Encoding Temporal and Spatial Vessel Context using Self-Supervised Learning Model (Student Abstract)

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Abstract

Maritime surveillance is essential to avoid illegal activities and for environmental protection. However, the unlabeled, noisy, irregular time-series data and the large area to be covered make it challenging to detect illegal activities. Existing solutions focus only on trajectory reconstruction and probabilistic models that do ignore the context, such as the neighboring vessels. We propose a novel representation learning method that considers both temporal and spatial contexts learned in a self-supervised manner, using a selection of pretext tasks that do not require to be labeled manually. The underlying model encodes the representation of maritime vessel data compactly and effectively. This generic encoder can then be used as input for more complex tasks lacking labeled data.

Introduction

Among main transportation methods, maritime transportation is of high importance for worldwide commercial sea shipping and regional level logistics, fishing, and recreational activities. Therefore, it is crucial to ensure maritime surveillance for vessel identification, control, search, and rescue missions, prevent trajectory collisions and maintain general traffic regulations. Moreover, modern traffic surveillance systems target at detecting prohibited activities such as illegal fishing, Exclusive Economic Zone (EEZ) intrusion, illegal transshipment, mugging, or maritime pollution monitoring. Automatic Identification System (AIS), as a tracking system, supports maritime traffic surveillance and control. Having AIS activated is mandatory for most vessels, especially commercial ones. An AIS transmitter broadcasts vessel information, such as its location, speed, or heading to nearby ships, coastal stations, and satellites, up to every 2 seconds. The vast amount of available data raises the interest to design intelligent methods for their processing and analysis of anomalies for safety reasons, to identify illegal activities, e.g., operate in restricted zones or perform illegal maneuvers. However, we face multiple challenges in applying machine learning to these data, the varying messages' frequency, the continually changing situation of the nearby vessel, and the loss of many messages due to collisions between messages or the limited capacity in the AIS protocol. The existing work in maritime traffic management and surveillance have focused on prediction of destinations, trajectories, and anomaly detection in an observed ship irrespective of the nearby vessel information (Perera, Oliveira, and Guedes Soares 2012; Filipiak et al. 2018). Other related works model vessel behavior from historical AIS information using probabilistic models, e.g. Auslander, Gupta, and Aha (2012) and Fridman et al. (2019) construct Markov models, such as Markov logic networks and Markov chains, or hierarchical neural networks (Kim and Lee 2018). Nguyen et al. (2018, 2019) have explored the idea of multi-task machine learning. Their method learns a probabilistic model of typical vessel trajectories from the AIS data stream via a static embedding that regularizes the frequency and completes the missing data.

Our idea is to create a self-supervised (DeSa 1993; Jing and Tian 2020), multitask-capable, representation learning model. It extracts a generic representation vector for vessels and the nearby vessels. That vector is then used as inputs to multiple tasks such as intentional AIS signal shut down detection, illegal rendez-vous, false AIS signal detection, or vessel type identification.

Method

We propose a solution that consists of layers shared between boats and tasks, as shown in Figure 1. The shared layers are trained using a set of self-supervised pretext tasks: the current heading of a vessel, which vessel travels the longest distance between two, which vessel sends messages for a longer time, can a given message be the next of a vessel, what is the next position of a vessel or what is the evolution of the distance with the satellite. These pretext tasks are not fixed and will have to change as the experiments progress. Their selection is a key ingredient in self-supervised learning to get an expressive and useful representation. The pretext tasks perform feature engineering and selection by enforcing the representation to include information from those features that are relevant to solve the pretext tasks. The model is trained on the pretext tasks in parallel by performing backpropagation over the weighted sum of all partial losses. This pre-trained representation model becomes a foundation for the main tasks, and we use it to encode the data of the main tasks relevant to maritime surveillance.

Currently, we implemented two main tasks that represent

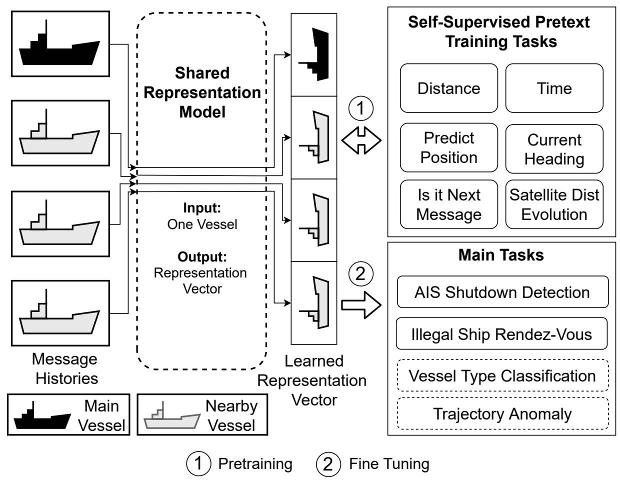

Figure 1: The model is shared between vessels and between tasks

actual illegal activities sought by the maritime control. The first is the detection of intentional AIS shutdown. The shutdown of AIS allows a fisher to hide illegal fishing quite easily. On the other hand, it can be challenging to detect because a vessel's connection is lost regularly. The second task is the detection of illegal vessel rendez-vous for secret exchange of goods. Both tasks have a small self-labelled dataset, that is not sufficient to train an end-to-end model, due to which we look into self-supervised pretraining.

