Learnt by (machine) heart

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Data from fleet management, ship operations, and port logistics have become an exceedingly valuable resource. This 'new oil,' as it is being called, already drives much of the transformation we see in the maritime industry today. Future-oriented maritime services will rely even more on the careful processing and analysis of data from maritime supply chains and transport markets to extract meaningful information and support decision-making. Data science plays a key role in this context, providing the necessary tools, from statistics to mathematical optimisation. Here are the key takeaways from our recently published free white paper *Machine Learning in Maritime Logistics*.

Beyond these 'classical' methods, more and more attention has recently been paid to new concepts from the field of Artificial Intelligence (AI). In particular, machine learning techniques are very promising for a number of maritime applications. In the right use cases, machine learning is seen as an important means to leverage data, allowing companies to, among many, reduce costs through optimised operations and data-driven decision making; improve quality control and safety through digital monitoring solutions; and capture knowledge hidden in past business records.

As diverse as

Machine learning is a sub-discipline of AI, a wide field within computer science concerned with equipping machines with certain human capabilities – but at a superior level. Traditional optimisation algorithms provide customized steps, or rules, for solving a given problem. Finding suitable rules can be a complicated and time-consuming task, and it is often difficult to verify the quality of the solution. In contrast to that, machine learning automatically identifies rules for obtaining answers from data during a so-called training phase. Subsequently, these rules can be applied to new data to derive answers for specific, clearly defined problems. Typically, three main types of machine learning are distinguished – supervised, unsupervised, and reinforcement learning – each with a variety of different algorithms, distinct application areas, strengths, and weaknesses. What all of these algorithms have in common is that they require a certain minimum of high-quality, carefully pre-processed data.

Accordingly, using machine learning in maritime logistics always starts with checking the available database and implementing a suitable information architecture. Together with industry partners, Fraunhofer CML has conducted several studies and research projects on machine learning in maritime logistics, thereby following a modular approach (Fig. 1). During the initial phase, promising use cases are identified and evaluated in accordance with company goals, available data, and suitable algorithms. Then, a proof of concept is implemented, which includes several iterations of training and testing of the machine learning model to improve a prototype, and finally, the deployment of the solution in practice.

The individual application fields of machine learning in maritime logistics are just as diverse as the algorithms and machine learning models. Deep learning can enable machines to understand and process previously inaccessible information of digital images, text, or audio files. Reinforcement learning algorithms are promising for complex control problems where other optimisation methods reach their limits. Hybrid approaches help to integrate experience and expert knowledge in machine learning models. However, all things considered, using machine learning methods to develop data-based forecasting and prediction models for maritime logistics is probably the most promising field of application right now.

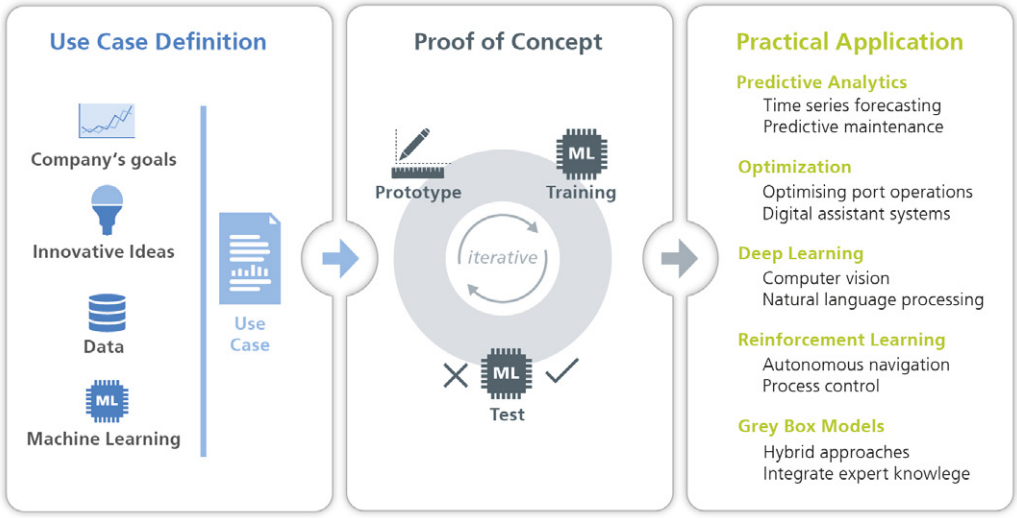
Machine learning in practice

Decision-making in maritime logistics often involves external, fluctuating factors that are stochastic in nature (meaning that something is well-described by a random probability distribution) and therefore complicate identifying and planning well-considered actions. This underlines the importance of reliable forecasts for making optimal business decisions under uncertainty.

By using predictive analytics methods based on machine learning, forecasts can reach a new level of accuracy; reliable predictions for decision-relevant values, such as demand and freight volumes, expected arrival times, or remaining lifetime estimations of components, now become achievable. The approach identifies correlations and patterns in historical datasets and uses these dependencies to predict future developments or events (Fig. 2). In this way, both scope and accuracy of information presented to decision-makers on a daily basis can be increased. Let's take a closer look at three practical examples of how this can be done.

