Collision Risk Assessment and Forecasting on Maritime Data (Industrial Paper)

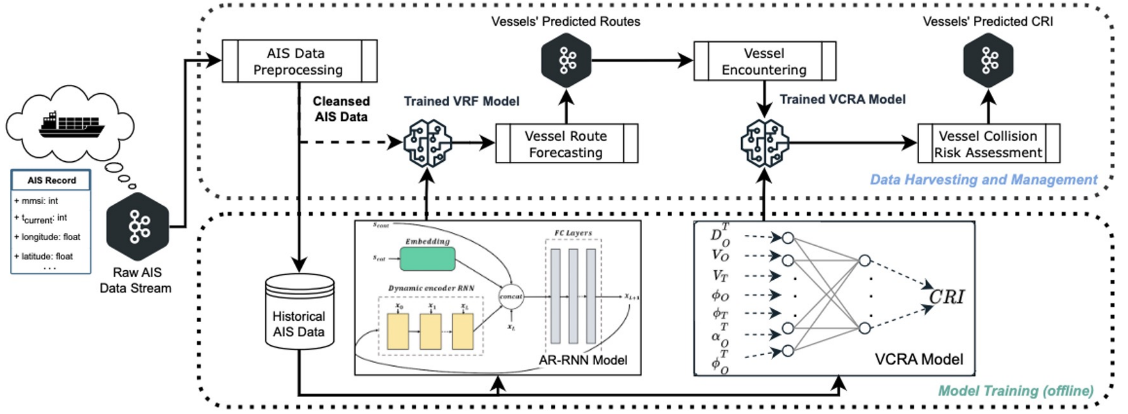
Andreas Tritsarolis[1], Brian Murray[2], Nikos Pelekis[1], and Yannis Theodoridis[1]

[1]Data Science Lab., University of Piraeus
{andrewt, npelekis, ytheod}@unipi.gr

[2]Department of Energy & Transport, SINTEF Ocean
brian.murray@sintef.no

Outline

1. Introduction & Related Work
2. Our Contribution (at a glance)
3. Problem Formulation
   - Vessel Collision Risk Assessment (VCRA)
   - Vessel Collision Risk Forecasting (VCRF)
4. Experimental Study
   - Datasets and Preprocessing
   - Experimental Results
   - Discussion on VCRA/F Model Transparency
5. Conclusions & Future Work



Introduction

- MDA task at hand: Assess the **collision risk** of vessels that are in an **encountering process**, either at **present** (hence, **VCRA**) or at a **future** time (hence, **VCRF**)
  - … via a measure called **Collision Risk Index** (**CRI**)
- Accurate VCRA/F → critical operation
  - see e.g., Unmanned Surface Vessels (USVs)
- Model complexity → Trade-off between quality and responsiveness
  - ML models may balance this trade-off by providing accurate and timely results

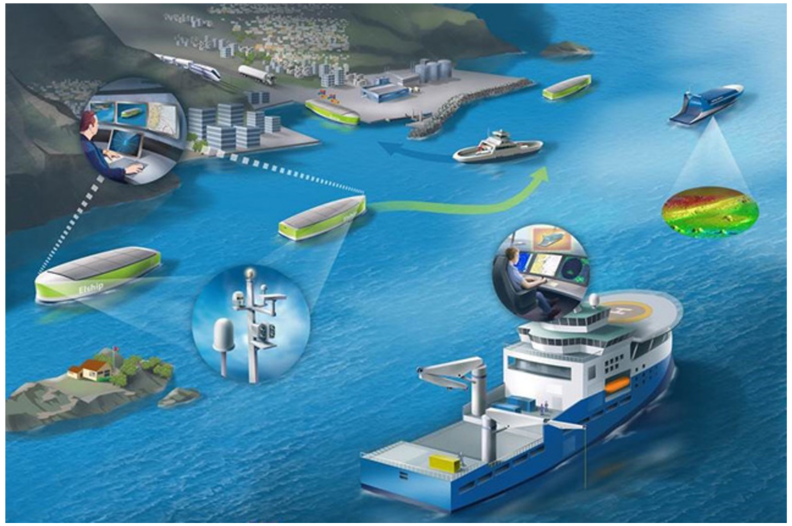
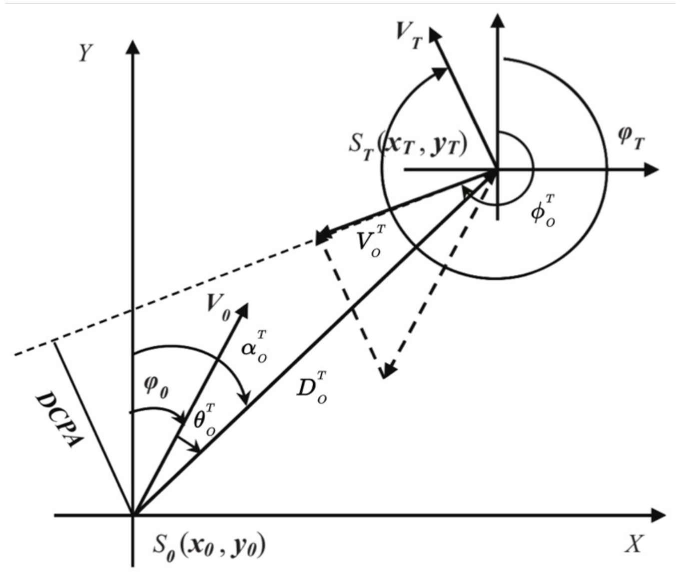


