GeoTrackNet – A Maritime Anomaly Detector using Probabilistic Neural Network Representation of AIS Tracks and *A Contrario* Detection – paper review

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Agenda

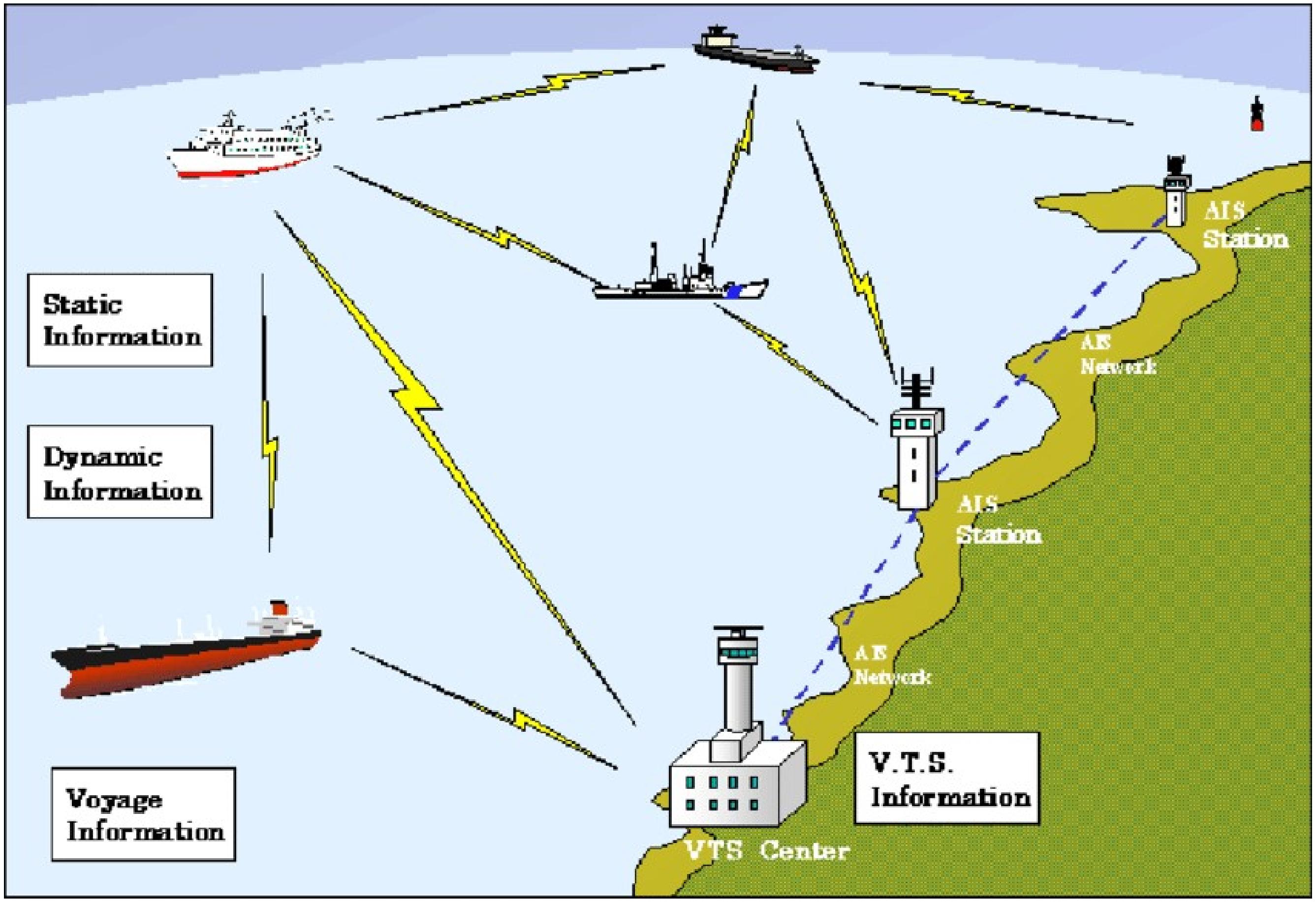
1. Automatic Identification System (AIS)
2. GeoTrackNet - idea
3. Neural network architecture
   - Data representation – „four-hot vector”
   - Variational Recurrent Neural Network (VRNN)
   - *A contrario* detection
4. Experiments and results
5. Conclusions
6. Bibliography