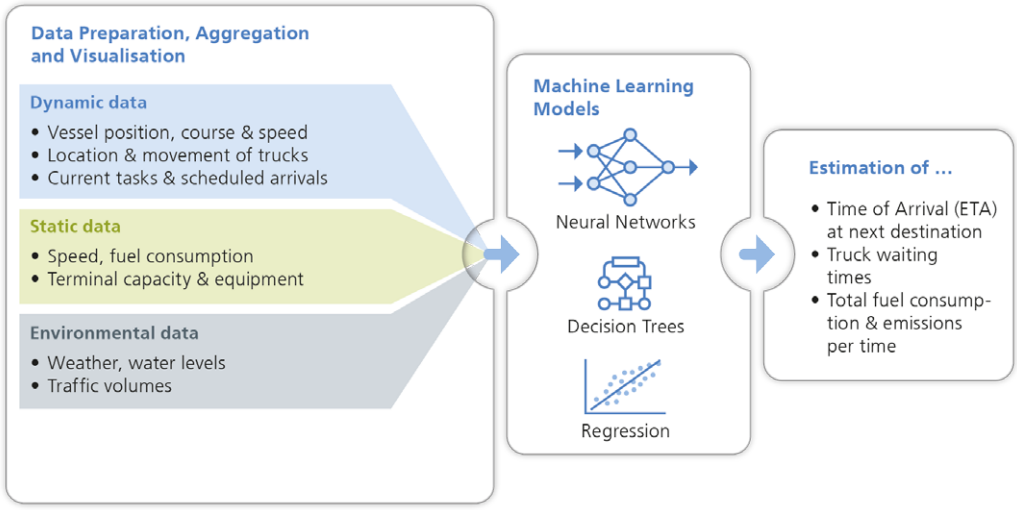
First, applications based on data from the Automatic Identification System (AIS). The introduction of the AIS was an important milestone of maritime digitalisation, with direct positive effects on maritime safety. Moreover, by recording worldwide vessel movement data on a day-by-day basis, a unique maritime dataset, associated with a multitude of potential use cases for machine learning, has been established. Fraunhofer CML has worked on several solutions based on AIS data. One particularly successful application concerns the prediction of ship-port arrivals. Technically, the implemented approach is based on a correlation of position and motion data from AIS with meteorological and hydrographic parameters, like wind, wave, current, and water level, using machine learning. Between three and four million AIS data records were processed daily to provide a forecast of up to 72 hours. Accuracy of predicted arrival times in all major German ports is in the range of +/-1 hr on a time horizon of 24 hrs, and +/-3 hrs when looking 72 hrs ahead, while departure times can be determined correctly in 90% of cases. Both accuracy levels surpass the minimum

Fig. 1. The modular approach to machine learning projects



Source for figs. 1-2: Fraunhofer Center for Maritime Logistics and Services CML

Fig. 2. Forecasting with machine learning



requirements previously defined by stakeholders for this particular problem.

Second, predicting truck arrivals and waiting times. Although truck waiting times at logistics terminals and in ports fluctuate and can seem sudden, in fact, they are usually far from unpredictable. In order to demonstrate that truck arrivals and waiting times can be predicted with machine learning, Fraunhofer CML entered into a co-op with a Hamburg-based container depot and service provider. Technically, the approach utilises a digital representation of the handling processes at the terminal. Historical and current data are processed by an artificial neural network (which can easily be modified to consider additional input data available for a specific location or terminal). The machine learning-based model has proven to be quite capable of forecasting expected truck arrivals and waiting times at the depot. Taking the predicted values into account enables trucking companies to make better dispatching and routing decisions. At the same time, the forecasts help the terminal to schedule sufficient equipment and staff to meet demand and better cope with peaks.

The last example is associated with worldwide empty container deployment. Similar to the previous two solutions, the idea is to use innovative forecasting methods to improve the basis for making logistics decisions. In this case, the goal is to predict the supply of and demand for empty containers per region in the form of a Container Availability Index. Technically, statistics and machine learning techniques are used to evaluate millions of individual container journeys in order to predict their future whereabouts. In turn, the availability forecast can be integrated into decision support systems as a basis to initiate, postpone, or cancel repositioning of container equipment.

Up-and-coming?

Not claiming to be a panacea, machine learning does, however, hold the potential to impact many business processes, increase efficiency, and reduce workloads. Early adaptions of the technology in the maritime sector are quite promising, as highlighted above. Nonetheless, a majority of maritime companies are only starting to explore machine learning in its different forms. Especially for small- and mid-sized companies, the implementation of machine learning projects can strain available personnel, time, or financial resources. Even more, often the sheer number of possible applications, algorithms, and data sources can be difficult to navigate. Thus, success in the field is by no means a given but requires careful selection of suitable use cases and pooling of necessary expertise either in-house or by involving external partners.

Fraunhofer CML has lately released the free to download ***Machine Learning in Maritime Logistics*** white paper that covers both the basics of AI and machine learning and goes through the important elements of a successful implementation of machine learning in maritime applications. The publication shows how data, technology, and machine learning interact to create innovative maritime solutions, providing an overview of machine learning use cases in the maritime industry. ■

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