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Continual Learning for Handling Maritime Data Shifts in Vessel Trajectory Prediction

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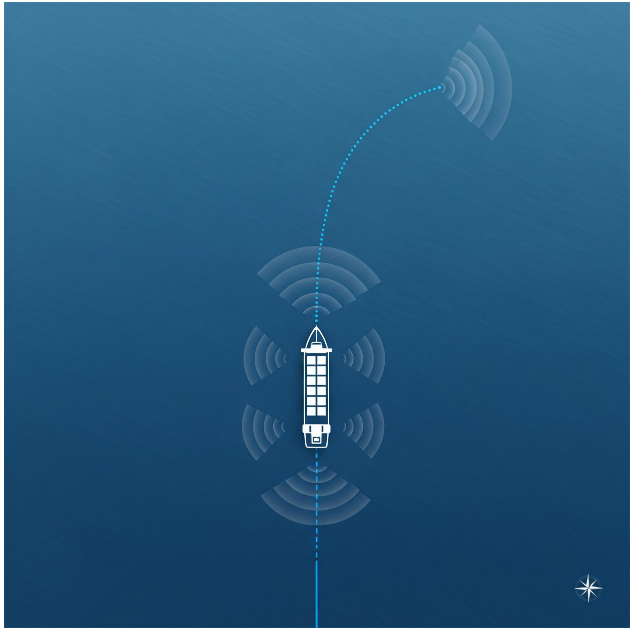
Introduction

Predicting a trajectory of the vessel is critical for maritime safety and efficiency.

The dynamic and unpredictable nature of the maritime environment presents significant challenges.

Maritime conditions constantly evolve due to:

- **Natural factors:** e.g., wind, waves, currents.
- **Vessel-specific factors:** e.g, hull shape and propulsion efficiency.
- **Operational factors:** e.g., rudder configuration and load distribution.



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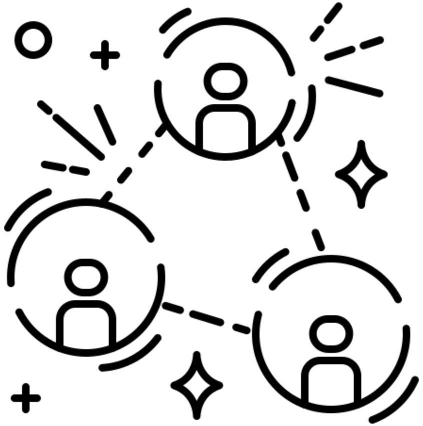
Related work

Methods that achieve good performance:

- **Statistical Methods:** Kalman filters and Gaussian processes handle uncertainty but struggle with complex, non-linear dynamics in real-world data.
- **Deep Learning Models:** RNNs, LSTM, and GNN learn temporal patterns.



What is the open issue?

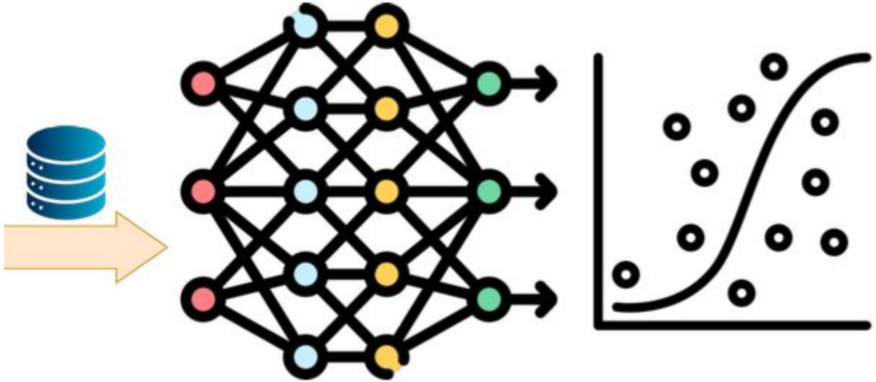
Open Issue

Traditional AI models are trained on static datasets and assume stationary data.

They **struggle** to **adapt** to **new or changing conditions**, leading to performance degradation when faced with novel situations or data shifts.

In **Maritime environments** data distribution frequently changes due to:

- Evolving traffic patterns.
- Changing weather conditions.
- Shifts in the vessel's operational state.



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Our Methodology

Continual Learning (CL) enables models to acquire knowledge from continuous data streams without forgetting previously learned patterns.