Automatic Identification System (AIS)

AIS is an international ship identification standard that allows vessels to transmit and recieve information, such as:

- IMO number, MMSI - vessel unique id's
- Position, speed, heading, rate of turn
- Navigation Status, Destination, ETA (Estimated Time of Arrival)
- Type of Ship
- Timestamp
- ...

Automatic Identification System (AIS)

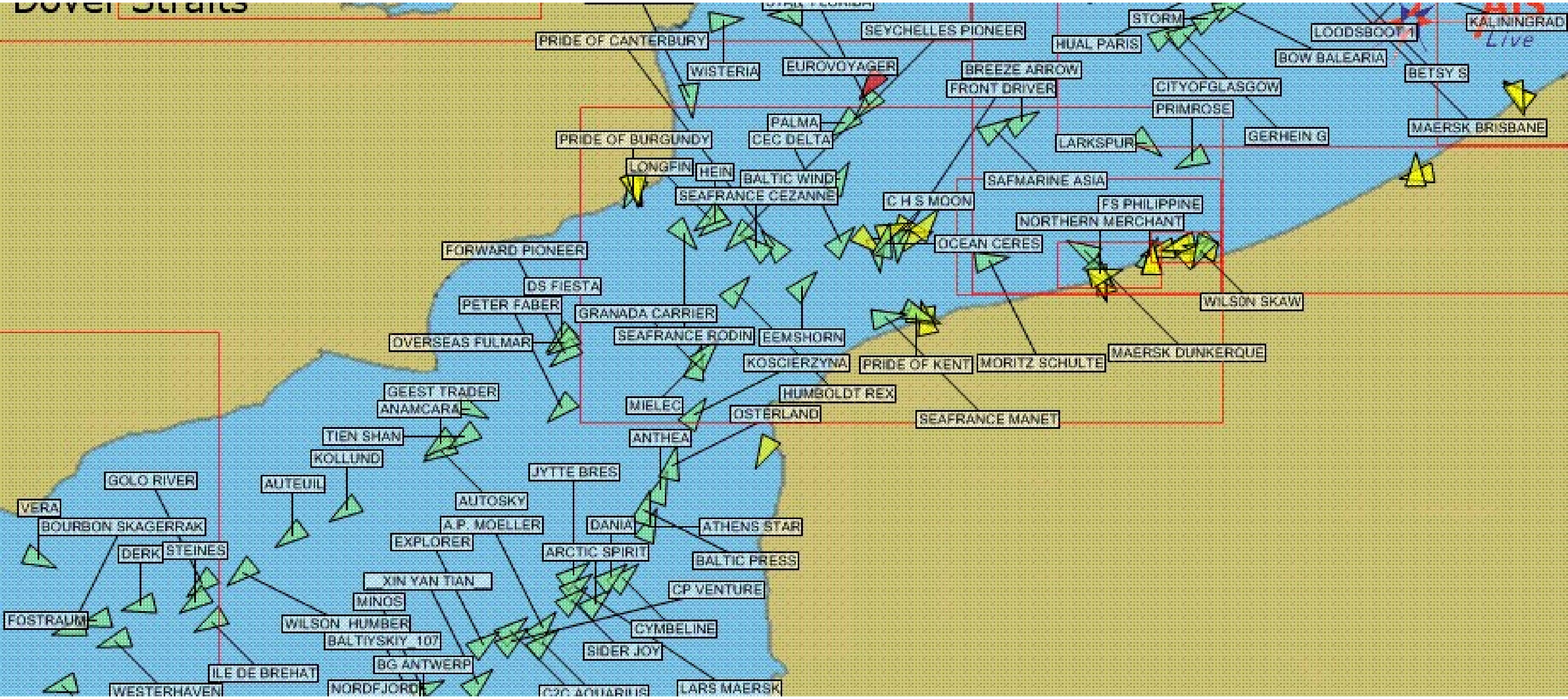


Automatic Identification System (AIS)

International Maritime Organisation (IMO) requires **all passengers' vessels**, as well as, **all commercial vessels over 299 Gross Tonnage** (GT) that travel internationally to carry a Class A AIS transponder (which **transmits and receives** AIS data) aboard (smaller vessels can also be equipped with a Class B AIS transponder). This decision came as a result of the 2002 **SOLAS** (Safety of Life at Sea) agreement's relative mandate.

