

# Machine learning for vessel trajectory forecasting

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# Automatic Identification System (AIS)

Apr-Sep '12



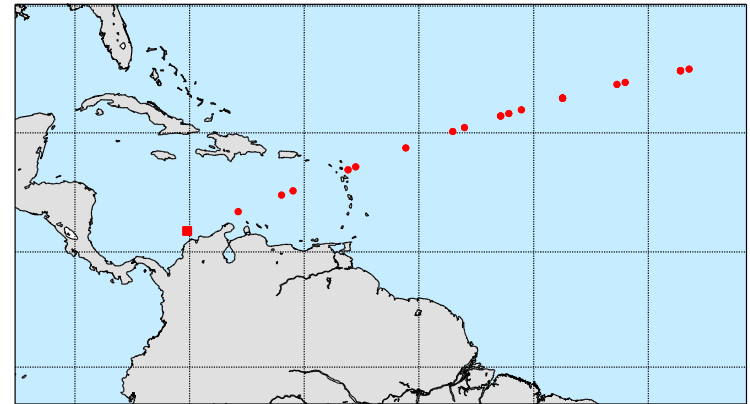
**approx. 50,000 commercial ships regularly broadcast AIS**

# Outline

1. Vessel prediction: motivation
2. Statistical prediction
3. Sequence-to-sequence models

# Vessel prediction: Motivation

- Need to monitor vessels in open seas and across **sensor coverage gaps**
- Accurate **long-term** state prediction is **crucial** to, among other possibilities:
  - Maritime **traffic modeling**
  - **Search and Rescue (SaR)** operations
  - **Association of time-sparse data**, such as AIS and detections/tracks from radar/SAR

