1 Introduction

One of the most important sectors in the Norwegian economy, behind the oil sector, is the fishing industry. It creates a lot of value for Norway but it is also regulated in a way that will secure a sustainable population of fish in the oceans and also to secure a fair competition between fishing vessels. An important factor in making sure that these regulations are followed is controlling that when the vessel arrives at the port that they actually have reported the amount of fish correctly, and that the species is correct. This is done by dedicated controllers that have a limited amount of time and capacity to be everywhere and thus have to decide which port they want to control and hope that a fishing vessel arrives.

Today the controllers use their own knowledge about the reported AIS data, ERS messages and domain knowledge to estimate what port a vessel is most likely to head to. However this could be a time consuming task where making the wrong decision about which port to go to could end up costing money as the controller might be too late or be at the wrong port.

This thesis will investigate if real-time prediction of the destination port could make controls more accurate, earlier and be explainable. The investigation will be focused on finding out of deep learning on historical AIS data combined with static information about the vessel could give robust and interpretable decision support, and also importantly, that the prediction of the destination happens in a timely manner, as the controller might have to travel for a few hours.

The present thesis is also based on the work of Løvland who in a previous master thesis researched if it was possible to generate several prediction of the trajectories of a ship and infer from that which port it would arrive at, in that study it performed only slightly better than a baseline statistical model, but only if the timestep before predicting a trajectory was long enough. It also suggested for future work to include static information. Thus in this paper the goal is to investigate if this could be improved upon using a different model.

1.1 Problem definition

The problem can be defined as the desire to predict the destination port of fishing vessels with more accuracy than what we would get by just comparing it to statistics over previously visited ports. Since this prediction is currently done manually we would like to automate this to a larger extent.

Our research question is as follows:

> Is it possible to develop a deep learning model that can, with high precision, predict the arrival port of fishing vessels based on historical AIS data combined with vessel, catch, and route-history information?

And with sub-research questions as the following:

> 1. How much does each data source contribute to the end result? (AIS + static data, vs. AIS alone)

It is valuable to know which data sources have a high contribution to the prediction of a port. If we know that certain features barely change the result of the prediction, these could be removed from the training process, thus simplifying that process. It could also be important for Norges Råfisklag to have an even better understanding about why fishing vessels go to a specified fishing port.

> 2. What is the accuracy of the prediction based on how large a time step back in time we consider when predicting the port?

One issue when trying to predict the destination of a vessel is that we require a certain amount of data back in time to make accurate predictions about the future state. Thus we will investigate how many hours back we need to look to get an accurate prediction.

Fishing vessels are supposed to send ERS messages of type POR with information about the destination port; however, there is no legal compliance to do this and the fishing vessels face no repercussions for sending them even later. But assuming they are sent within 2 hours, this is often not enough time for the controllers to get to the port depending on where it is; thus it is important to investigate how accurate the predictions are several hours before it might arrive.

3. Can we also predict an accurate estimated time of arrival (ETA)?

As well as predicting the destination, it can also be useful and valuable to Norges Råfisklag and their controllers to have an estimation of when the ship will arrive. This will help them make better decisions about what time they should head to a port, to prevent unnecessary waiting at the port.

4. How robust is the prediction when considering potential noisy or missing data?

AIS often has a problem with the data quality as the farther away from shore you are, the higher the risk of the signals not reaching the receiver. AIS is also susceptible to spoofing attacks, which could get into our training data and cause erroneous results.

1.2 Scope

We limit the study to include only the regions of Troms and Finnmark

1.3 Limitations

1.4 Contributions

1.5 Outline

2

Background Theory

2.1 AIS

Automatic Identifaction System (AIS) is a navigation system used by all types of vessels above the length of 15 meters, it is used for exchanging navigation signals with other ships, but also with stationary stations on ground. As the name suggests these are required to function autonomously without having to be polled by external vessels or stations. Originally AIS was designed for safety purposes of vessels, where the goal was to reduce the incidence of collisions between vessels.

