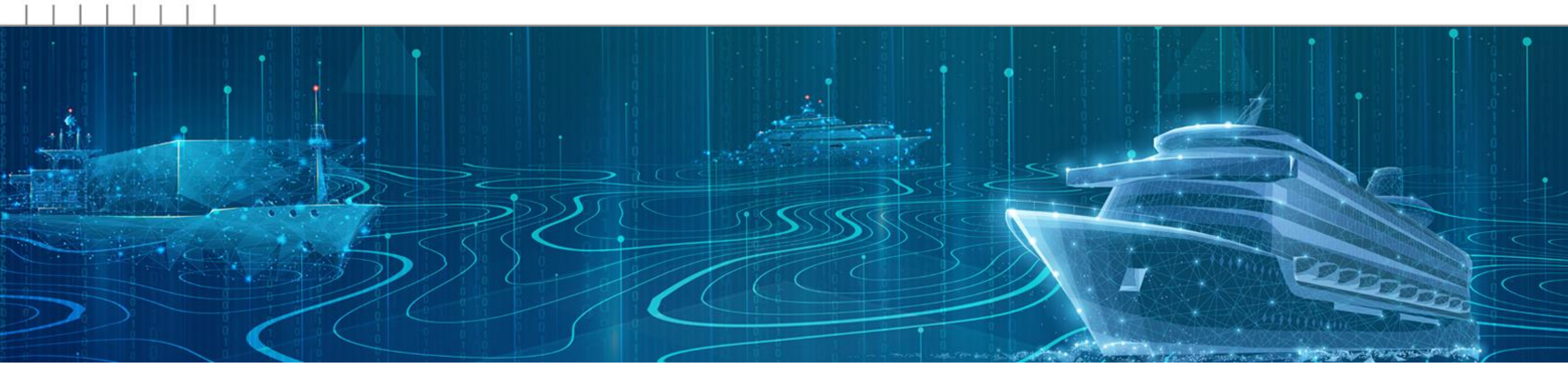

Data-driven ship trajectory prediction

Prediction of ship trajectories is an important application of artificial intelligence (AI) in support of future vessel traffic management. Given the digitization of shipping traffic and its accompanying data, in particular AIS data, machine learning techniques can let intelligent systems learn from the data. In return, the intelligent systems can provide insights and advice to human vessel traffic operators, as well as captains and pilots on board of ships. For MARIN, it is important to investigate and understand these techniques, to know how and where these can help the industry, but also to know their reliability and drawbacks.

In the data-driven trajectory prediction project, we focused on an interesting traffic hotspot: the approach area to the Port of Rotterdam (see Figure 1 below, where ship trajectories in the approach area are shown). The objective of this research is to build a data-driven model for a particular area that is able to predict ship trajectories 30 minutes into the future, based on the data from the past 60 minutes. From the AIS data, we only used positions, course over ground and speed of the vessels. The dataset contained a rich variety of ship types, as can be seen in Figure 2.

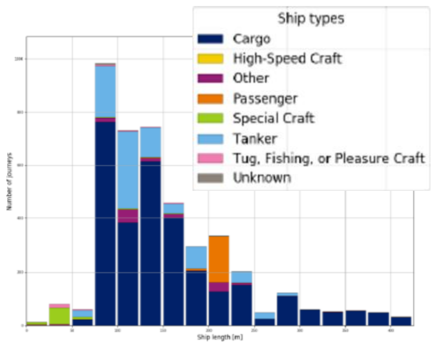

Figure 2: Distribution of ship types and lengths versus number of journeys.

We developed various machine learning models for this problem. They all followed encoder-decoder architecture. More information on these models can be found in our paper: https://doi.org/10.1080/17489725.2024.2306339.

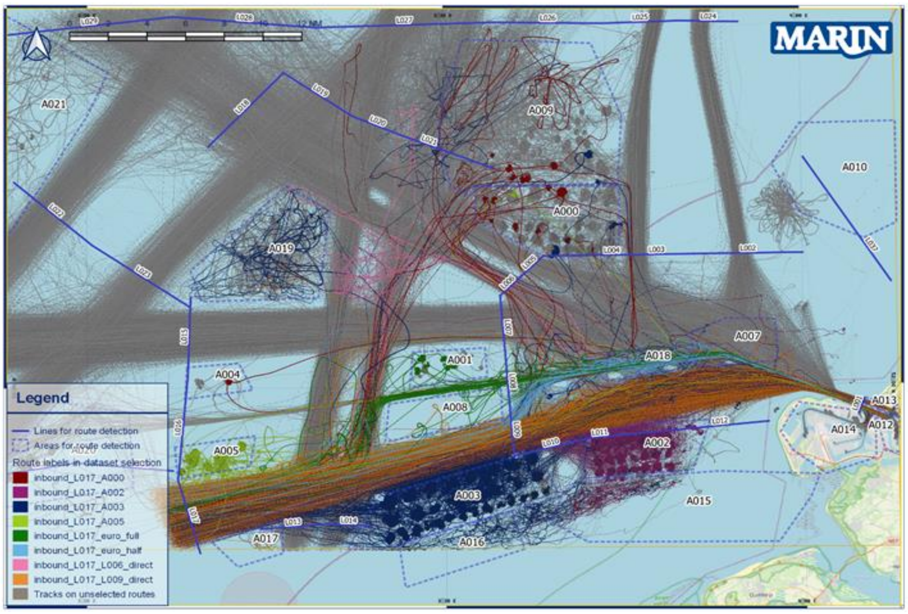

Figure 1: Example of a selection of the dataset for the ships arriving in Rotterdam from the west (line L017), now including labels for visiting particular areas or following particular routes.