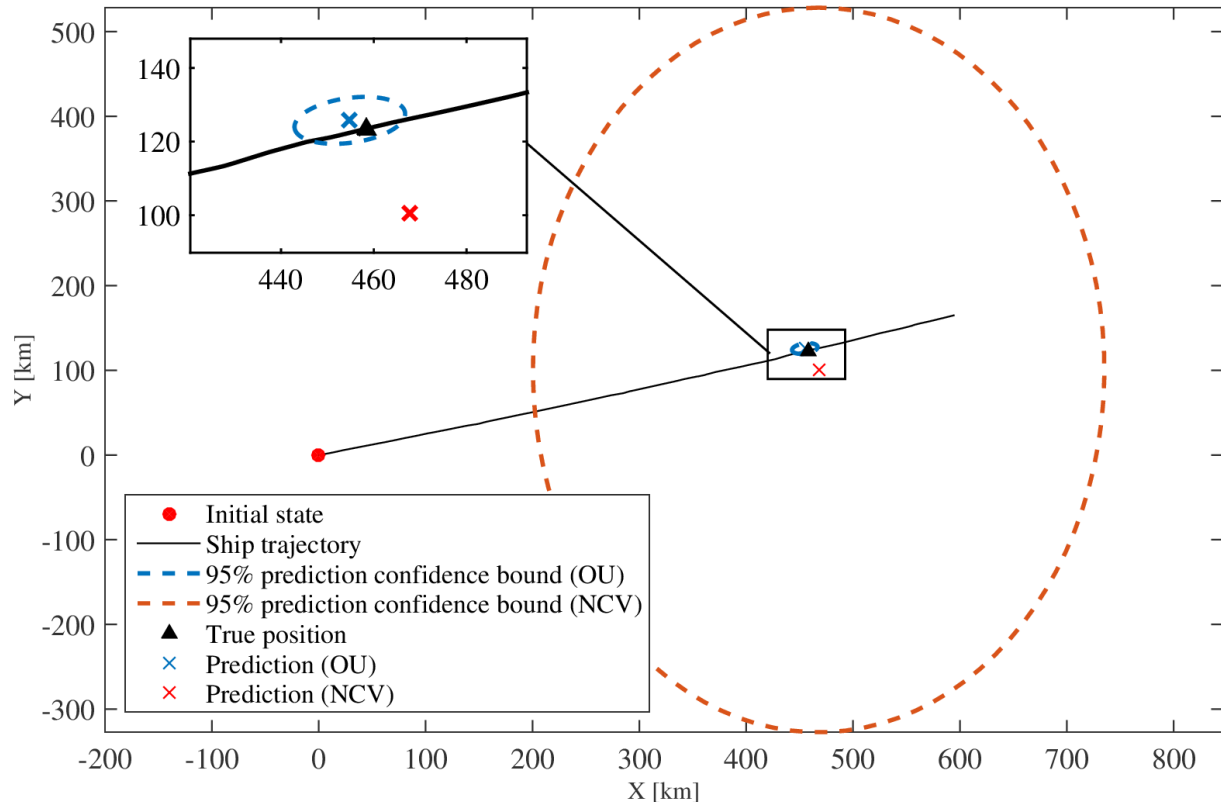




# Statistical prediction models

- **Traditional motion models** (nearly-constant velocity [**NCV**]) **overestimate** the actual prediction uncertainty
- **Mean-reverting models** (Ornstein-Uhlenbeck [**OU**])

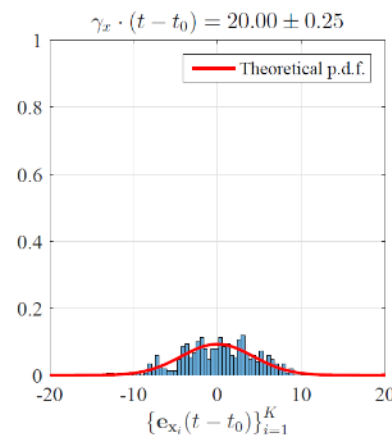
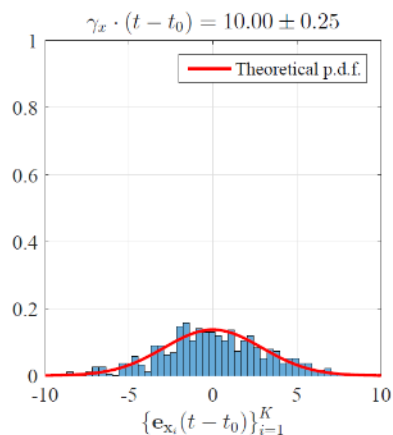
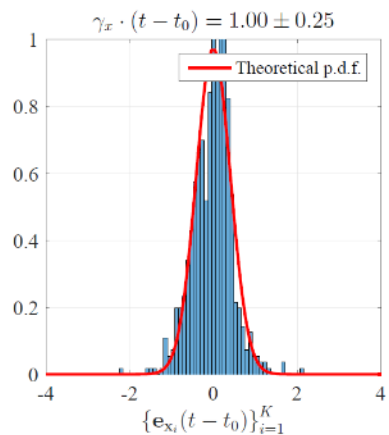
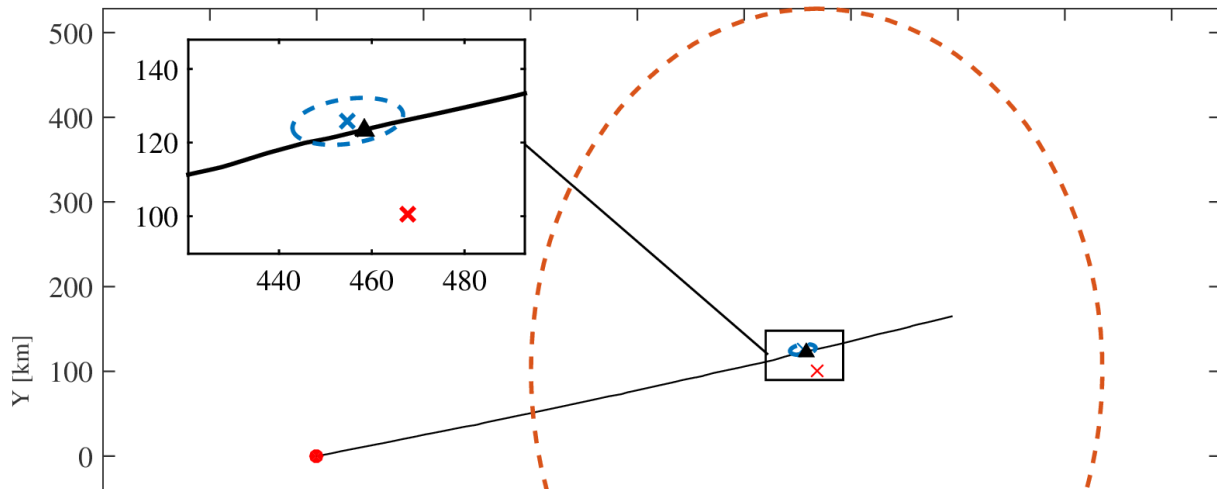
L. M. Millefiori, P. Braca, K. Bryan and P. Willett, "Modeling vessel kinematics using a stochastic mean-reverting process for long-term prediction," in *IEEE Transactions on Aerospace and Electronic Systems*, vol. 52, no. 5, pp. 2313-2330, October 2016.