Even though AIS was not designed for usage in trajectory prediction or destination prediction it still contains some useful fields that can help in those tasks. These fields are latitude, longitude, Speed over Ground (SoG) and Course over Ground (CoG), it also contains some relevant fields about the vessel characteristics that could be useful in the prediction of the destination.

What AIS actually transmits. Each AIS message contains a few types of messages, these are the following: *(i) Static ship data* entered at installation (name, MMSI, call sign, vessel type, dimensions); *(ii) Dynamic navigation data* which is the data that changes automatically as the vessel moces (latitude, longitude, Speed Over Ground (SOG), Course Over Ground (COG), heading, rate of turn, navigation status, time); *(iii) Voyage-related data* that is uptades as needed by the captain or similar (destination text, ETA, cargo); and *(iv) Safe-*

ty/application messages (for example addressed safety text, Aids-to-Navigation (AtoN) status). For the purpose of this thesis we will be focusing on the static ship data for the static data part and the dynamic navigation data for our time series part.

AIS uses two VHF radio channels and divides time into small slots so many ships can transmit without a central controller. Each ship's unit picks a free slot and adjusts how often it sends: more often when moving fast or turning, less often when slow or at anchor. Because VHF is line-of-sight, ship-to-ship and coastal reception typically reaches a few tens of nautical miles (around 40 nautical miles). Satellites can also receive AIS offshore, extending coverage, though in very busy areas they may miss some messages.

In Norway, AIS is integrated into a coastal monitoring network run by the Norwegian Coastal Administration (Kystverket), which receives AIS messages along the coast and creates large historical archives. National rules, aligned with EU requirements, mandate Class A AIS on larger commercial based ships and require AIS usage to fishing vessels with overall length 15 meters (including 15 meters). Foreign fishing vessels over 15 meters that land catch in Norway are also required to carry AIS. Getting access to Norwegian AIS is done by polling Kystverkets API endpoints. public use is available with restrictions (especially for vessels under 15 m and recreational crafts under 45 meters).

2.2 VMS

2.3 ERS

Fishing vessels are also required to utilize Electronic Reporting System (ERS) on their vessels. The ERS system requires the crew of the vessel to manually send messages containing information related to the potential fishing activities the vessel has done. This usage is tightly regulated and requires specific messages containing specific information and requirements for when the specific messages are to be sent. Some of these message types include the following: Departure report (DEP), the Detailed Catch and Activity report (DCA) and the Port report (POR). These messages contain mostly different information but all of the may also include information such as ID of the vessel, timestamps and so on.

2.3.1 POR Messages

This type of ERS message is a message that is sent as the vessel starts heading towards shore. The fishing vessels are required to send these messages two hours before landing, regardless of whether they have any catch or not. An important part of this message including the time of arrival is what port the vessel is heading to, contained in the port field of the message. They also have to report the quantity of fish they have in their cargo and also the amount of fish they plan on landing, this has to be per separate species of fish.


```json
{
  "messageType": "POR",
  "messageNumber": 784,
  "sequenceNumber": 1,

  "radioCallSign": "LNAB",
  "vesselName": "Sea Breeze",
  "registrationMark": "N-123-AB",
  "skipper": "Jane Doe",

  "messageDate": "20250923",
  "messageTime": "1015",

  "positionAtSend": {
    "latitude": "58.123",
    "longitude": "005.456"
  },

  "portOfCall": {
    "unlocode": "NOOSL"
  },

  "landingFacility": "Oslo Pier 5",
  "landingDate": "20250924",
  "landingTime": "0730",

  "etaDate": "20250923",
  "etaTime": "1830",

  "quantitiesToLand": [
    { "speciesCode": "COD", "quantity": 500, "unit": "KG" },
    { "speciesCode": "HAD", "quantity": 200, "unit": "KG" }
  ],

  "catchOnBoard": [
    { "speciesCode": "COD", "quantity": 800, "unit": "KG" },
    { "speciesCode": "HAD", "quantity": 250, "unit": "KG" }
  ],

  "cancellationCode": null
}
```


