





Climate projections

Downscaling



Can we train one neural network model that encapsulates all Earth system dynamics by self-supervised training on large amounts of spatio-temporal observations?

Motivation

- Availability of petabytes of unlabelled observational and quasi-observational data
- Data contains critical information, e.g. about unresolved process and their feedbacks to coarser scales
- Self-supervised, large scale representation learning allows one to make use of this data and amortizes training costs

Benefits

- Pre-trained network can be used with small computational costs for a wide range of applications
 - Highly compact representation of ERA5 with O(GB)
 - Better performance than directly training for application
- Methodology has led to breakthroughs in natural language processing and computer vision (e.g. GPT-3)
- Amortize training costs on very large data sets
- Weather forecasting, climate projections, downscaling, ...
- Possible new scientific insights by accessing the spatio-temporal interactions encoded in the network (e.g. attention)

Proof-of-concept: train one transformer neural network on O(PB) of ERA5 reanalysis data

Multiformer

• Transformer-based architecture

- Scales well to very large datasets
- Local network applied to neighbourhood in space-time
- One transformer per physical field and possibly vertical level
- Respects different properties of fields, coupling through attention
- Fields can easily be added and

Training

Self-supervised training with spatio-temporal extension of BERT masked language model:



Ensemble loss

Training with ensemble of tail networks to learn statistical representation of quasi-chaotic atmospheric dynamics and improve training behaviour:



Zero-shot forecasting performance

removed

Example for predictions

Prediction MSE test loss error error 0.6 2.5 - no ensemble, MSE zero shot, BERT 0.50 Reference ensemble=10, MSE+stats 0.5 zero shot, embedding ■ 0.35, conditional Prediction 2.0 persistence 0.25, conditional 0.20 0.4 0.15, conditional 1.5 0.15, no ensemble 0.10 0.3 Reference 0.075, conditional 1.0 ■ 1 token 0.05 0.2 0.5 Ensemble 0 0.5 -0.5 0.1 Prediction 0.02 0.0 epoch 10 15 5

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