



**Scenario**  
DOCTORAL TRAINING PARTNERSHIP

**NERC**  
SCIENCE OF THE  
ENVIRONMENT

## Deep Learning Atmospheric Features

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The detection of interesting features (cyclones, atmospheric rivers, fronts) in meteorological data has a long history of ever-increasing fidelity as newer techniques have been developed exploiting increasing computer power and more mathematical sophistication. Recently, the armoury of tools has been increased by the addition of newer techniques borrowed from Computer Vision. Early work suggests they may have higher levels of accuracy in feature detection than existing techniques, but in the case of Deep Learning this comes with enormous requirements on computing - at least when applied to the raw data - and with that enormous requirements on data storage.



*The 2017 Atlantic hurricane season: tracks on the left, and Hurricane Ophelia in the middle (over the Azores) en route to landfall in Europe. We have great tools for finding and tracking mature cyclones, but we do not have good tools for identifying incipient cyclones in model simulations, particular in climate ensembles while the simulation is running on a supercomputer. (Cyclone figures from Wikipedia. Supercomputer is JASMIN, <https://jasmin.ac.uk>)*

In the future we expect to run large ensembles of climate simulations (that is, many realisations of what might occur under a specific set of scenarios). Today we would write out all the data, and then investigate the output data for interesting features. As resolution increases, just storing all that data will be difficult, let alone doing the feature detection on the stored data. A possible way to handle this in the future would be to look for the features in each one of the ensemble members as the model runs - and only write out the simulations which we already know have interesting features.

This project is about testing and comparing the fidelity of a range of detection techniques to both raw high-resolution climate model data and both reduced precision and reduced resolution variants of the same data. The goal will be to develop a learning technique that can be used during the model simulation and identify such features without itself being enormously computationally expensive. This will most likely be done by using reduced versions of the data, rather than changing the techniques, but different techniques may work better at

different levels of reduced data. However, if we do need to change and/or modify techniques, we will be asking ourselves “Which are the most important building blocks for a robust and versatile learning? Which are the crucial inner layers and neurons for effective training?”

**Training opportunities:**

The project will involve exploiting a range of data analytic techniques, ranging from completely unsupervised learning, to data reductions based on a priori meteorological knowledge. The student will be exposed to a range of modern data science algorithms, and in particular, will learn how to exploit both traditional machine learning techniques (such as k-means analysis) and deep learning (also known as Artificial Intelligence) on a range of computing platforms from GPU workstations to supercomputers.

**Student profile:**

The project will be suitable for a student with a degree in Engineering, Physics, Mathematics or Computer Science, or related, and the desire and aptitude to work with sophisticated mathematics, complicated codes and large amounts of data.

**Background Reading:**

(Don't be worried if these seem intimidating ... one of the first goals of the project will be to make all these concepts familiar ... no background in any of these will be assumed.)

1. LeCun et.al. (2015). Deep Learning. Nature. <https://doi.org/10.1038/nature14539>
2. Neu et. al. (2013) IMILAST: A Community Effort to Intercompare Extratropical Cyclone Detection and Tracking Algorithms, BAMS, <https://doi.org/10.1175/BAMS-D-11-00154.1>
3. Matsuoka, D. et. al. (2017), Detecting precursors of tropical cyclones using deep neural networks, available at [https://www.researchgate.net/publication/321267980\\_Detecting\\_Precursors\\_of\\_Tropical\\_Cyclone\\_using\\_Deep\\_Neural\\_Networks](https://www.researchgate.net/publication/321267980_Detecting_Precursors_of_Tropical_Cyclone_using_Deep_Neural_Networks)
4. Catto, J., (2018): A New Method to Objectively Classify Extratropical Cyclones for Climate Studies: Testing in the Southwest Pacific Region. Journal of Climate, <https://doi.org/10.1175/JCLI-D-17-0746.1>
5. Kurth et. al. (2017): Deep learning at 15 PF: supervised and semi-supervised classification for scientific data. SC '17 Proc. Int. Conf. High Perf Computing, Networking, Storage and Analysis. <https://doi.org/10.1145/3126908.3126916>

<http://www.reading.ac.uk/nercdtp>