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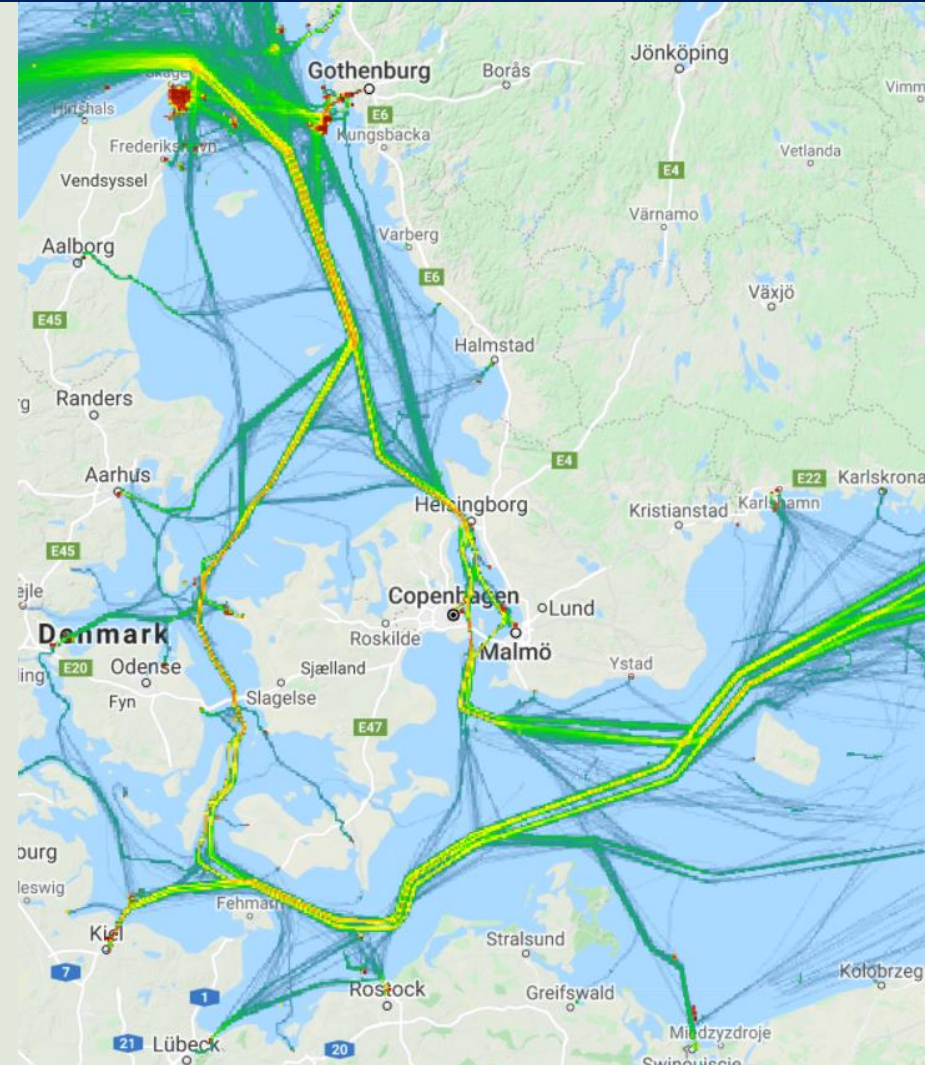
time →