Figure 2.1: POR message

2.3.2 DEP Messages

This type of ERS message is sent out as a vessel leaves a port and contains information about the destination of fishing, the time it departs from port (estimation) and also what type of fish the vessel plans to catch. Aswell as the planned catch the vessel also have to report the amount of and type of fish they have on board at departure (if they have any catch)


```
{
  "messageType": "DEP",
  "messageNumber": 123,
  "sequenceNumber": 1,
  "radioCallSign": "LNAB",
  "vesselName": "Sea Breeze",
  "registrationMark": "N-123-AB",
  "skipper": "Jane Doe",
  "messageDate": "20250923",
  "messageTime": "1405",

  "positionAtSend": {
    "latitude": "58.123",
    "longitude": "005.456"
  },

  "portOfDeparture": {
    "unlocode": "NOOSL"
  },

  "departureDate": "20250923",
  "departureTime": "1410",

  "catchOnBoard": [
    { "speciesCode": "", "quantity": 100, "unit": "KG" },
    { "speciesCode": "", "quantity": 100, "unit": "KG" }
  ],

  "plannedFishingStart": {
    "date": "20250924",
    "time": "0600",
    "latitude": "59.000",
    "longitude": "004.900"
  },

  "harvestingActivity": "TOW",
  "targetSpecies": "COD",
  "cancellationCode": null
}
```


Figure 2.2: Example departure message

2.3.3 DCA Messages

This type of ERS message contains information about the catch and activity of the vessel, if it was steaming (STE) or fishing (FIS) and more general information about when the acticity startet, GPS positions at the start and end of fishing, the quantity of fish and its species and how long the fishing activity lasted.

DCA messages are required to be sent once a day and at 23:59 UTC at the latest. If the vessel was fishing, the AC field will be set to FIS and the block B part of the message has to be sent. Some of the required content of this message is what fish was caught and the tools they used to fish it with. As well as the start and end positions during the fishing. If fishing was done several times in one day then one DCA message will contain several fishing activities.

Highlighted below is the Block A message, this type of message is to be sent by the vessel if the AC field of block A is set to STE, which means the vessel is only steaming, and performing no fishing activities.


```json
{
  "messageType": "DCA",
  "messageNumber": 3921,
  "sequenceNumber": 2,

  "radioCallSign": "LNAB",
  "vesselName": "Sea Breeze",
  "registrationMark": "N-123-AB",
  "skipper": "Jane Doe",

  "messageDate": "20250923",
  "messageTime": "1130",

  "positionAtSend": {
    "latitude": "58.123",
    "longitude": "005.456"
  },

  "fishingPermits": [
    "PERMIT-001"
  ],

  "harvestingActivity": "TOW",

  "correctionCode": null,
  "messageVersion": 3,

  "port": {
    "unlocode": "NOOSL",
    "requiredBecauseFishingEnded": true
  }
}
```


Figure 2.3: DCA message Block A

3

Related Work

There are several studies done on the subject of utilizing transformers on AIS tracks and of course time-series data in general, usually this has mostly just been done on predicting the trajectories and not on predicting destinations directly. Even so, there might be relevant knowledge to be had based on that as well.

3.1 Predicting the Destination Port of Fishing Vessels

- The paper predicts destination ports for fishing vessels by combining AIS trajectory forecasting with a final logic that infers harbor probabilities from generated paths
- Region of interest is Troms and Finnmark in Norway with focus on vessels heading to ports within this area
- AIS messages from 2016 to 2023 are combined with ERS events to isolate steaming segments after fishing stops and before arrival
- Ports are curated to 68 unique delivery locations and voyages must end within five kilometers of a listed port

- Preprocessing removes implausible speeds and long message gaps, interpolates tracks to five minute intervals, and applies min max normalization on latitude longitude speed and course