image source: ntnu.edu

Related Work

- Formulaic vs. Deep Learning approaches
  - Kinematic CRI equations combined with ML models (e.g., SVM)
- VCRA related work: Combine CRI equations with…
  - … SVM (Gang et al. 2016)
  - … CART (Li et al. 1018)
  - … RVM (Park & Jeong, 2021)
- VCRF related work: Predict CRI via…
  - … Bi-LSTM \w Attention (Ma et al. 2020)



Vessel collision geometry diagram, adapted from (Gang et al. 2016)

- Gang et al. (2016) Estimation of vessel collision risk index based on support vector machine. Advances in Mechanical Engineering, 8(11).
- Li et al. (2018) Calculation of Ship Collision Risk Index Based on Adaptive Fuzzy Neural Network. Proc. MSAM.
- Park & Jeong (2021) An Estimation of Ship Collision Risk Based on Relevance Vector Machine. J. Marine Science & Engineering, 9(5).
- Ma et al. (2020) A Data-Driven Approach for Collision Risk Early Warning in Vessel Encounter Situations Using Attention-BiLSTM. IEEE Access, 8.

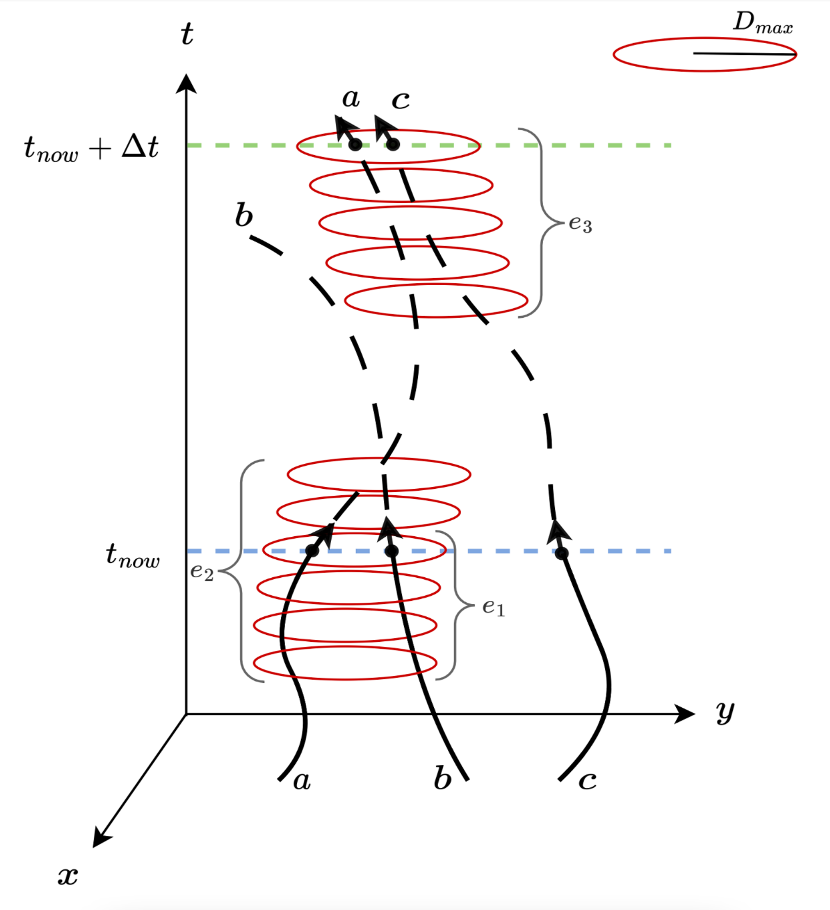
Our Contribution (at a glance)

- Our contribution consists of:
  - An ML-based method to address the VCRA problem
    - …which outperforms related work by a significant margin
  - A DL-based method to address the VCRF problem
    - …via Vessel Route Forecasting (VRF) algorithms
- Our experimental study, using a large-volume real-world maritime dataset (Norway), verifies:
  - The efficacy of our approach w.r.t. efficiency and effectiveness
  - Its soundness w.r.t. further decisions made
    - …hence, its value towards a unified framework able to monitor and uphold traffic safety

$$CRI = W \cdot U = W_{DCPA}U_{DCPA} + W_{TCPA}U_{TCPA} + W_{D_O^T}U_{D_O^T} + W_{\theta_O^T}U_{\theta_O^T} + W_K U_K$$