In the shared layer, we learn a shared representation vector v of vessel information for maritime surveillance by encoding its temporal and spatial context. For each vessel a sequence x of T message vectors is encoded to as a temporal state vector $v = \mathcal{M}(\{x_1, x_2, \ldots, x_T\})$, where $x_t \in \mathcal{R}^m$ is the feature vector for the t-most recent message, $v \in \mathcal{R}^d$, and $\mathcal{M}$ is a non-linear function that encodes the messages into a single vector, for example a recurrent neural network (Sutskever, Vinyals, and Le 2014) or a transformer network (Vaswani et al. 2017). The temporal context is encoded to a single, fixed-width state vector v by a many-to-one sequence model. The spatial context collects the neighbourhood information for the vessel, consisting of the state vector of the N closest vessels ordered by increasing distance. The final representation then jointly consists of the main vessel state vector v_0 and the spatial context: $v = [v_0, v_1, v_2, \ldots, v_N], v \in \mathcal{R}^{n(N+1)}$, where $[\cdot, \cdot]$ is the concatenation operator. It is to be noted that the encoder function f is shared for all vessels, independent of whether it is the main vessel or belongs to the spatial context. The representation is composed of all the needed vessels for a certain task like the main vessel and the nearest neighbours in AIS shutdown.

Results and Discussion

The shared layers that encode the representation vector are trained with six pretexts tasks. The representation vector is then used for intentional AIS shutdown and illegal rendez-vous detection, two of the useful maritime surveillance task. We obtain an accuracy of 92% for AIS shutdown detection and 89.7% for illegal rendez-vous detection. These first results are encouraging considering the wide range of diverse inputs. The relevance of the spatial context is also shown by a baseline that does not consider neighbour vessels as part of the spatial context and only reaches an accuracy of 79.4% for AIS shutdown detection. Moreover, the low number of labeled training samples for illegal rendez-vous tasks do not lead to overfitting, because we only train the output layer while the pre-trained shared layer is frozen. Further, we can improve the performance by increasing the number of pretext tasks. This will lead to better feature coverage and increase the representation vector's expressiveness. We plan to add more tasks like vessel type identification and trajectory anomaly detection to cover other maritime surveillance challenges and extend the method's evaluation.

References

Auslander, B.; Gupta, K. M.; and Aha, D. W. 2012. Maritime Threat Detection Using Probabilistic Graphical Models. In *Twenty-5th Int. FLAIRS Conf.*

DeSa, V. R. 1993. Learning Classification with Unlabeled Data. In *Proc. of the 6th Int. Conf. on NIPS*, 112–119.

Filipiak, D.; Stróżyna, M.; Wecel, K.; and Abramowicz, W. 2018. Big data for anomaly detection in maritime surveillance: spatial AIS data analysis for tankers. *Scientific Journal of Polish Naval Academy* 215(4): 5–28.

Fridman, N.; Amir, D.; Douchan, Y.; and Agmon, N. 2019. Satellite Detection of Moving Vessels in Marine Environments. In *Proc. of the AAAI Conf.*, volume 33, 9452–9459.

Jing, L.; and Tian, Y. 2020. Self-Supervised Visual Feature Learning with Deep Neural Networks: A Survey. *IEEE Trans. on Pattern Analysis and Machine Intelligence* .

Kim, K.-I.; and Lee, K. M. 2018. Deep Learning-Based Caution Area Traffic Prediction with Automatic Identification System Sensor Data. *Sensors* 18(9): 3172.

Nguyen, D.; Vadaine, R.; Hajduch, G.; Garello, R.; and Fablet, R. 2018. A Multi-Task Deep Learning Architecture for Maritime Surveillance Using AIS Data Streams. *IEEE 5th Int. Conf. on Data Science and Advanced Analytics (DSAA)* 331–340. doi:10.1109/DSAA.2018.00044.

Nguyen, D.; Vadaine, R.; Hajduch, G.; Garello, R.; and Fablet, R. 2019. GeoTrackNet-A Maritime Anomaly Detector Using Probabilistic Neural Network Representation of AIS Tracks and A Contrario Detection. *arXiv:1912.00682* .

Perera, L. P.; Oliveira, P.; and Guedes Soares, C. 2012. Maritime Traffic Monitoring Based on Vessel Detection, Tracking, State Estimation, and Trajectory Prediction. *IEEE Transactions on Intelligent Transportation Systems* 13(3): 1188–1200. doi:10.1109/TITS.2012.2187282.

Sutskever, I.; Vinyals, O.; and Le, Q. V. 2014. Sequence to Sequence Learning with Neural Networks. In *NeurIPS 2014*, 3104–3112. doi:10.1007/s10107-014-0839-0.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention Is All You Need. In *NeurIPS 2017*, 5998–6008.