Incremental Learning

System learns from sequential data streams without retraining from scratch.

Knowledge Preservation

Replay-based approach prevents catastrophic forgetting of past vessel movements.

Dynamic Adaptation

Model tracks and adapts to shifting environmental factors and vessel behavior variations.

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Catastrophic Forgetting

When **models learn new information,** they often **lose previously** acquired **knowledge**, this phenomenon is called **catastrophic forgetting**.

Replay-based method stores representative samples from past data in a memory buffer, enabling the model to reinforce understanding while learning new patterns.

1. **New Data Arrives**

   Model encounters changing conditions

2. **Memory Buffer Activated**

   Past samples replayed alongside new data

3. **Knowledge Retained**

   Critical information preserved

Costa Concordia dataset

7.5M

Data Samples

High-frequency trajectory recordings

81

Features Captured

Comprehensive navigational parameters

4-5

Samples/Second

Real-time recording rate

23

Days Analyzed

December 19, 2011 - January 10, 2012

Dataset sourced from Voyage Data Recorder (VDR) compliant with IMO standard A.861(20), capturing critical navigational parameters including latitude, longitude, speed, course, heading, wind conditions, and propeller/rudder data.

Dataset analysis

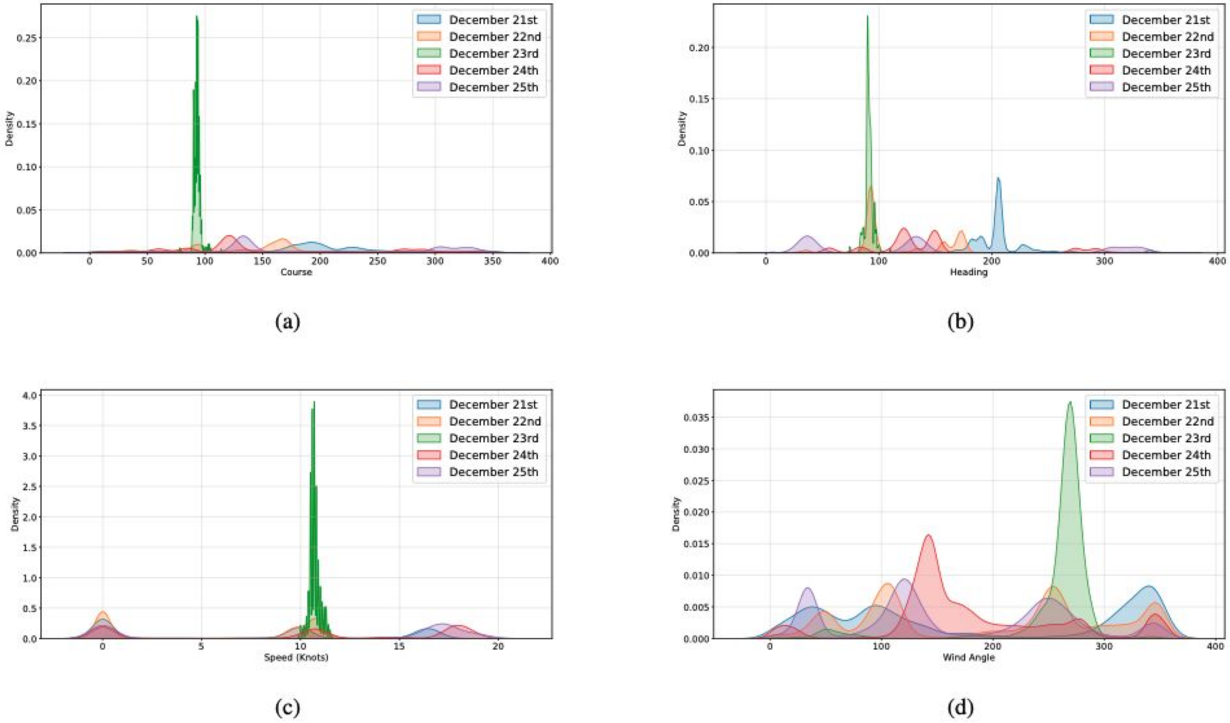

Fig. 1: Daily variability in some vessel navigational parameters from December 21^{st} to December 25^{th}, visualized using the distribution show daily patterns for the vessel (a) `Course`, (b) `Heading`, (c) `Speed (knots)`, and (d) `Wind Angle`. The distinct shapes and peak locations of the distributions across the different days (indicated by color) highlight the dynamic nature of vessel movement.