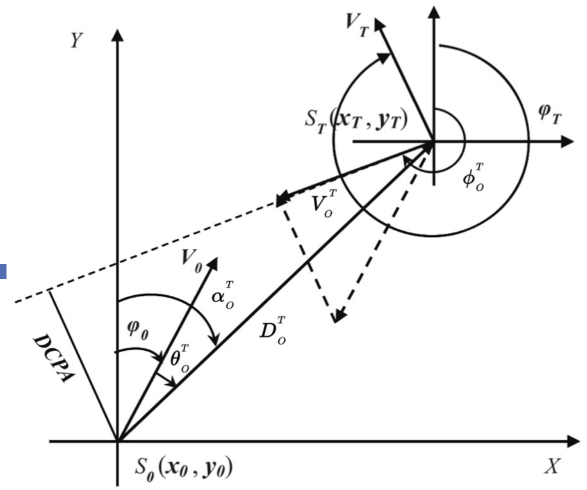
Problem Formulation

- Recall the problem: Assess the **collision risk** of vessels that are in an **encountering process**, either at **present** (hence, **VCRA**) or at a **future** time (hence, **VCRF**)
  - In a nutshell, assess the Collision Risk Index (CRI) of a pair of vessels
  - **Encountering Process**: Two vessels, own (**O**) and target (***T***), are in an encountering process when their distance is lower than a threshold and monotonically decreasing for at least some time period.

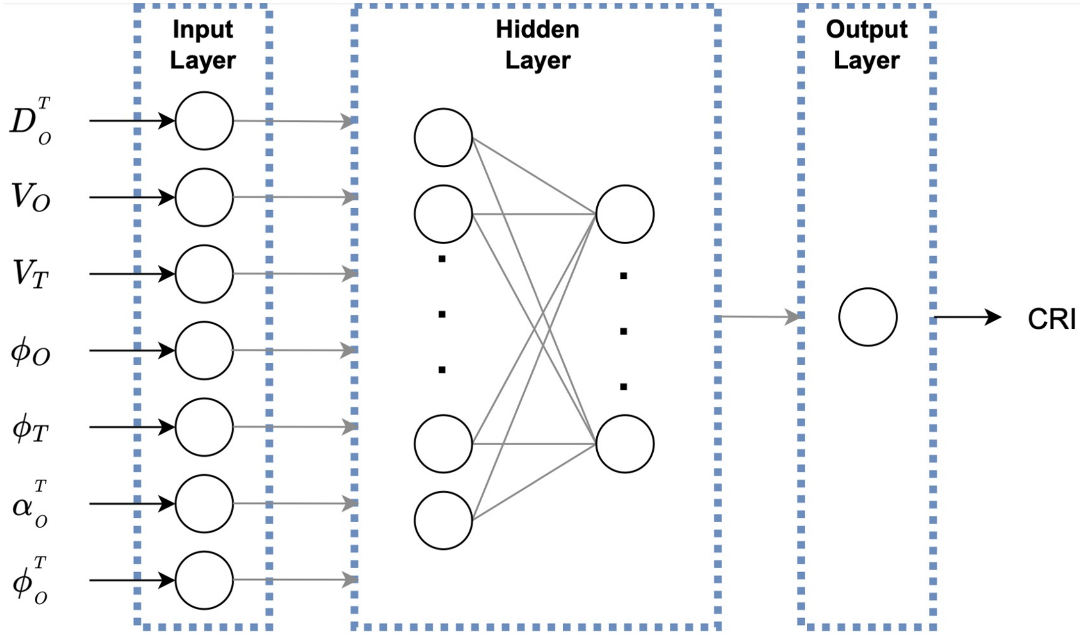


Example: VCRA detects encountering e_1 (a,b), whereas VCRF detects encounterings e_2 (a,b) and e_3 (a,c).

