THE UNIVERSITY OF WESTERN AUSTRALIA

Machine Learning methods to correct spectral ocean wave forecasts

General information

- **Location**: University of Western Australia, School or Earth Sciences, Ocean Institute
- **Research Council**: Transforming energy Infrastructure through Digital Engineering
- **Supervisors**: Associate Professor Jeff Hansen, Research Fellow Arthur Filoche
- **starting date**: early 2025
- **salary**: 42k AUD$/year for 3 years (tax free)
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keywords: Ocean weather forecast, learning from under-sampled measurements, directional wave spectra, inverse problem, geometric data analysis

Research Topic

Numerical weather forecasts are classically produced using physics-based numerical models that in some instances assimilate sparse observations. Errors in these numerical forecasts can arise from many different sources including incomplete physics, choice of the data assimilation algorithm, initial and boundary conditions, and model numerics. Similar to many numerical forecasts, ocean wave forecasts are computed on a large spatial grid for computational efficiency. Evaluation of numerical wave forecasts, using in situ buoy measurements, reveals models can perform poorly in site-specific areas. However, the buoy dataset used for comparison also constitutes an opportunity to learn site-specific corrections. Also, a machine learning model would naturally allow the use of any contextual variables which is not always possible using a physics-based wave model.

Objectives

The main goal of the thesis is to design a machine learning based correction of the wave forecast using historical wave buoy measurements and relevant contextual variables (e.g. tides, currents, wind). A simple yet important question is: **What are the relevant contextual variables?** This might be answered combining physics-based reasoning and empirical evidence of improvement.

The core challenge of the project lies in the fact that forecasts and measurements live in different spaces. Forecasts are produced using a physics-based wave model, which operates in the spectral domain: at each point of the spatial grid, the state of the ocean wave conditions are described using the two-dimensional spectra which gives the energy of the waves as a function of directions and frequencies. On the other hand, buoy measurements provide the one-dimensional spectra and first directional Fourier coefficients. There is a direct and known integration relationship between a two-dimensional spectra and these measurements. However this relationship is not invertible so that recovering the two-dimensional spectra from the measurements is an ill-posed inverse problem [1]. **In this situation of under-sampled measurements, what supervision mechanism should we use?**[2] [3]. **Can we take inspiration from classical variational inversion methods ?**[4] [5].

Directional wave spectra are usually stored as square arrays and so it may be convenient to process them like images. However these data are more representative on a polar grid. **Which geometry and associated deep architectures would be the most relevant? Should we design shape preserving algorithms?** [6]

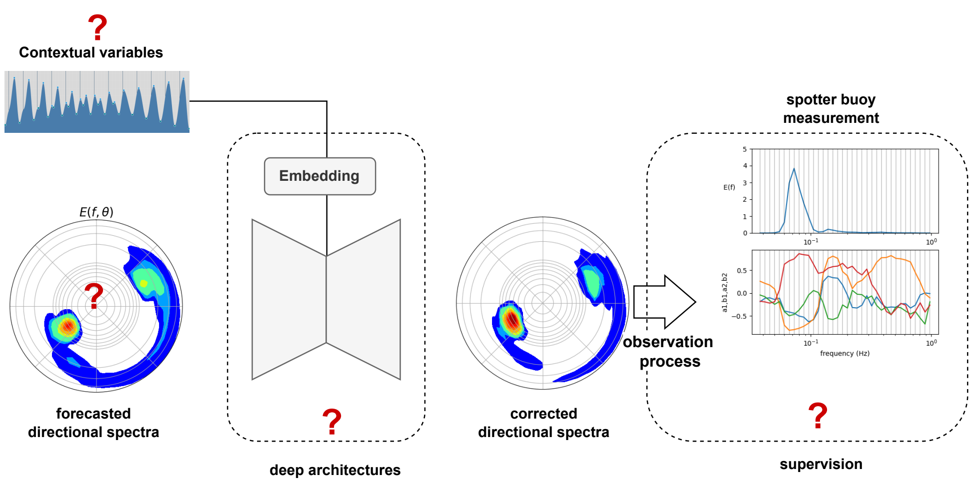

Figure 1: Initial schematic view of the learning problem

Significance

Recent advances in machine learning are logically enhancing numerical weather forecasts which are data intensive by nature. These improvements operate at different stage of the forecasting process [7] and the proposed topic falls at first glance into the the post-processing category which is a novelty regarding wave forecasting. On the machine learning side, there is a real challenge in translating the image and language processing breakthrough into geo-scientific application, as data are from very different nature. This topic has potential for meaningful contribution to an emergent interdisciplinary field.

If successful, the project might have a non-negligible economic impact for industry partners (TIDE research hub) operating in Australian and globally. Further, accurate wave forecasts are also important for the growing marine renewable energy sector.

Finally, the project could lead to deeper conclusion on how to merge numerical wave model outputs and wave buoy measurements. In that case, developed methods could be use in the data assimilation process, upstream of the forecast processing pipeline.

Relevant educational content

Oceanography: Waves in Oceanic and Coastal Waters, Spotter buoy measurement, Wave modelling

Machine Learning: Deep Unsupervised Learning, Deep Generative Models, Geometric Data Analysis

References

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