- TrAISformer is used for multi hour path generation with four hot encoding and categorical cross entropy and trajectories are smoothed with a moving average before port inference

- Destination inference expands a proximity radius from two to five kilometers and uses low speed near a port to decide arrival versus passing by

- The system generates multiple candidate futures per input track and converts port hits across these futures into a probability distribution over ports

- A simple baseline ranks ports per vessel by historical visit frequency and predicts the most frequent one with optional top k evaluation

- Dataset after preprocessing contains 17 thousand tracks from 370 vessels with an eighty ten ten split for training validation and test

- Trajectory error decreases and port prediction accuracy increases as the length of input history grows from thirty minutes up to four hours

- Top one and top three port accuracies are reported, invalid cases arise when no predicted path enters any port radius, and invalids reduce as input length increases

- Training takes a little over two hours on the reported hardware and predicting sixteen futures for one input takes about nine seconds

- Chosen hyperparameters include five minute sampling sixteen generated trajectories and one hundred prediction steps which correspond to a look ahead of about eight hours and twenty minutes

- Future work proposes adding static vessel and route attributes and reframing the final step as direct classification rather than logic after sequence generation

[1]

3.2 AIS Data-Driven Maritime Monitoring Based on Transformer: A Comprehensive Review

The paper "AIS Data-Driven Maritime Monitoring Based on Transformer: A Comprehensive Review" is a survey paper on how transformer architectrues are used for the purpose of AIS based maritime monitoring, organizing prior work into three subjects: vessel trajectory prediction, vessel behavior detection and vessel behavior prediction. The paper argues that transformers are well suited because the self attention mechanism helps in capturing long range dependencies in AIS sequences and handles long inputs more efficiently than recurrent models. The review also summarizes recurring AIS data issues, outliers, missing values, and reception gaps and describes some preprocessing practices seen across the literature, including filtering erroneous positions/speeds/courses and gap filling strategies that some studies adopt before modelling.

Beyond comparing methods, the authors also compiled and cleaned a public AIS dataset drawn from the studies they reviewed, totalling around 640 million messages from 19016 vessels across six ship categories. They provide descriptive statistics by vessel type, noting differences between voyage lengths across classes, and present the dataset as a resource to support future transformer based research on AIS. In the task overviews, the survery distinguishes between generative trajectory forecasting and classification style forecasting (predicting discretized future states or regions), and it outlines behavior oriented applications ranging from anomaly detection to state prediction of vessel activity. Finally, the paper also mentions some future dtirections, ehmphasizing the need for improved handling of data quality and trajectory reconstruction, as well as multi source data fusion (incorporating environmental information) and it recommends exploring different transformer variants and hybrids to better capture interactions in complex traffic. Overall the paper contributes to a good overview of different ways of using transformers for the purpose AIS research. And it provides a curated dataset and some guidance on data preprocessing [2]

3.3 Multi-path long-term vessel trajectories forecasting with probabilistic feature fusion for problem shifting

- Goal is to forecast vessel positions up to 12 hours ahead using only 1 to 3 hours of AIS data by reconstructing the likely path to reduce uncertainty

- Study area is the Gulf of St Lawrence where ships follow several possible routes so multiple futures must be considered

- The ocean region is partitioned into equal hexagon cells at about 0.3 degree resolution to capture route level behavior

- A probabilistic module predicts a likely route polygon and a likely destination cell and these become added features for learning

- Cyclic transforms turn longitude latitude and bearing into sine cosine style features that are easier for a network to learn

- The deep model uses parallel dilated convolution blocks for spatial cues followed by a bidirectional LSTM with position aware attention and a decoder for future coordinates

- Data comes from satellite AIS between 2015 and 2020 cleaned segmented and focused on cargo and tanker vessels

- The probabilistic features reach about eighty five F1 for route prediction and about seventy five F1 for destination on held out data

- Final forecasting shows mean error about 11 km and median about 6 km with R squared above 98 percent due to many straight segments