Validation with  
~200,000 AIS messages:  
1,370 cargo • 370 tanker  
150 passenger

# Regularity of maritime traffic

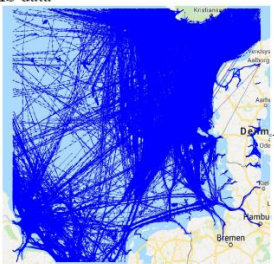
- Maritime traffic is *inherently* regular
  - Traffic regulations, fuel consumption minimization
- Large availability of historical data

**Q: Can we learn recurrent patterns and use them to make better predictions?**

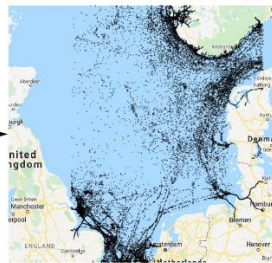


# Statistical multi-waypoint prediction

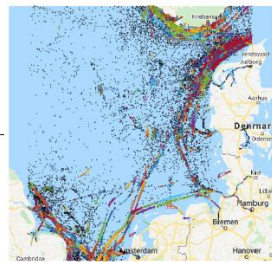
INPUT: Extracted tracks from historical AIS data



1) Detection of navigational waypoints



2) Clustering of navigational waypoints

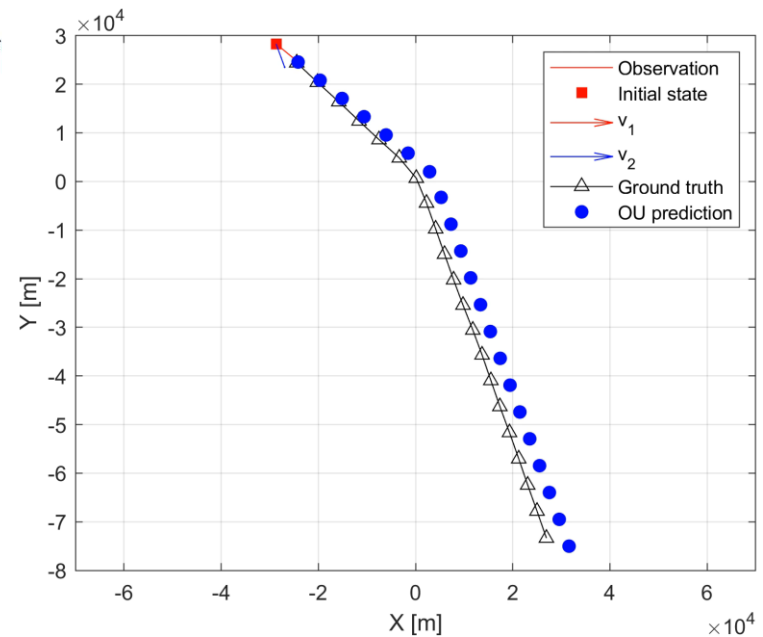


3) Merging and pruning

OUTPUT: Maritime Traffic Graph



- **Pros**
  - Fully analytic
  - Does not require resampling
- **Cons**
  - Requires scene-dependent fine-tuning
  - Actual performance depends on the quality of the clustering of waypoints



N. Forti, L. M. Millefiori and P. Braca, "Unsupervised extraction of maritime patterns of life from Automatic Identification System data," OCEANS 2019, Marseille, France, 2019.