Automatic Identification System (AIS)

- AIS system works on VHF range, which is around 10–20 nautical miles (18 – 37 km)

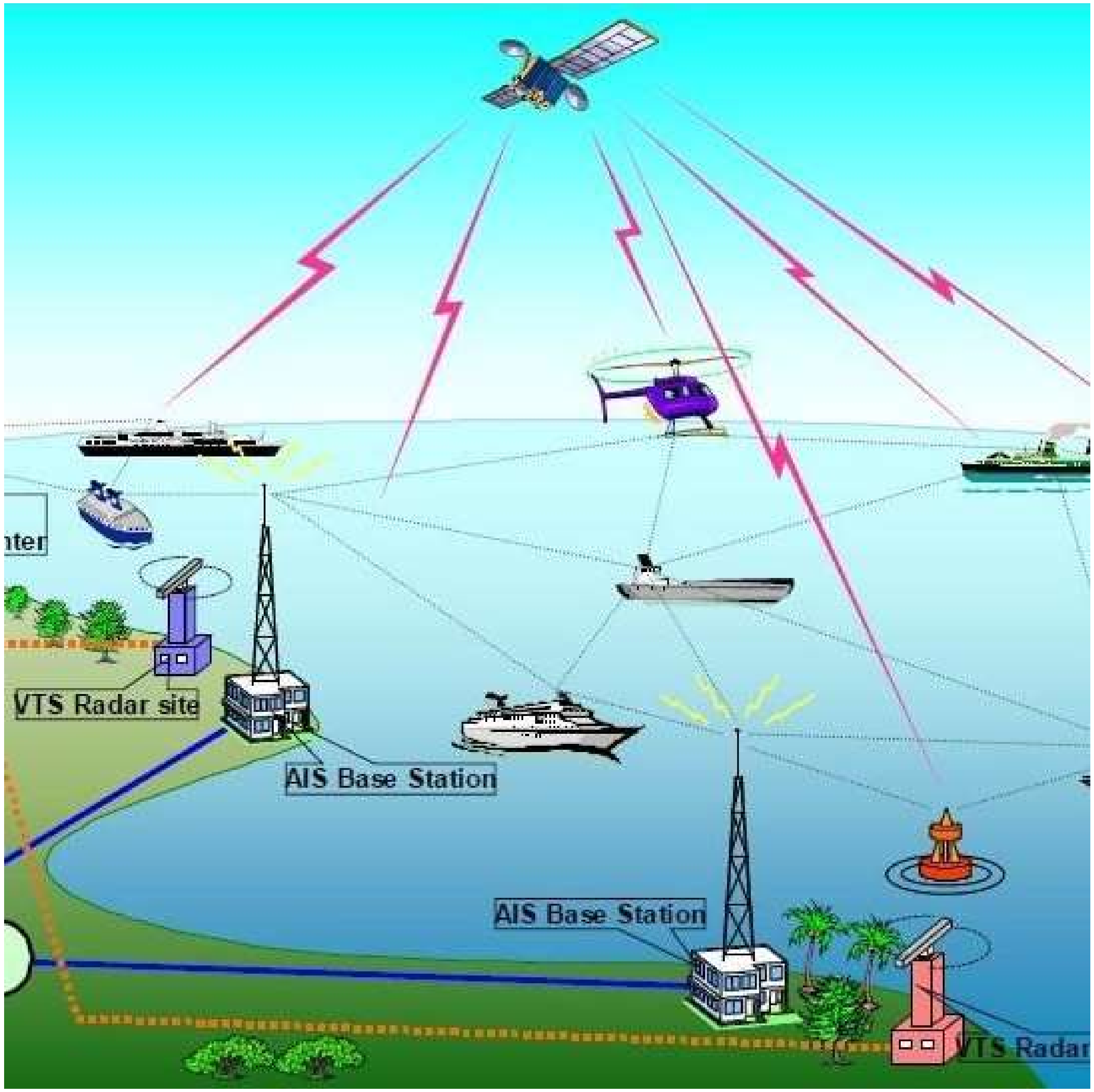


Automatic Identification System (AIS)


KOSCIERZYNA
POLSTEAM

Satellite-based AIS (S-AIS)