Problem Formulation: VCRA

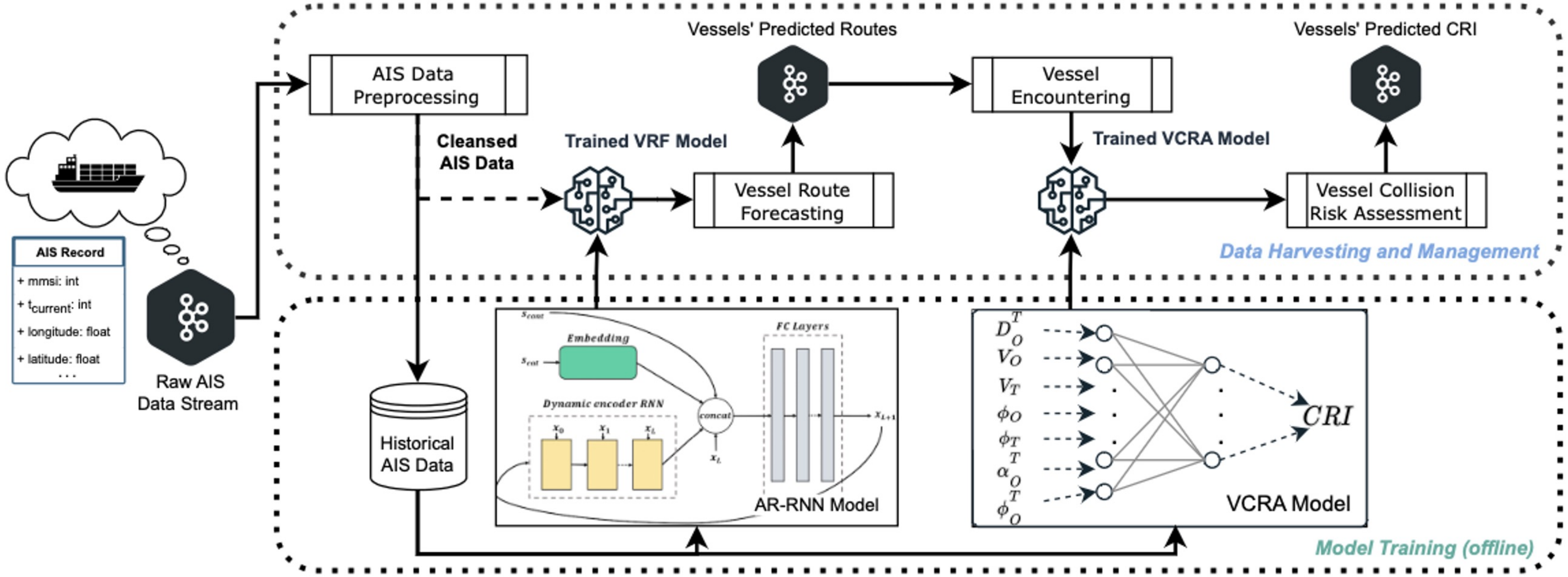


- **What**: Assess a Point of Approach (CPA) -based Risk Index
  - Calculate the risk of collision given the vessels' kinematic characteristics (ground truth)
- **How**: Train an ML model (e.g., MLP) over a $<V_O, V_T, CRI>$ dataset
  - **V_O, V_T**: Motion vector (speed, direction, etc.) of the two vessels
- wrt. related work:
  - Higher CRI assessment accuracy
  - Lower inference latency



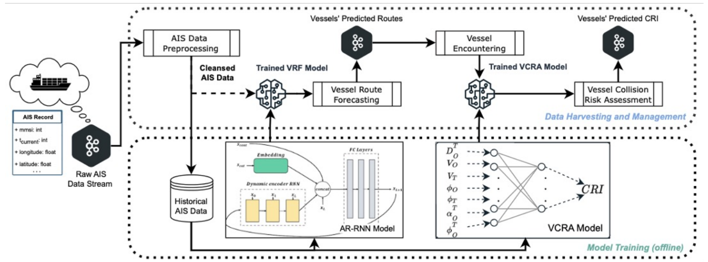
Problem Formulation: VCRF (1/2)

- **What**: Predict the encountering vessels' CRI in a short-term horizon
- **How**:
  - 1st) predict the vessels' future locations;
  - 2nd) assess CRI on the predicted locations