P. Coscia, P. Braca, L. M. Millefiori, F. A. N. Palmieri and P. Willett, "Multiple Ornstein–Uhlenbeck Processes for Maritime Traffic Graph Representation," in IEEE Transactions on Aerospace and Electronic Systems, vol. 54, no. 5, pp. 2158-2170, Oct. 2018.



# Sequence-to-sequence models

- Input sequences (length  $l$ )

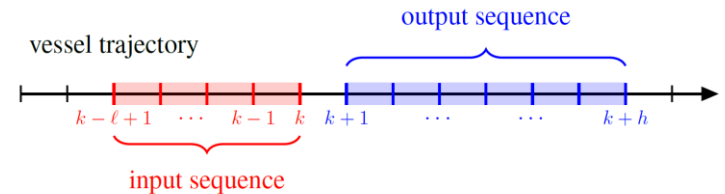
$$\tilde{\mathbf{x}}_{k,l} \triangleq \{\mathbf{x}_\tau\}_{\tau=k-l+1}^k \subseteq \mathcal{S}, \quad \mathbf{x}_\tau \in \mathbb{R}^d$$

- Output sequences (length  $h \neq l$ )

$$\tilde{\mathbf{y}}_{k,h} \triangleq \{\mathbf{y}_\tau\}_{\tau=k+1}^{k+h} \subseteq \mathcal{S}, \quad \mathbf{y}_\tau \in \mathbb{R}^d$$

- Goal:** learn a mapping  $\phi_{l,h}$  between input and output sequences to model a predictive distribution  $\mathcal{P}(\tilde{\mathbf{y}}|\tilde{\mathbf{x}})$

$$\tilde{\mathbf{y}}_{k,h} = \phi_{l,h}(\tilde{\mathbf{x}}_{k,l})$$

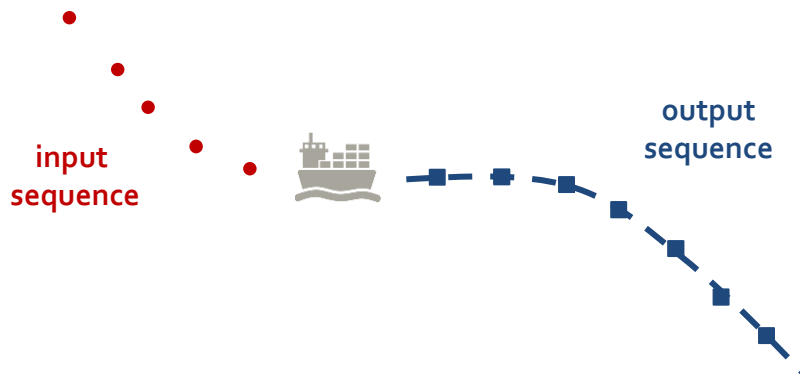


## Recurrent Neural Networks (RNNs)

- Extension of feedforward NNs to capture the temporal dynamics

$$\mathbf{h}_k = f(\mathbf{W}^{hx} \mathbf{x}_k, \mathbf{W}^{hh} \mathbf{h}_{k-1})$$

$$\mathbf{y}_k = \mathbf{W}^{yh} \mathbf{h}_k$$



- With standard RNNs, the input-output **sequence alignment** must be known ahead of time
  - Not clear how to apply RNNs with input and output sequences of different length

- A simple strategy can be to use **two RNNs** in an **encoder-decoder architecture**

# Sequence-to-sequence models

1. The **encoder RNN** processes the input sequence  $\tilde{x}$  and produces a **fixed-dimensional vector representation**