Since 2005, various entities have been experimenting with detecting AIS transmissions using satellite-based receivers and, since 2008, companies such as exactEarth, Orbcomm, Spacequest, Spire and also government programs have deployed AIS receivers on satellites.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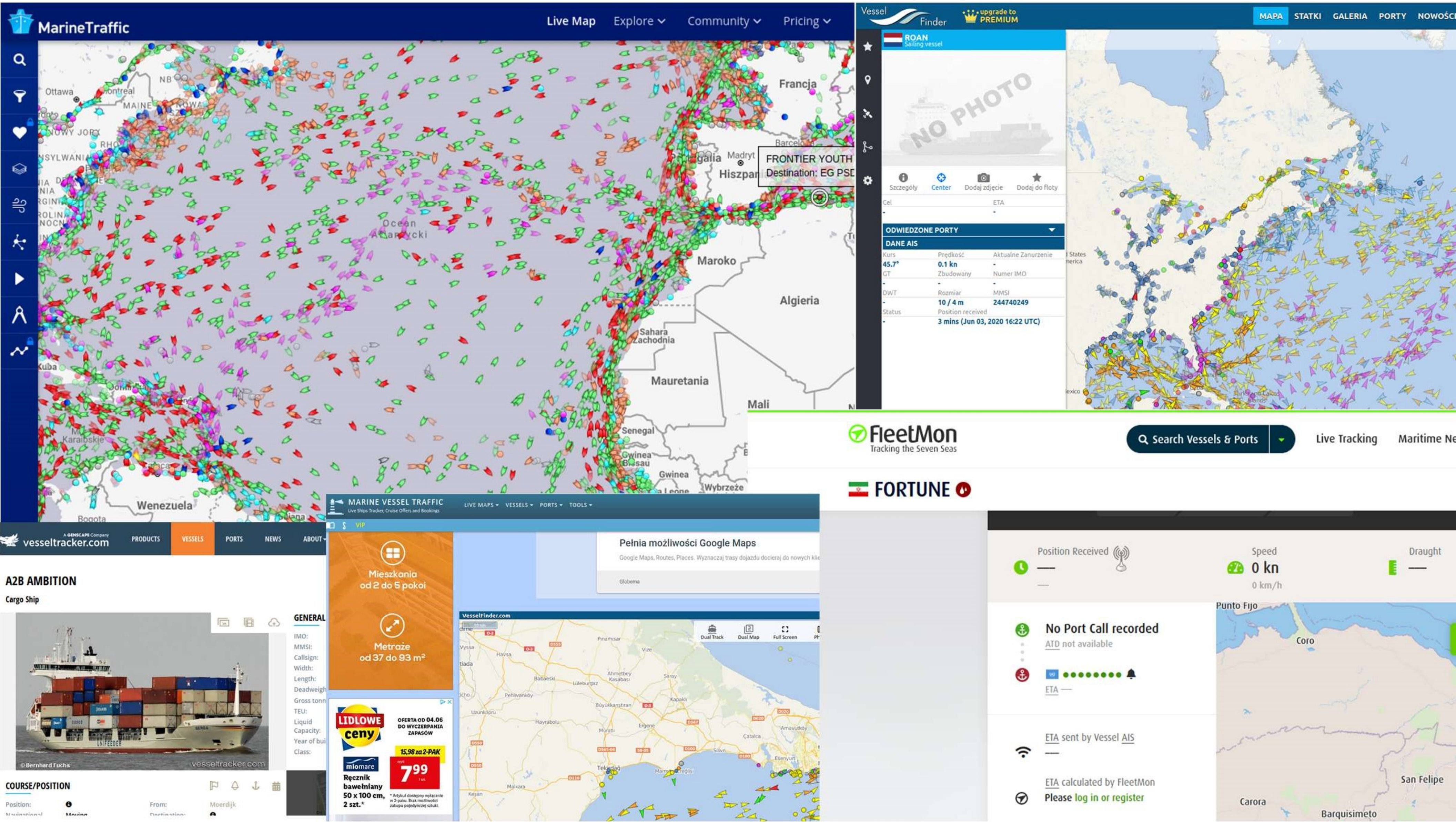
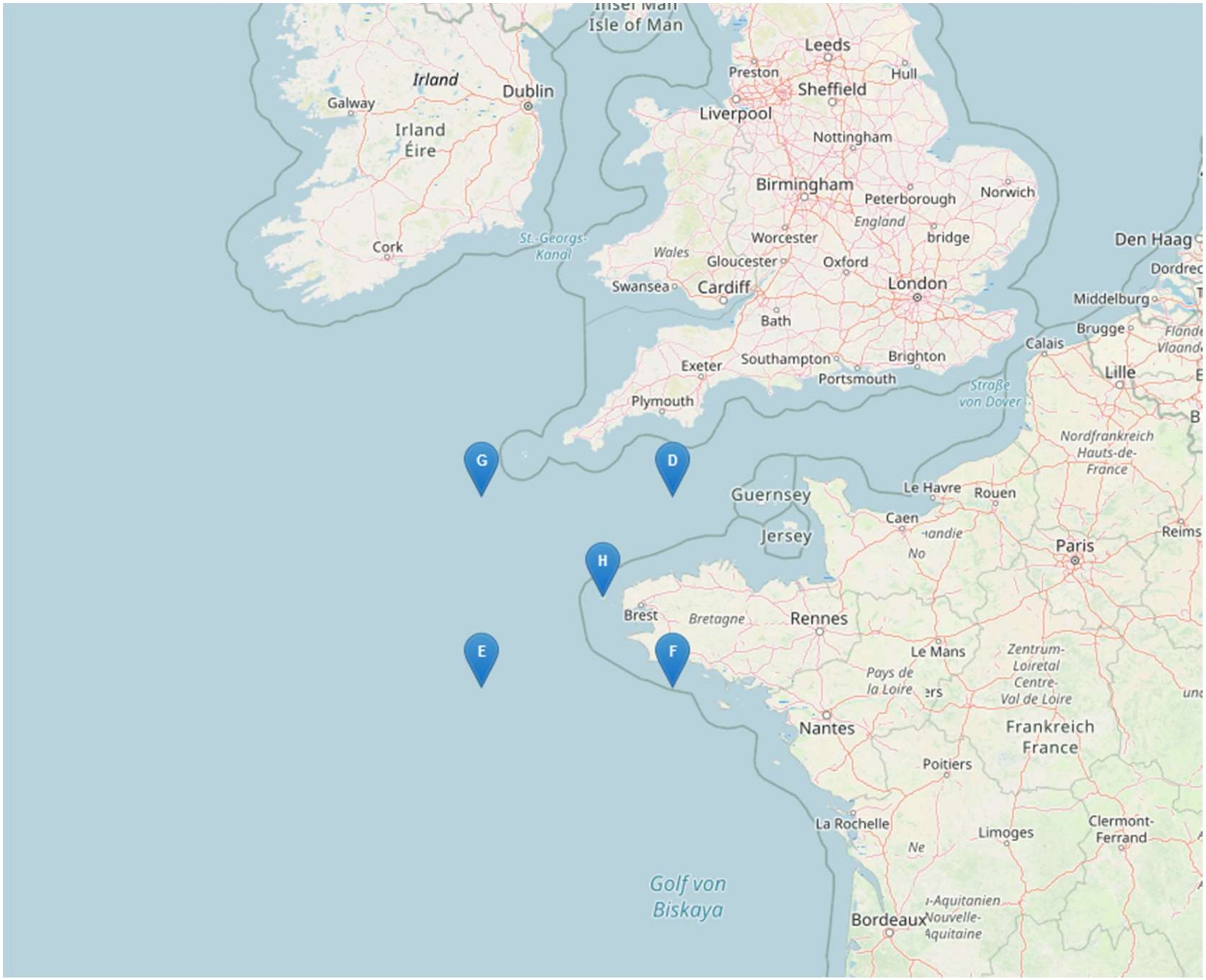
VTS Radar site
AIS Base Station
AIS Base Station
VTS Radar