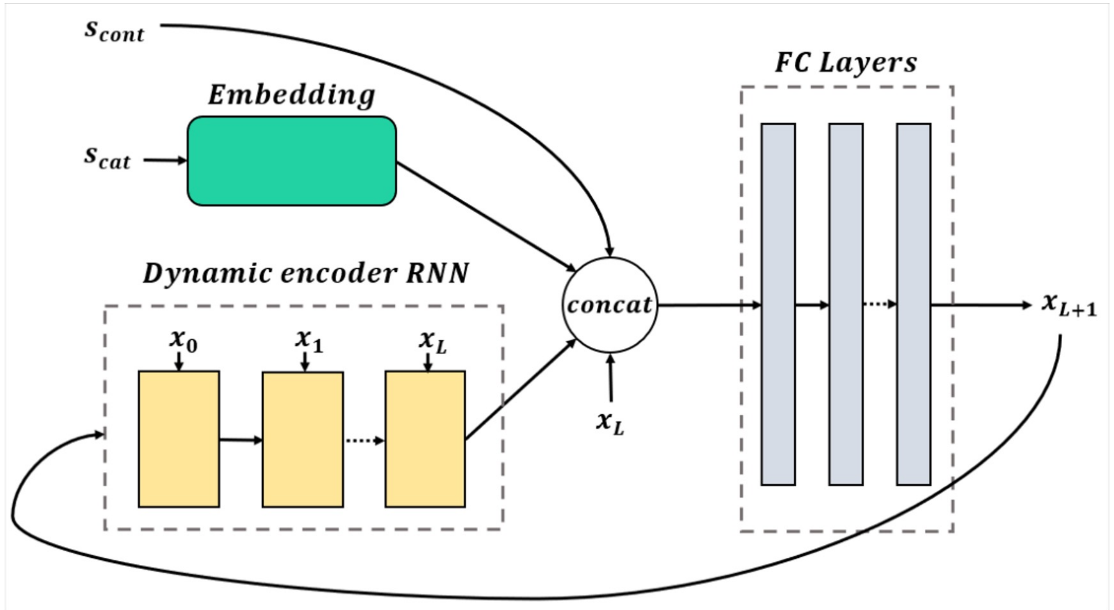


- Architecture: orthogonal w.r.t. underlying VCRA and VRF models …

Problem Formulation: VCRF (2/2)



- VCRF architecture
  - Underlying VRF: AR-RNN (Murray & Perera, 2021)
- Methodology:
  - For a given region of interest, group routes with common origins and destinations (each O-D group → AR-RNN)
  - Given a vessel's O-D, select the respective AR-RNN to forecast its future trajectory
  - If no route available, train a single model (caveat: reduced prediction fidelity)



- Murray & Perera (2021) An AIS-based deep learning framework for regional ship behavior prediction. Reliability Engineering & System Safety, 215.

Experimental Study (1/4)

- Dataset: Norway (NCA)
  - 8.4M transmitted AIS locations from 732 vessels (Jan. 2019)
- Preprocessing
  - Noise elimination (drop records with speed > 50 knots)
  - Trajectory segmentation

    (1) port-to-port segmentation

    (2) temporal gap segmentation (Δt > 30 min.)
  - Fixed rate resampling (one signal every 30 sec.)

Snapshot of the Norway dataset on Jan. 10th, 2019

#Records	8,352,352
#Vessels	732
#Segments	7267
#Points per Segment *(min; med.; avg.; max.)*	20; 172; 1153; 77759
Vessels' Speed *(min; avg.; max.)*	0; 3; 50 knots
Sampling Rate	30 sec.

- Norwegian Coastal Administration (NCA) Historical AIS data in Norwegian waters. URL: https://ais-public.kystverket.no/ais-download

Experimental Study (2/4)

- Experimental results @35% of the dataset
  - VCRA/F clearly outperforms related work
    - up to 70%, in terms of R^2 score
    - low RMS[Log]E → Our model has less tendency to underestimate danger

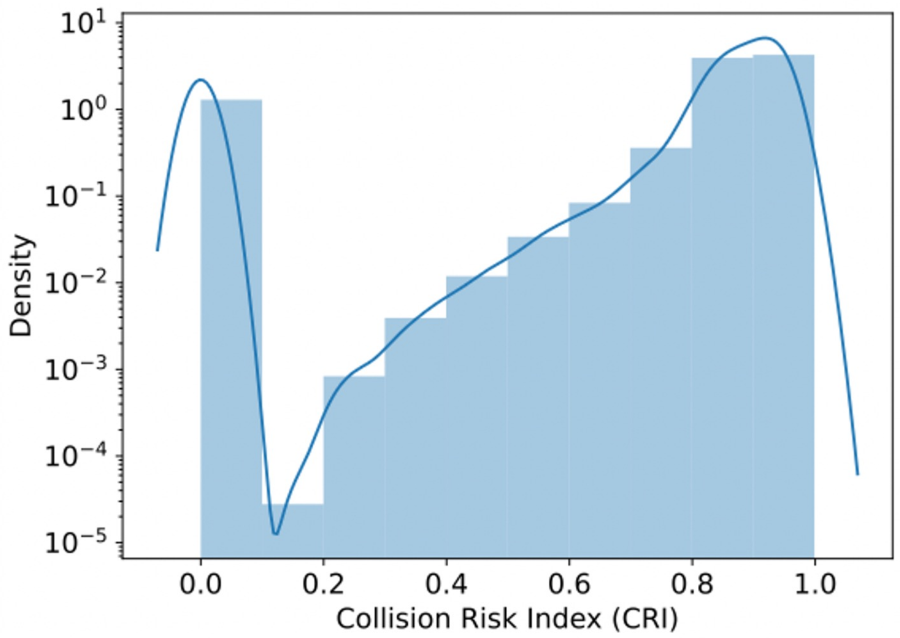
	MAE	RMSE	RMSLE	R^2
Gang et al. [12]	0.1194	0.1969	0.1452	0.5766
Li et al. [18]	0.0395	0.1165	0.0853	0.8517
Park et al. [29]	0.1272	0.1936	0.1379	0.5906
VCRA/F	**0.0246**	**0.0607**	**0.0440**	**0.9597**