- Compared with heavier transformer style baselines the proposed models are smaller and train faster while matching or beating accuracy especially in turns and route choices

- Ablations show gains mainly from the probabilistic augmentation the cyclic transforms and attention that favors recent timesteps

- The trained model is used in the smartWhales decision system to help reduce encounters between vessels and North Atlantic Right Whales in Atlantic Canada [3]

3.4 Vessel Destination Prediction Using a Graph-Based Machine Learning Model

This study investigated the vessel destination prediction problem as a multiclass link prediction on a heterogeneous maritime graph built from AIS voyages. Ports are retrieved from the world port index, arrivals/departures are inferred from stop behavior and speed threshold to reconstruct the voyages. The graph contains vessel nodes and port nodes; with edges representing voyages and also carrying information such as month of departure, draught, cargo type, and the weight at departure time. The model learns node and link embeddings via a random walk with a word2vec style training, then deriving link embeddings for vesel, port pairs that is then fed to a k nearest neighbors (KNN) classifier for infering the destination. The authors experiments used AIS data from Danish waters between the January 2014 to March 2021 only looking at tanker ships. The graph model was implemented using StellarGraph and scikit-learn.

The authors write that this graph based approach outperforms many classical baselines, such as logistic regression. KNN, random forests and CatBoost on accuracy, precision, recall and F1, and adding graph topology features further improve the precision and F1. A comparison against manually endtered AIS destination fields show that many entries are incorrect, while the model does attain a higher correctness, most residual errors cluster on the low frequency ports, with a stronger performance on often visited destinations. The paper also notes some limitations, such as a regional scope, possible class imbalances, possible overfitting to vessel identifiers and points to future work on global data and graph neural networks [4].

This information provides some useful knowledge for the present study as it also is directly focused on destination prediction rather than trajectory regression, thus it could motivate the testing of a graph based model as well.

3.5 Vessel Trajectory Prediction Based on AIS Data: Dual-Path Spatial–Temporal Attention Network with Multi-Attribute Information

The paper studies the task of trajectory prediction for maritime vessels using AIS data. The authors extract the motion patterns and then predict future tracks; they also perform bench marking against several deep kearning and graph bases baselines. Their own model DualSTMA runs two attention paths (temportal to spatial, and spatial to temporal) and explicitly fuses multi-attribute information, where they seperate dynamic inputs from static inputs using a gating mechanism. For the inputs they use latitude, longitutede, speed, heading, and various static fields such as vessel type and size. Their study is designed for pure trajectory prediction but not a final destination prediction, with evaluation in degrees/meters over horizons up to 50 minutes.

On U.S. coastal AIS data (2021) the method the authors propose outperforms LSTMs, GRUs, Transformers STGAT and METO-S2S across Average Displacement Error (ADE), Final Displacement Error (FDE), and Mean Absolute Error (MAE). The reported gains are large, especially at longer horizons (approximately a 69% improvement in 50 minute ADE/FDE vs the best baseline), and qualitative ploits show stronger performance on turns and interaction heavy scenes. The authors also run ablations showing that modeling both temporal dynamics and spatial interactions matter and that treating static attribnutes with a gate is better than concatenation.

Compared to the goals of this thesis, the paper tackles a closely related problem, that is predicting where the track will go rather than predicting which port it will reach. Still, the AIS features overlap with the usage of the dynamic and static information, thus this paper gives a strong rationale for the usage of both dynamic and static information in an attention based sequence model [5].