MarineTraffic
Live Map
Explore
Community
Pricing
FRONTIER YOUTH
Destination: EG PSD
Ocean Atlantycki
Francja
Hiszpania
Maroko
Algieria
Sahara Zachodnia
Mauretania
Mali
Senegal
Gwinea Bissau
Gwinea
Wenezuela
Vessel Finder
upgrade to PREMIUM
MAPA
STATKI
GALERIA
PORTY
ROAN
Sailing vessel
NO PHOTO
Szczegóły
Center
Dodaj zdjęcie
Dodaj do floty
Cel
ETA
ODWIEDZONE PORTY
DANE AIS
Kurs
Prędkość
Aktualne Zanurzenie
45.7°
0.1 kn
GT
Zbudowany
Numer IMO
DWT
Rozmiar
MMSI
10 / 4 m
244740249
Status
Position received
3 mins (Jun 03, 2020 16:22 UTC)
FleetMon
Tracking the Seven Seas
Search Vessels & Ports
Live Tracking
FORTUNE
Position Received
Speed
0 kn
0 km/h
Draught
No Port Call recorded
ATD not available
ETA —
ETA sent by Vessel AIS
ETA calculated by FleetMon
Please log in or register
Punto Fijo
Coro
San Felipe
Carora
Barquisimeto
vesseltracker.com
PRODUCTS
VESSELS
PORTS
NEWS
ABOUT
A2B AMBITION
Cargo Ship
GENERAL
IMO:
MMSI:
Callsign:
Width:
Length:
COURSE/POSITION
Position:
From:
Moerdijk
MARINE VESSEL TRAFFIC
LIVE MAPS
VESSELS
PORTS
TOOLS
Mieszkania
od 2 do 5 pokoi
Metraże
od 37 do 93 m²
Pełnia możliwości Google Maps
LIDLOWE ceny
Ręcznik bawełniany 50 x 100 cm, 2 szt.
7.99
VesselFinder.com
Dual Track
Dual Map
Full Screen

GeoTrackNet

- Look for anomalies in vessel movement based on real-time stream of AIS data
- Use for this probabilistic RNN-based representation of AIS tracks and *a contrario* detection



