Deep Learning for Ocean Models

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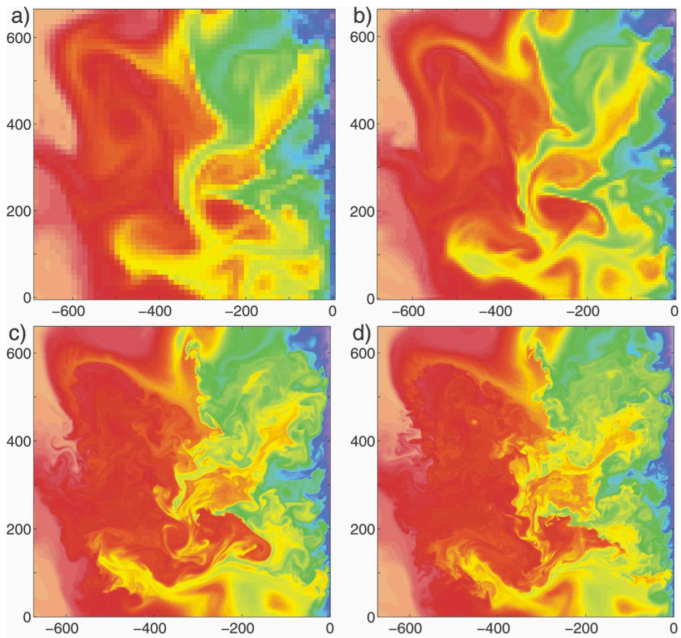
In ocean modelling there are always processes that are too small to be resolved by the model grid size (dx). Yet, in turbulent flows, these unresolved processes are coupled to the resolved ones by nonlinear transfers across scales and thus cannot be neglected. There is a necessity to parameterize the effect of the subgrid-scale processes. A lot of techniques have been proposed. It boils down to having a relation between the Reynolds fluxes (typically. $\overline{u'T'}$-like quantities) and the resolved model variables. In practice, only few techniques are really routinely used: diffusion, hyperdiffusion, implicit numerical diffusion, Smagorinsky and Gent-McWilliams parameterizations. It is well accepted that there is a huge place for improvement.



Sea Surface Temperature in the California Current in simulations with increasing resolution, from Capet et al., 08.

The advent of deep learning offers a new possibility to derive better parameterizations. Deep neural networks (DNN) can learn how Reynolds fluxes are related to well resolved variables because DNN are able to find abstract relations between variables that emerge despite the relative simplicity of the equations. The best proof of this ability is the recent breakthrough made by AlphagoZero that rediscovered alone the whole knowledge of 3000 years of human Go playing (Sing et al 2017). The DNN will be trained using data from realistic high resolution simulations that resolve the coupling between scales. The goal of this project is to do a first step toward this direction. The feasibility is motivated by a recent study (Ling, 2016) showing that such approach could do better than any other method in the case of turbulent flows in pipes. The DNN was trained on direct numerical simulations (DNS) and then used as a parameterization for Reynolds averaged simulations.

In realistic large scale ocean modelling there is no hope to have DNS, instead we will use

realistic high-resolution simulations with fine grid dx_{fine} able to resolve mesoscale and submesoscale dynamics. From the data on the fine grid we will compute coarse variables on a coarser grid (typically dx_{coarse}>10 dx_{fine}). These coarse variables correspond to the best solution we could achieve with a coarse model using dx_{coarse} and having an optimal subgrid-scale parameterization. We will also compute the averaged Reynolds fluxes at dx_{coarse}, that encodes the effect of the unresolved processes onto the resolved ones. The DNN will be trained to relate the two. The parameterization then consists in calling the DNN to get the Reynolds fluxes from the coarse variables. Somehow, we want to encapsulate the knowledge we can acquire from realistic high-resolution simulations into a DNN and then benefit from this knowledge to run low resolution simulations. We expect that the parameterization will depend on dx_{coarse}. Namely the DNN will learn differently whether the unresolved processes are in the submesoscale range or in the mesoscale range. The comparison of the two outcomes is interesting in itself.

Thus, the project's aim is to test the feasibility of training a DNN with high-resolution data (coarse-grained at dx_{coarse}) to predict Reynolds fluxes for a coarse resolution simulation.

It will use sets of idealized (double gyre) and realistic simulations (North-Atlantic) using the model CROCO at various horizontal and vertical resolutions. The DNN will be built in Python using Keras and TensorFlow.

References

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Location

The work will be done at LOPS, IUEM, Brest, France, under the supervision of Jonathan Gula, Guillaume Roullet, and Guillaume Maze (LOPS), which are oceanographers and modellers, in close collabroation with Pierre Tandeo and Ronan Fablet (IMT-A), which are specialists of machine learning methods.

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