FengWu – Skillful Global Weather Forecasting Beyond 10 Days Lead

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Large-scale Deep Learning for the Earth System
Who we are?

Shanghai AI Laboratory

- Established in 2021, Shanghai
- Focusing on developing cutting-edge AI techniques
- CVPR 2023 best paper, Intern (foundational model for CV and LM), FengWu
- Open research with top tier universities (THU, PKU, SJTU, CUHK, NTU) and companies.

AI4Earth Team

- A research group at Shanghai AI Laboratory, co-lead by Prof. Wanli Ouyang and Dr. Lei Bai
- More than 20 research scientists, PhD students, and research interns
What are we doing?

- Build AI-powered chip for global weather and climate forecasting
ECMWF's ML Strategy: with a very busy and FAST evolving landscape

- **Jan 2021**
  - Machine Learning Roadmap

- **2018**
  - ECMWF's ML scientific publication

- **Feb 2022**
  - Full medium-range NWP

- **Oct 2022**
  - 1km² global

- **Nov 2022**
  - Tropical cyclones

- **Dec 2022**
  - Extensive predictions

- **Apr 2023**
  - 7-day+ scores improve

**ECMWF**
- Peter Dubeen and Peter Bauer publish a paper on using ERA5 at ~500km resolution to predict future at 500km.

**Keisler**
- GraphNN 1st, competitive with GFS
- NVIDIA – FourCastNet Fourier+, 0.25° O(10^4) faster & more energy efficient than IFS
- 1x1km global
- 48 hours lead time
- 5 minute timesteps

**Huawei**
- PanguWeather 0.25° hourly product
- "More accurate tracks" than the IFS

**DeepMind**
- GraphCast 0.25° 6-hour product

**Microsoft**
- ClimaX
  - Forecasting various lead-times at various resolutions, both globally and regionally
  - Improves on GraphCast for longer leadtimes (still deterministic)

**FengWu**
- China academia + Shanghai Meteorological Bureau
  - 0.25° 6-hour product
Problem and modeling

- **Problem**: Predicting future global atmospheric conditions up to fourteen days ahead
  - Resolution: 0.25
  - Region: Global
  - Height level: 37 levels
  - Atmosphere variables: geopotential, temperature, humidity, u component of wind, v component of wind

- **Modeling**:
  - Like physical model, the goal of FengWu is to predict the atmospheric variables at the next moment, and then all predictions are obtained by autoregressive method.
- How to represent the high-dimensional weather data efficiently
  - Multi-modal: treat each variable as a separate modality
  - Independent encoders and decoders
  - Cross-modal Fuser: learning the interactions among different variables
How to optimize the network efficiently

- Multi-task learning: treat the optimization of each variable at each location as a task
- Uncertainty loss: automatically generating the weights of each variable at each location based on the loss [1]

How to achieve long-lead forecasting

- **AutoRegressive Finetuning: FourCastNet and GraphCast**

(b) Fine-tuning

- **Training with larger time steps: Pangu**
How to achieve long-lead forecasting

- FourCastNet and GraphCast: Autoregressive finetuning
- Pangu: Training with Larger time steps
- FengWu: Replay buffer mechanism

The training of deep learning involves optimizing the network for a large number of iterations with the data sampled from the dataset.

Replay buffer stores the predictions of prior iterations and samples training data from for the network optimization in the following iterations.
Training Details

• Data:
  • ERA5: the fifth generation ECMWF reanalysis for the global weather [1]
  • Six-hourly: original data is hourly and we only use 1/6 of it
  • Vertical levels: all 37 levels in the ERA5 data on pressure levels
  • Variables:
    • 5 atmospheric variables: geopotential, temperature, humidity, u component of wind, v component of wind
    • Surface variables: mean sea level pressure, 2-meter temperature, 10-meter u component of wind, and 10-meter v component of wind.
  • Spliting: 1979-2015 for training (37 years), 2016-2017 for validation, 2018 for testing

• Resource
  • 32 A100 GPUs
  • 17 Days

FengWu achieves better performance than GraphCast (prior best model released by Deepmind in Dec of 2022) on 80% of the metrics (lower RMSE indicating better prediction).

FengWu reduces forecast errors by 10.87% compared to GraphCast and by 19.4% compared to IFS-HRES (the best physical model from ECMWF) for the ten days lead time.
Performance of FengWu and GraphCast

- ACC of FengWu and GraphCast
Effect of the replay buffer

Effects of the autoregressive training with the proposed replay buffer mechanism (red lines) or without it (blue lines)
Predictions and errors visualization for Z500 and T850. Initialization time: 2018-Feb-11-00:00

Figure 5: Forecast images and absolute error for Z500. Figures of z500 on days 3, 5, and 10 are presented with initialization time at 2018-02-11 00:00 UTC. The subtitles at the top of the columns indicate the dates of prediction. The first row and second row show FengWu and ERA5 ground truth, respectively. Row 3 shows the absolute error between FengWu and ERA5.

Figure 6: Forecast images and absolute error for T850. The plot demonstrates ERA5 ground truth and FengWu's prediction for T850, with forecast initialization 2018-02-11 00:00. Other settings are similar to Figure 5.
Core benefits

- **Long lead skillful forecasting**
  - from 8.5 days to **10.75 days**
- **Fast development**
- **Efficiency:** Generating the predictions for the next 10 days of all regions in the world with 1 GPU cards with 30 seconds
Towards operational forecast

A new version of FengWu is trained with 13 levels ERA5 data for operational forecast

Evaluated on the year of 2022 with both ERA5 inputs and operational analysis inputs
Towards operational forecast

**FengWu** achieves the best tropical Cyclones tracking performance within 5 days.

**Evaluated on all the tropical Cyclone occurred in the year of 2022 (the same samples)**
Towards operational forecast

Tropical Cyclone Track Prediction of Mawar

2023-05-20T00:00MAWAR_control

2023-05-21T00:00MAWAR_control

2023-05-22T00:00MAWAR_control

2023-05-23T00:00MAWAR_control
Tropical Cyclone Track Prediction of Khanun (ensure same samples)

2023-Aug-1-00:00:00

2023-Aug-5-00:00:00

* Data provided by Shanghai Typhoon Institute of China Meteorological Administration
Operational Tropical Cyclone Prediction

Operational Khanun track prediction analysis for ECMWF-IFS, NCEP-GFS, and FengWu

* Figures provided by Shanghai Typhoon Institute of China Meteorological Administration
Future Works

• **Direct upgrade**
  • Higher spatiotemporal resolution
  • More variables

• **Shorter and longer forecasting**
  • Short-term precipitation – especially extreme precipitation
  • Sub-seasonal forecasting

• **Better methods to decrease the error accumulation**
  • Physics constrains?

• **Explanation**
  • Open the black box
Future Works

Reanalysis Data (ERA5, ERA6)  Optimization Target  Others?

Pre-processing steps  Analysis & forecast  Post-processing steps  Downstream steps

Observation data
Collection of real-time observations for forecast initialization

Quality control
Quality control of observations

Data assimilation
Combining observations with the model to provide an initial state

Model forecast
Model run forward in time to produce forecast(s)

Verification
Model forecast verified against observations

Post-processing
Raw model outputs processed to ensure that data are suitable in product generation

Product generation
Generation of products that meet the needs of users

Dissemination
Delivery of products to users

Data pre-processing and data assimilation  Model downscaling, bias correction  Extreme event detection/attribution & causality

AI for model parametrization  Classification, reduced models, bifurcation, changes in predictability  Product generation

Published in the WMO library in March 2023
Thanks

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