Insel Man
Isle of Man
Leeds
Preston
Hull
Sheffield
Irland
Dublin
Galway
Liverpool
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Nottingham
Birmingham
Peterborough
Norwich
England
Worcester
bridge
Cork
St.-Georgs-
Kanal
Wales
Gloucester
Oxford
Den Haag
Dordrec
Swansea
Cardiff
London
Middelburg
Bath
Brugge
Calais
Exeter
Southampton
Brighton
Lille
Portsmouth
Straße
von Dover
Plymouth
Nordfrankreich
Hauts-de-
France
G
D
Le Havre
Rouen
Guernsey
Caen
Jersey
Reims
Paris
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Brest
Bretagne
Rennes
E
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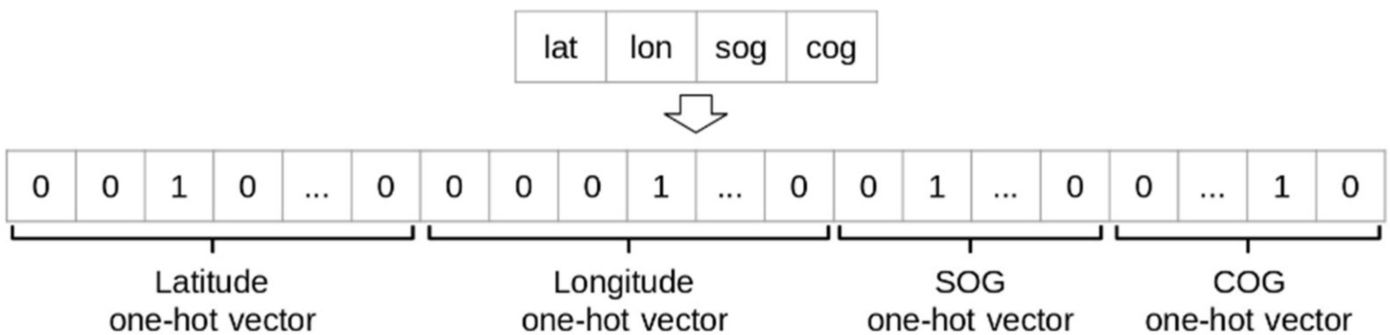
Le Mans
Zentrum-
Loiretal
Centre-
Val de Loire
Pays de
la Loire
Nantes
Frankreich
France
Poitiers
La Rochelle
Limoges
Clermont-
Ferrand
Golf von
Biskaya
Bordeaux

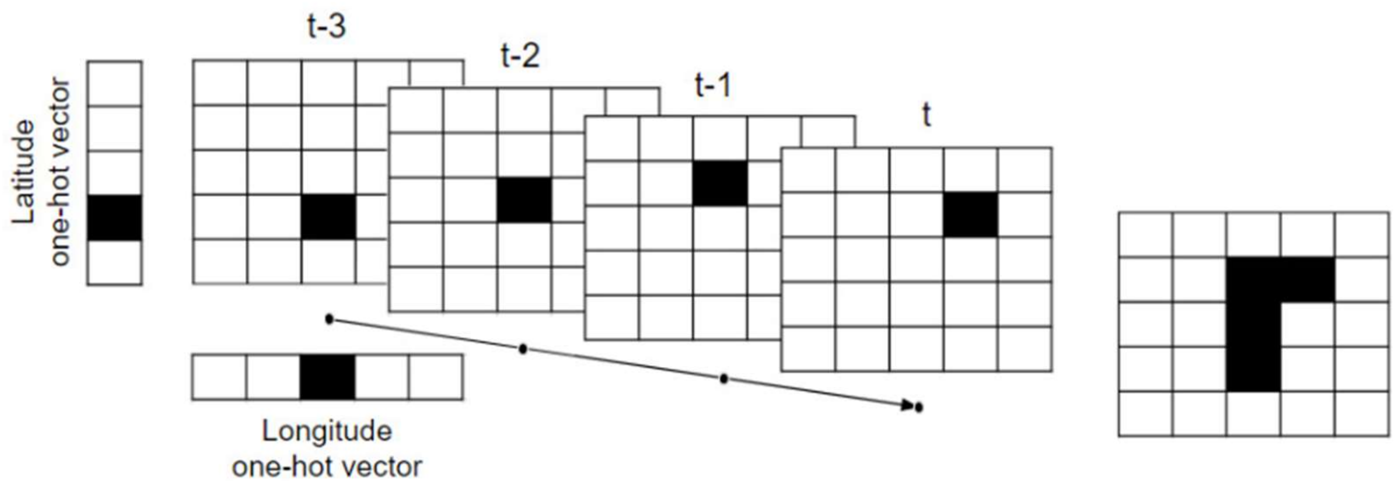
Four-hot encoding as an input for neural network

- The most common way to represent an AIS message is a 4-D real-value vector (two dimensions for the position and the other two for the velocity – $[\text{lat}, \text{lon}, \text{SOG}, \text{COG}]^T$). However, it's difficult for neural network to disentangle the underlying meaning of these numbers.
- Instead, we can represent each AIS point by a „four-hot vector". For each dimension, we generate one-hot vector by bucketize value and then we concatenate vectors.
- Experiments suggested that resolutions of 0.01° for longitude and latitude, 1 knot for SOG and 5° for COG are relevant
- the four-hot vector helps disentangle the geometric features as well as the phase (time-space) patterns of AIS tracks.