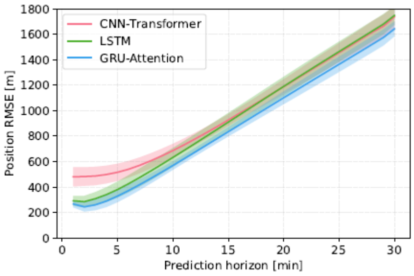

Figure 3: Root mean squared error (RMSE) of the position predictions from the three machine learning models. The solid lines indicate the mean and the shaded areas indicate ±1 standard deviation of the five-fold cross-validation.

The results indicated that the models were able to make trajectory predictions with an average root mean squared distance error of 1.6 km, 30 minutes into the future (see Figure 3). Considering the variety of ship types and routes in the dataset, this is a reasonable performance. Additional information such as ship types, dimensions, and environmental data is available in the datasets, but was not used yet. This would most likely improve the predictions, particularly regarding ship types and dimensions.

Next to analysis, we also worked on visualization of the predictions, so that the context of the results can be interpreted, for example to judge whether prediction errors can be due to boarding of pilots, or to encounters with other ships on traffic junctions (see Figure 4).

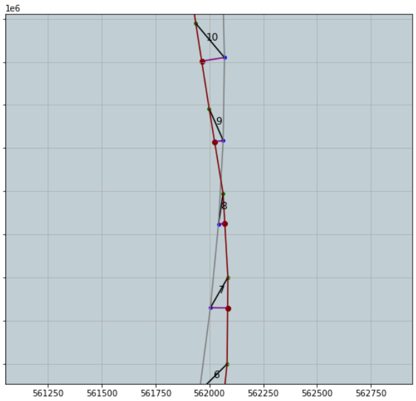

Figure 5: Calculation of cross-track and along-track error for the predicted trajectory (grey line, blue positions), relative to the actual trajectory (red line, green positions). The bigger red points are the projections of the prediction onto the actual trajectory lin.

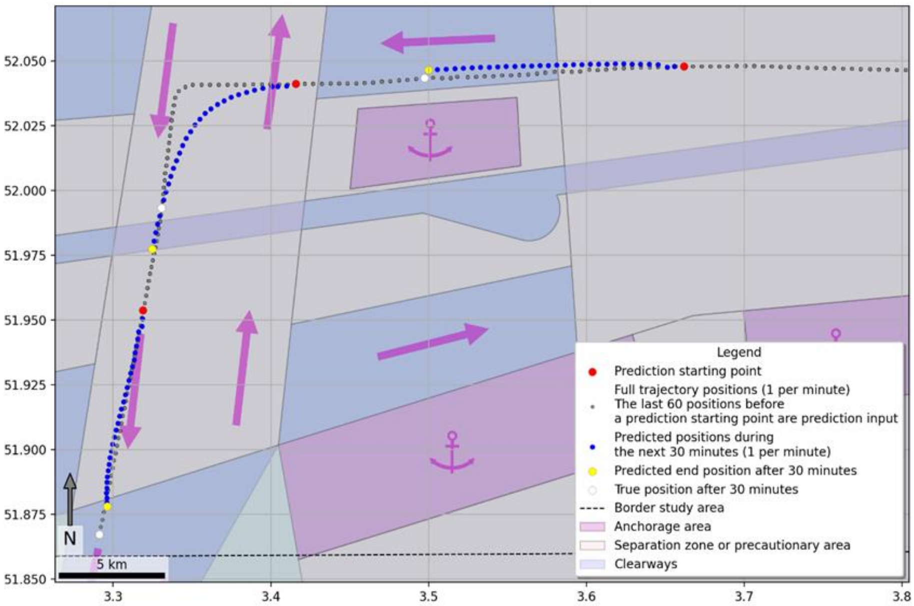

Figure 4: Visualization of three trajectory predictions relative to the actual trajectory, for three moments of the same journey.

Also, calculation of cross-track error and along-track error was added (see Figure 5). This allows for distinction between errors of the predicted position along the route and the deviation from the route (see Figures 6 and 7).

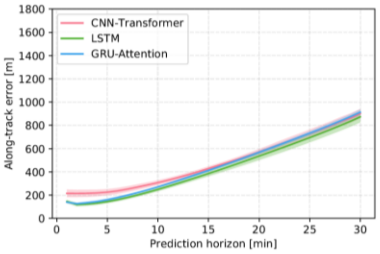

Figure 6: Prediction errors: along-track error.

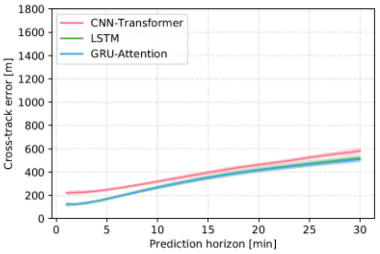

Figure 7: Prediction errors: cross-track error.

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