Dataset preprocessing

- **Feature selection**: to identify and isolate the 19 most relevant features for vessel trajectory.
- **Min-max normalization**: this approach incorporates a buffer that stores the minimum and maximum values observed across all processed sequences up to the current point. The buffer is updated whenever new extreme values are encountered in the incoming data.

7.5M

Data Samples

High-frequency trajectory recordings

17

Features Captured

Without the target features

TABLE I: Dataset description

Feature	Description
Date	Recorded date and time (CET).
Latitude	Latitude (decimal deg., GMM format).
Longitude	Longitude.
Heading	Heading (deg., true north).
Course	Course over ground (deg., true north).
Speed (Knots)	Speed over ground (knots).
Wind Speed (Knots, True)	True wind speed (knots).
Wind Direction (True)	Wind direction (deg., true north).
Wind Speed (m/s, True)	True wind speed (m/s).
Wind Angle	Wind angle relative to vessel (deg.).
Wind Speed (Knots, R/T)	Relative wind speed (knots).
Prop. ORD (PORT)	Ordered RPM for port propeller.
Prop. ORD (STBD)	Ordered RPM for starboard propeller.
Prop. ACT (PORT)	Actual RPM of port propeller.
Prop. ACT (STBD)	Actual RPM of starboard propeller.
Rudder ORD (PORT)	Ordered angle for port rudder.
Rudder ORD (STBD)	Ordered angle for starboard rudder.
Rudder ACT (PORT)	Actual angle of port rudder.
Rudder ACT (STBD)	Actual angle of starboard rudder.

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Results

TABLE III: RMSE Comparison with and without Continual Learning (CL) to predict the vessel trajectory.

Day	RMSE with CL	RMSE without CL
December 19th	0.0191	0.3498
December 20th	0.0242	0.4244
December 21st	0.0204	0.9741
December 22nd	0.0240	1.1812
December 23rd	0.0431	1.6081
December 24th	0.0169	0.9405
December 25th	0.0193	0.7950
December 26th	0.0168	0.9496
December 27th	0.0150	0.8786
December 28th	0.0062	0.0384
December 29th	0.0150	0.3457
December 30th	0.0135	1.0056
December 31st	0.0123	0.6639
January 1st	0.0180	0.2574
January 2nd	0.0316	0.1918
January 3rd	0.0252	1.0052
January 4th	0.0298	1.1694
January 5th	0.0237	1.2289
January 6th	0.0169	0.8827
January 7th	0.0210	0.9652
January 8th	0.0129	1.0983
January 9th	0.0225	0.9907
January 10th	0.0212	0.3231

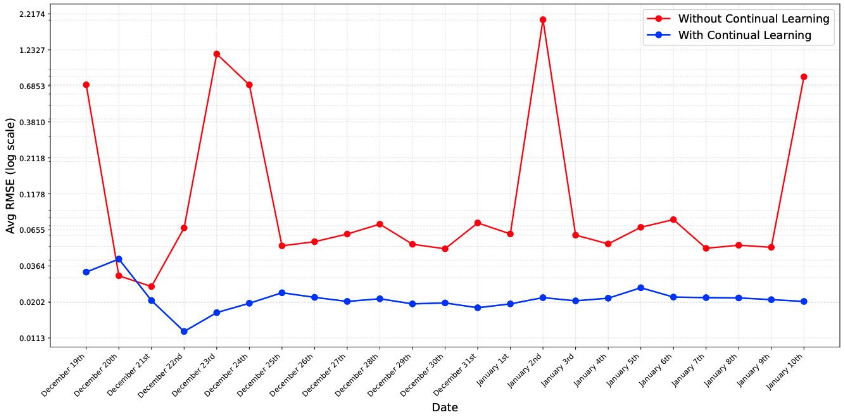

Fig. 2: Comparative analysis of Average RMSE in vessel trajectory prediction across time, shown on a logarithmic scale. The plot highlights the superior performance of the Continual Learning model (blue line) against the static approach (red line) over the evaluation period.

Conclusions

Lower Prediction Error

Consistently outperforms static models with significantly reduced RMSE across all test periods.

Dynamic Adaptation

Adjusts to data shifts and non-stationarities inherent in real-world maritime operations.

Enhanced Reliability

Maintains high performance over time in continuously changing environments.

Future works

Leverage adaptive learning to identify deviations signaling safety risks or operational inefficiencies.

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