$$c = f_{enc}(\tilde{x})$$

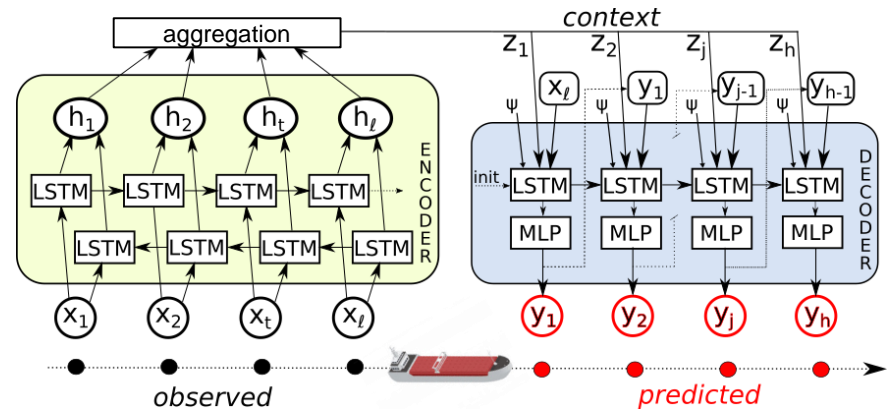
2. The **decoder RNN** recursively generates the output sequence **conditioned on the context** of the input

$$\mathcal{P}(\tilde{y}|\tilde{x}) = f_{dec}(c)$$

- Standard RNNs would be **difficult to train** due to **long-term dependencies** and **vanishing gradient**
- Complex activations such as **LSTM** comes to help to capture long-term dependencies and use previous context more efficiently than standard RNNs

## Probabilistic interpretation

$$\mathcal{P}(y_1, \dots, y_h | x_1, \dots, x_l) = \prod_{k=1}^h \mathcal{P}(y_k | c, y_{k-1}, \dots, y_1)$$

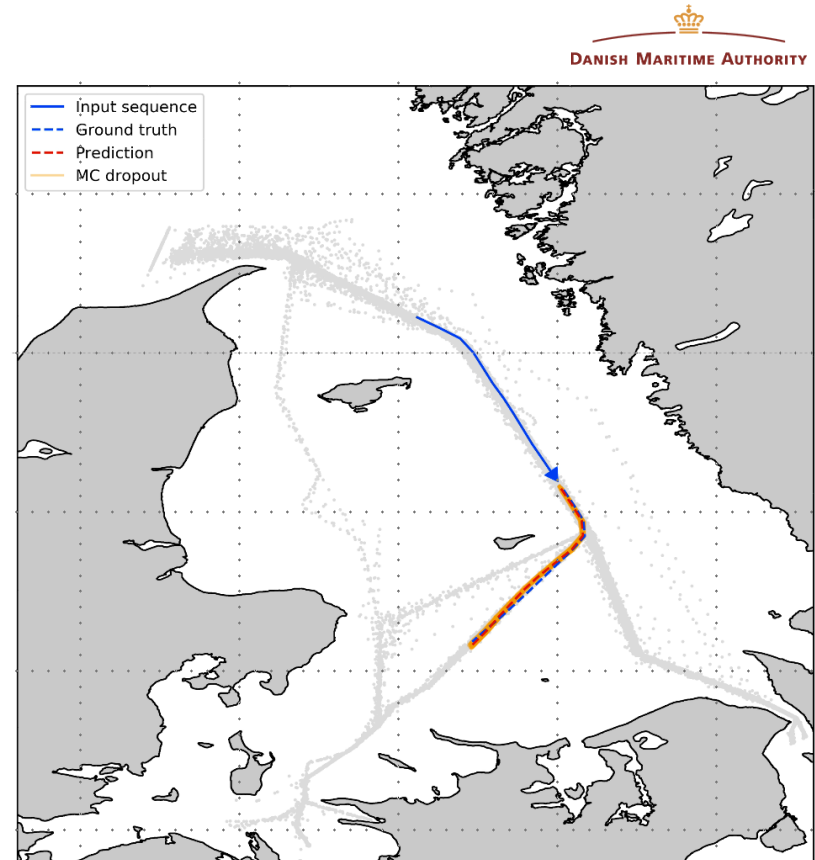


S. Capobianco, L. M. Millefiori, N. Forti, P. Braca and P. Willett, "Deep-learning methods for vessel trajectory prediction based on recurrent neural networks," *in preparation*, 2020.