- Experimental results @100% of the dataset (in particular, vs. Li et al.)
  - Confident predictions on low (< 0.2) and high (> 0.6) CRI
    - CRI ∈ (0.2, 0.4] tends to be assessed as (0.4, 0.6]

	[0, 0.2]	(0.2, 0.4]	(0.4, 0.6]	(0.6, 0.8]	(0.8, 1]
Li et al. [18]	0.1795	**0.0663**	0.0675	0.0585	0.0389
VCRA/F	**0.0869**	0.0760	**0.0496**	**0.0312**	**0.0215**

Experimental Study (3/4)

- In terms of latency – using the most populated timeslice of the dataset
  - VCRA significantly outperforms related work
    - response time: 0.22 msec. (± 110 μsec.)
  - … also outperforms CRI formula calculation
    - response time: 2.30 msec. (± 47 μsec.)
- As such, feasible alternative for real-time streaming frameworks

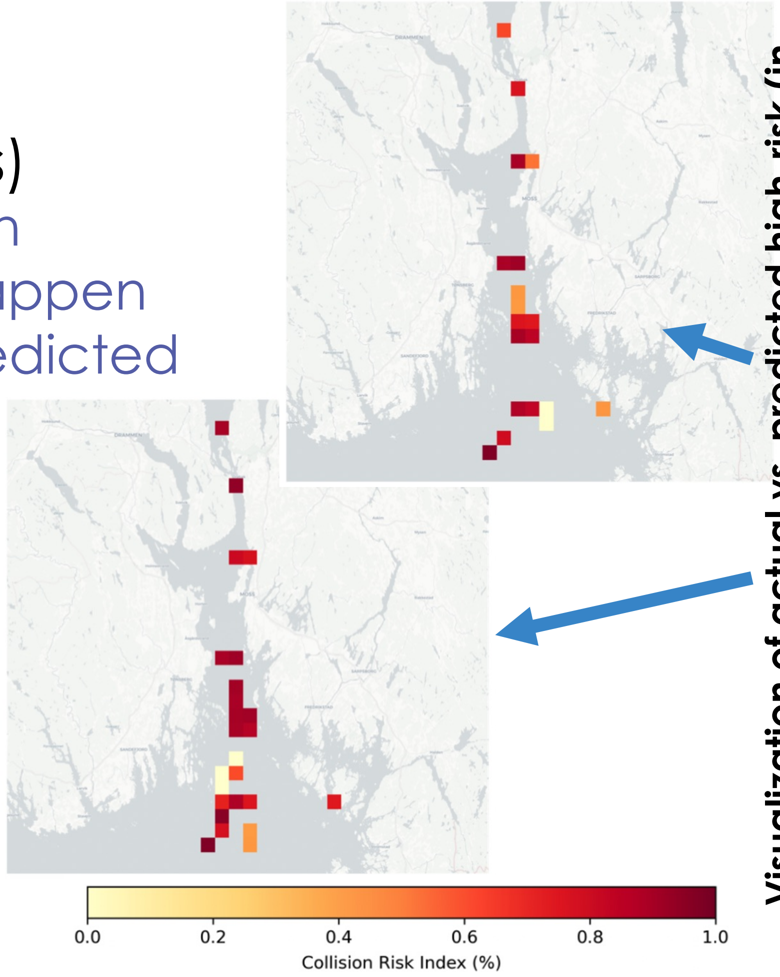


Method	Latency ($\mu \pm \sigma$)
CRI Formula (Eq. 1)	2.30 msec. $\pm 47 \mu$sec.
Gang et al. [12]	43.4 msec. $\pm 430 \mu$sec.
Li et al. [18]	3.38 msec. $\pm 56 \mu$sec.
Park et al. [29]	0.29 msec. $\pm 45 \mu$sec.
VCRA/F	**0.22 msec. $\pm 110 \mu$sec.**

Experimental Study (4/4)

$$Sim(EP_{pred}, EP_{act}) = \frac{Interval(EP_{pred}) \bigcap Interval(EP_{act})}{Interval(EP_{pred}) \bigcup Interval(EP_{act})}$$

