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## Developing a data-driven ocean model

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The recent boom in machine learning and data science has led to a number of new opportunities in the environmental sciences. In particular, climate models represent the best tools we have to predict, understand and potentially mitigate climate change, however these process-based models are incredibly complex and require huge amounts of high-performance computing resources. Machine learning offers opportunities to greatly improve the computational efficiency of these models.

Here we discuss our recent efforts to reduce the computational cost associated with running a process-based model of the physical ocean by developing an analogous data-driven model. We train statistical and machine learning algorithms using the outputs from a highly idealised sector configuration of general circulation model (MITgcm). Our aim is to develop an algorithm which is able to predict the future state of the general circulation model to a similar level of accuracy in a more computationally efficient manner.

We first develop a linear regression model to investigate the sensitivity of data-driven approaches to various inputs, e.g. temperature on different spatial and temporal scales, and meta-variables such as location information. Following this, we develop a neural network model to replicate the general circulation model, as in the work of Dueben and Bauer 2018, and Scher 2018.

We present a discussion on the sensitivity of data-driven models and preliminary results from the neural network based model.

*Dueben, P. D., & Bauer, P. (2018). Challenges and design choices for global weather and climate models based on machine learning. Geoscientific Model Development, 11(10), 3999-4009.*

*Scher, S. (2018). Toward DataDriven Weather and Climate Forecasting: Approximating a Simple General Circulation Model With Deep Learning. Geophysical Research Letters, 45(22), 12-616.*