# Experimental results

- **Data labeling**
  - Augment data with additional inputs about the vessel's **high-level intention behavior** (e.g., destination)

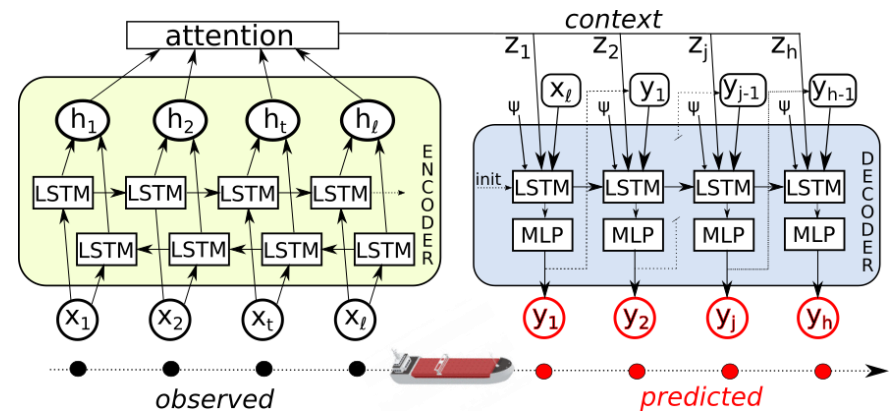
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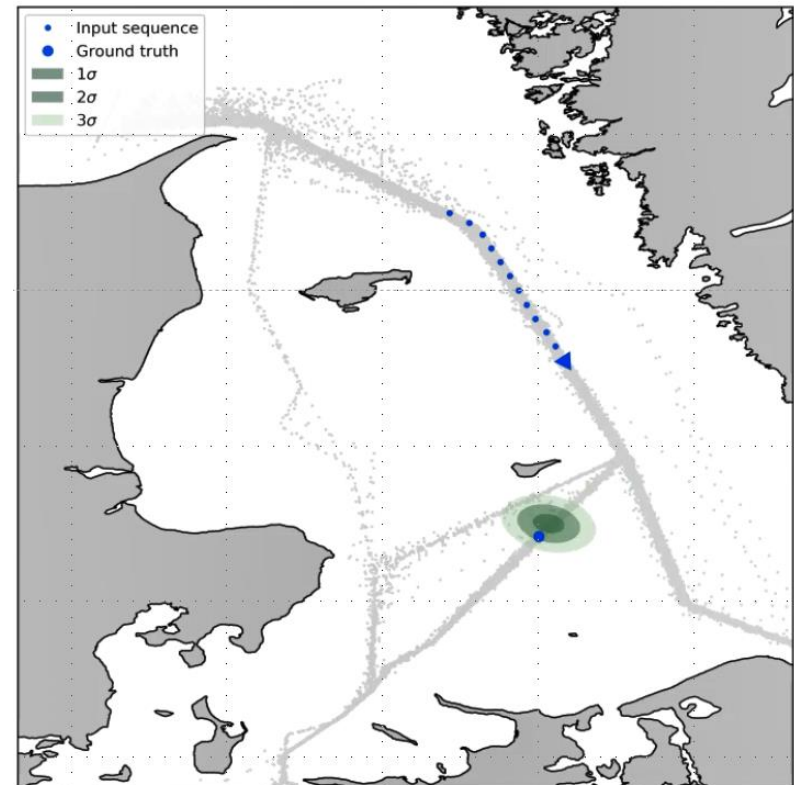
- **Attention mechanism**
  - Intermediate layer between encoder and decoder
  - Provides the decoder with information from every encoder hidden state
  - **Selectively focus on useful parts of the input sequence** (learns the input/output alignment)



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# Experimental results

  
DANISH MARITIME AUTHORITY



- Prediction **uncertainty modeling**
  - Aleatoric-epistemic uncertainty modeling
  - Gaussian distributions are computed in output (parametrized in mean and covariance)
    - Comparison with statistical motion models



THANK YOU