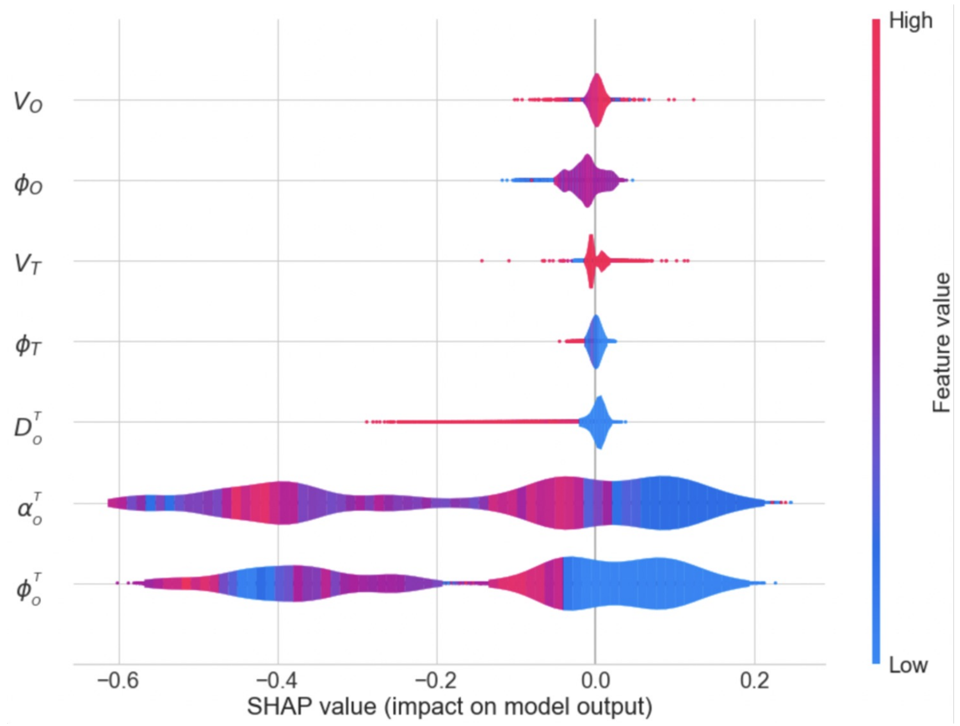
- Evaluating the accuracy of VCRF
- Method: match predicted vs. actual encounter(s)
  - True Positive (TP): predicted encounter did happen
  - False Positive (FP): predicted encounter did not happen
  - False Negative (FN): actual encounter was not predicted
- Experiment:
  - Oslo Fjord: 36 actual vs. 26 predicted encounters
  - Results: 24 TP encounters; 2 FP encounters; 12 FN encounters
  - Overall Accuracy → 77%



Visualization of actual vs. predicted high-risk (in terms of CRI) areas of interest within the Oslo Fjord

VCRA/F Model Transparency (1/2)

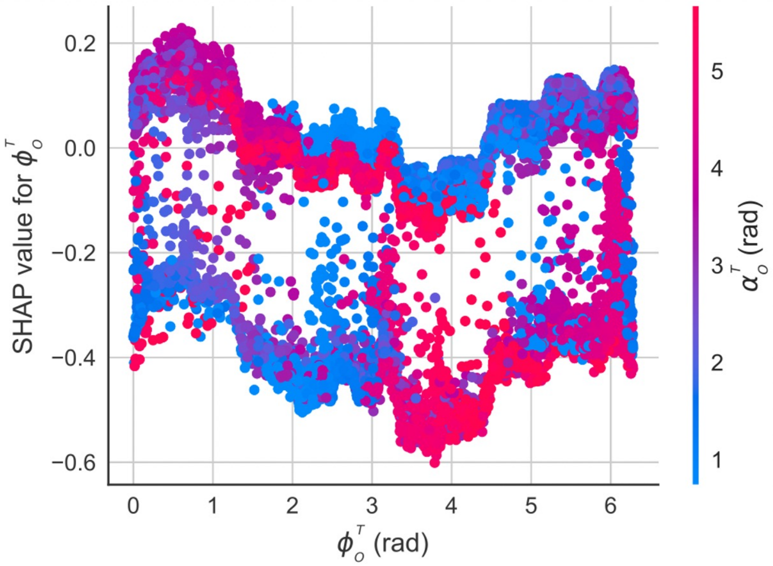
- SHAP Values
  - Random subset of test set
- Findings:
  - Speed ($V_{O,T}$) and Direction ($\varphi_{O,T}$)… …**minor impact** on CRI calculation
  - Distance (D_O^T), Azimuth (α_O^T), Rel. Bearing (ϕ_O^T)… …**major impact** on CRI calculation
  - Proximity / relative positioning
- In accordance with the vessel collision regulations / providence measures (see next slide)



