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Deep Learning on the sphere for weather/climate applications

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Deep Learning (DL) has the potential to revolutionize numerical weather predictions (NWP) and climate simulations by improving model components and reducing computing time, which could then be used to increase the resolution or the number of simulations. Unfortunately, major progress has been hindered by difficulties in interfacing DL with conventional models because of i) programming language barriers, ii) difficulties in reaching stable online coupling with models, and iii) the inability to exploit the horizontal spatial information as classical convolutional neural networks can't be used on spherical unstructured grids.

We present a solution to perform spatial convolutions directly on the unstructured grids of NWP models. Our convolution and pooling operations work on any pixelization of the sphere (e.g., Gauss-Legendre, icosahedral, cubed-sphere) provided a mesh or the pixel's locations. Moreover, our solution allows mixing data from different grids and scales linearly with the number of pixels, allowing it to ingest millions of inputs from 3D spherical fields.

We show that a proper treatment of the spherical topology and geometry of the Earth (as opposed to a projection to the plane, cylinder, or cube) i) yields geometric constraints that provide generalization guarantees (i.e., the learned function does not depend on its localization on the Earth), and ii) induces prior biases that facilitate learning. We demonstrate that doing so improves prediction performance at no computational overhead for data-driven weather forecasting. We trained autoregressive ResUNets on five spherical samplings, covering those adopted by the major meteorological centers.

We believe that the proposed solution can find immediate use for post-processing (e.g., bias correction and downscaling), model error corrections, linear solvers pre-conditioning, model components emulation, sub-grid parameterizations, and many more applications. To that end, we provide open-source and easy-to-use code accompanied by tutorials.