Geometric Deep Learning for Smart Shipping

Graph neural networks for short- and long-term weather forecasting

Geometric Deep Learning for Smart Shipping Graph Neural Network for short-long-term weather forecasting Samaneh Abolpour Mofrad Bergen International Shipping Conference 18 October 2024 Samaneh Abolpour Mofrad

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Background and motivation

My background is in mathematics, and I hold a master's in pure mathematics with a focus on geometry, as well as a master's in applied mathematics, in porous media and oil reservoirs. My Ph.D. was in machine learning and data analysis in collaboration with the Department of Radiology, focusing on aging and dementia and modelling a memory network. After my PhD I worked as a data scientist at a consulting company in Oslo, and currently I pursuing my SEAS postdoctoral fellowship in collaboration with Imperial College London. My research project is in an area that combines all my background knowledge, including geometry, deep learning and fluid mechanics in one of my favourite topics, renewable energy and marine sustainability.



Project description

Despite the revolution in weather and climate forecasts during the past half-century, accurate forecasting of the weather is still a challenge. State-of-the-art data- driven approaches such as topological and geometric deep learning techniques have recently shown success with similar forecasting tasks. We propose a new weather forecasting graph neural network that can reduce greenhouse gas emissions by increasing the use of renewable energy.

Objective

- Design and develop a graph neural network for local marine weather forecasting.
- On vessels this will enable the optimization of shipping routes and more efficient transitions between diverse energy sources such as solar, wind, and tidal power.
- Additionally, optimize the number and strategic placement of weather sensors in maritime environments.

Graph structure

Graph nodes:

- weather stations, such as buoys in the marine area, are represented as graph nodes.
- Each node, providing real-time and historical weather data includes temperature, pressure, wind speed, and geographic information.

example which applies this aerodynamic design to harness wind power more efficiently.



Hurtigruten: An electric cruise ship with gigantic solar sails is set to launch in 2030 in Norway.

The ship will be 135 meters in length and have 270 cabins. The sails, when fully extended, will reach 50 meters in height.

Marine sustainability

- In 2012, the International Maritime Organization (IMO) reported that maritime transport emissions totalled approximately 940 million tons of CO2 annually.
- Without immediate mitigation efforts, these emissions are projected to increase by 50% to 250% by 2050 (IMO, 2015).
- Decarbonizing shipping and developing smart ships with advanced energy management systems are crucial steps toward reducing greenhouse gas emissions.



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Graph edges:

- Edges represent the relationships between the weather data of neighbouring nodes and their geographical distances
- Considering such graphs over time, we form a spatial-temporal graph neural network.

Main questions

- How effective a graph neural networks improve local weather forecasting in maritime areas compared to existing forecasting methods?
- How efficient are the results in optimizing shipping routes? \bullet
- How can we optimize the number and placement of weather sensors in the ocean?
- What is the relationship between the distance of weather stations from a ship and the forecast time horizon?
- How does improved weather forecasting impact the energy hybridisation of ships?



Accurate weather forecasting plays a vital role in this effort. It can optimize shipping routes, assist in estimating arrival times, and enhance the hybridization of energy sources, improving the overall efficiency of utilizing renewable energy.

Highlighted progress

- The blue point in Fig1, represents a ship, while the green points indicate the locations of surrounding buoys.
- These points are selected randomly, ensuring an initial minimum distance of 50 km and a maximum of 1000 km between them.
- The **Torch SpatioTemporal** (TSL) Python library is used to train several models, aiming to identify the optimal model and parameters for weather forecasting at these nodes.
- Post-processing steps will be designed to analyse the relationship between the forecast quality of and the number and distance of the nodes.
- In addition to TSL, the most important Python libraries used for this work are **PyTorch, PyG, and Pandas**.



- The data are selected from ERA5 hourly near-surface \bullet weather data.
- ERA5 represents the fifth generation ECMWF atmospheric reanalysis of the global climate from January 1940 to the present. It is produced by the Copernicus Climate Change Service (C3S) at ECMWF.







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