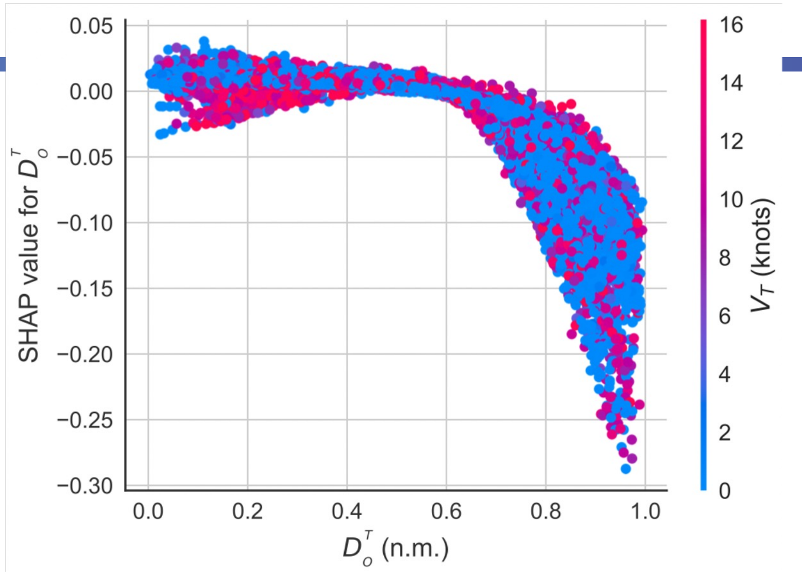
Impact of VCRA input variables on the model output

VCRA/F Model Transparency (2/2)

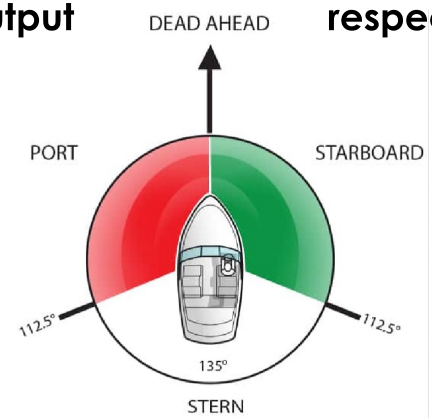
- Findings (cont.)
  - D_O^T increases → CRI decreases
    - $D_O^T > 0.7$ n.m.
  - ϕ_O^T / α_O^T → Correlated features
    - $\phi_O^T \leq \pi$, $\alpha_O^T \geq \pi$ → CRI increases
    - $\phi_O^T > \pi$, $\alpha_O^T \geq \pi$ → CRI decreases
  - Compliant with the stand-on / give-way rules in maritime



Impact of $\varphi_O{}^T$ vs. $a_O{}^T$ with respect to VCRA model output



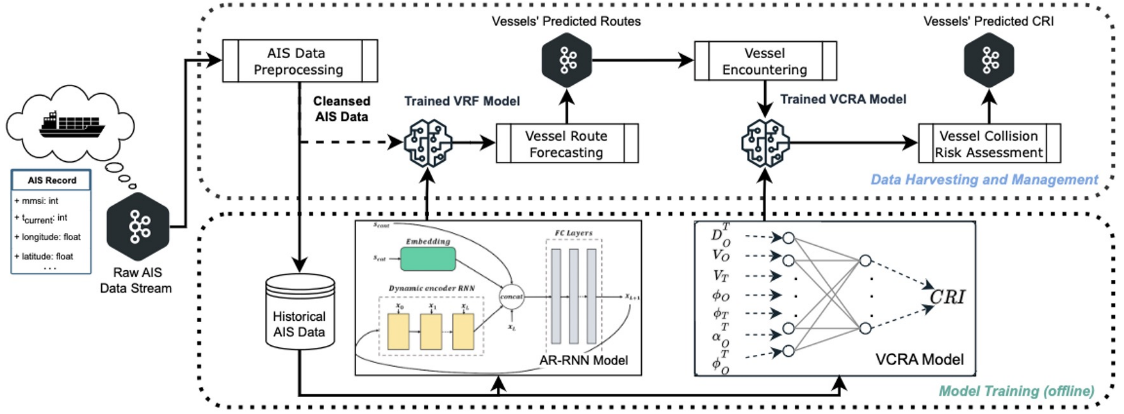
Impact of $D_O{}^T$ vs. V_T with respect to VCRA model output



Vessel collision regulations - determining right-of-way (image source: www.boatsmartexam.com)

Conclusions & Future Work

- In summary:
  - We proposed VCRA/F, a modular framework for short-term CRI forecasting
  - Our approach outperforms related work
    - higher accuracy; lower latency



- In the near future:
  - Advanced VRF models; VA tool

- Long-term goals:
  - Federated Learning → preserve vessel owners' privacy
  - Lifelong Learning → facilitate gradual model improvement

VCRA/F Code available @GitHub:
https://github.com/DataStories-UniPi/VCRA

More information about our Maritime research agenda:
https://www.datastories.org/maritime/

Thank you for your attention!
I'll be glad to answer your questions!

This work was supported in part by EU Horizon 2020 R&I Programme under Grant Agreement No. 957237 (project VesselAI, vessel-ai.eu).