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## Learning quasi-geostrophic turbulence parametrizations from *a posteriori* metrics

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Machine learning techniques are now ubiquitous in the geophysical science community. They have been applied in particular to the prediction of subgrid-scale parametrizations using data that describes small scale dynamics from large scale states. However, these models are then used to predict temporal trajectories, which is not covered by this instantaneous mapping. Following the model trajectory during training can be done using an end-to-end approach, where temporal integration is performed using a neural network. As a consequence, the approach is shown to optimize *a posteriori* metrics, whereas the classical instantaneous training is limited to *a priori* ones. When applied on a specific energy backscatter problem, found in quasi-geostrophic turbulent flows, the strategy demonstrates long-term stability and high fidelity statistical performance, without any increase in computational complexity during rollout. These improvements may question the future development of realistic subgrid-scale parametrizations in favor of differentiable solvers, required by the *a posteriori* strategy.