3.6 Temporal Fusion Transformer

- The paper introduces Temporal Fusion Transformer for high performance multi horizon forecasting with built in interpretability
- The method explicitly handles static covariates known future inputs and past observed inputs within one architecture
- Core components include gating mechanisms variable selection networks static covariate encoders temporal processing and quantile forecasts
- Instance wise variable selection is applied to static past and future inputs producing per variable weights at each time step
- Static covariate encoders create context vectors that condition temporal variable selection local processing and static enrichment
- Local temporal features are built with a sequence to sequence layer and long range dependencies are modeled with an interpretable multi head self attention decoder
- The interpretable multi head attention shares value projections across heads and averages attention weights to aid explanation
- Outputs are quantiles and training minimizes the quantile loss with evaluation using P50 and P90 risk across horizons
- Experiments cover electricity traffic retail and financial volatility datasets with defined look back windows and horizons
- Benchmarks include autoregressive and direct baselines and the method outperforms all compared models on P50 and P90 risk
- Ablations show the largest contributions from local processing and self attention with additional gains from static encoders variable selection and gating
- Interpretability use cases demonstrate global variable importance persistent temporal patterns and detection of regime shifts
- The study reports practical training details such as a single interpretable attention layer and single GPU training times
- Though not specifically designed for the purpose of predicting a certain

port, it can be odified to use a classification head.

[6]

3.7 On the Exploration of Temporal Fusion Transformers for Anomaly Detection with Multivariate Aviation Time-Series Data

- **Goal:** Explore a forecasting-based anomaly detection approach for aviation using the *Temporal Fusion Transformer* (TFT), trained to learn nominal behavior and flag anomalies as large forecast errors; proof-of-concept focuses on *unstable approaches (UA)*. :contentReference[oaicite:0]index=0

- **Data:** Multivariate time-series from MITRE's threaded track + digital flight data, plus weather/context (runway ID, head-/crosswind, wind dir/speed, visibility, wind–runway diff). :contentReference[oaicite:1]index=1

- **Sampling windows:** Last 20 minutes before touchdown (240 steps at 5 s); each sample uses a 64-step look-back (320 s) and 8-step look-ahead (40 s), yielding 169 overlapping samples per flight. :contentReference[oaicite:2]index=2

- **TFT bits that matter:** Variable Selection Networks (VSNs) provide global feature-importance scores; gating (GRNs) and static covariates enhance interpretability and performance. :contentReference[oaicite:3]index=3

- **Feature sets tested:** *TFT-1* (tracks + runway), *TFT-2* (+ headwind/crosswind), *TFT-3* (+ wind dir/speed, visibility, wind–runway diff). *TFT-2* generally gives the lowest speed-forecast error (mean RMSE 3.06). :contentReference[oaicite:4]index=4 :contentReference[oaicite:5]index=5

- **Baseline comparison:** A univariate "ARIMA-like" TFT (speed→speed) performs worst (mean RMSE 3.43), indicating multivariate inputs add value. :contentReference[oaicite:6]index=6

- **Single vs multi-output:** Predicting speed and altitude jointly is feasible, but single-output models are more accurate (e.g., speed RMSE 3.06 single vs. 3.13–3.27 multi; altitude mean RMSE 83.48 single vs. 88.72–96.77 multi). :contentReference[oaicite:7]index=7

- **Feature selection via VSNs:** Training with top-ranked features (*TFT-select*) matches *TFT-2* overall (mean RMSE 3.02 vs 3.06) and can reduce compute without hurting accuracy. :contentReference[oaicite:8]index=8 :contentReference[oaicite:9]index=9

- **Anomaly signal:** Use RMSE time profiles; Fisher's discriminant identifies strongest nominal–UA separation ~26 timesteps before touchdown, guiding where to threshold. :contentReference[oaicite:10]index=10 :contentReference[oaicite:11]index=11

- **Detection performance:** At that point, speed-only TP=38.63% (FP=6.99%), altitude-only TP=33.33% (FP=6.99%); combining speed+altitude at matched FP=6.99% boosts TP to 45.46% (and up to 56.96% TP with looser thresholds). :contentReference[oaicite:12]index=12

- **Takeaway:** Label-efficient, interpretable forecasting of nominal behavior can surface UA precursors and localize timing; broader datasets, tuning, and richer outputs could further improve detection. :contentReference[oaicite:13]index=13 [7]

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