Four-hot vector



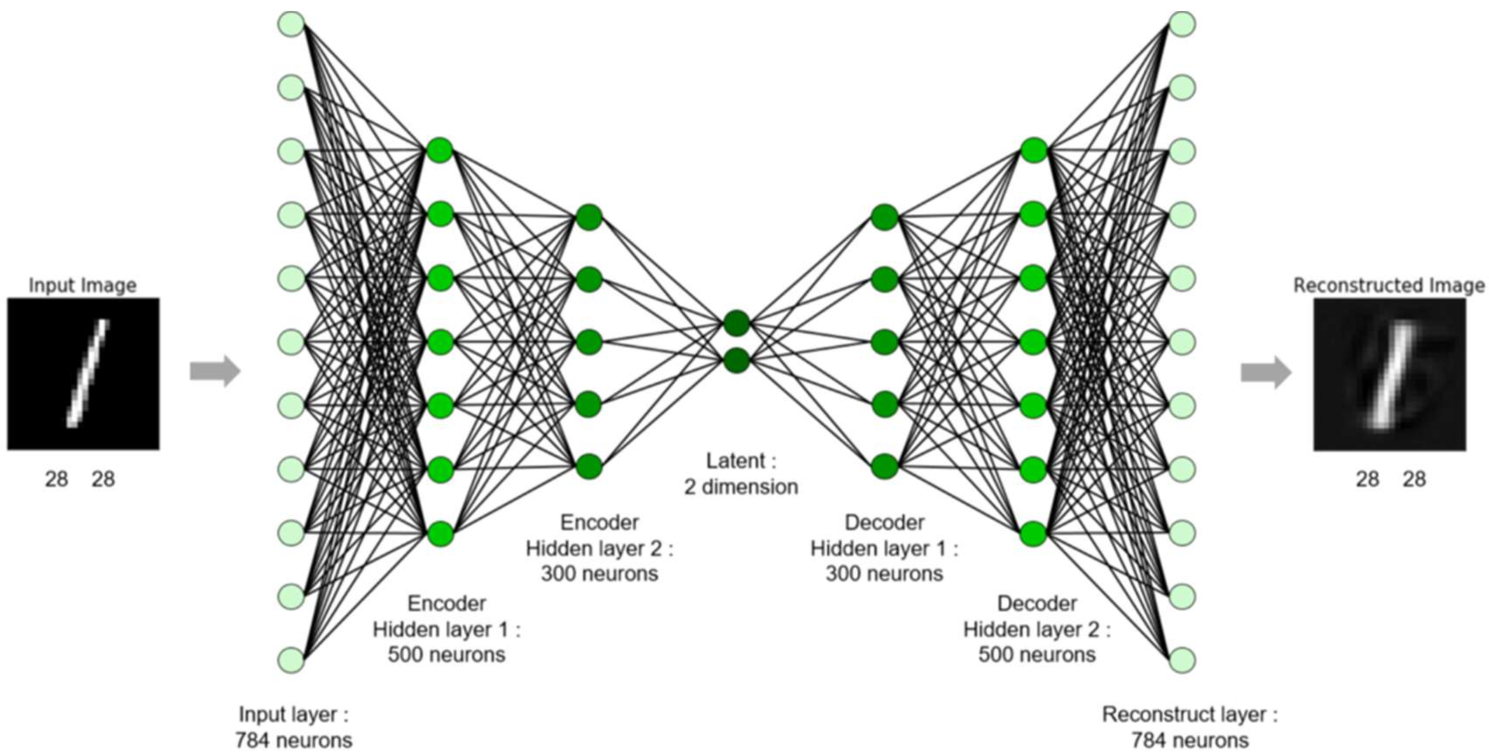
Geometric feature obtained by concatenating the one-hot vector of the latitude and the longitude coordinated of AIS messages



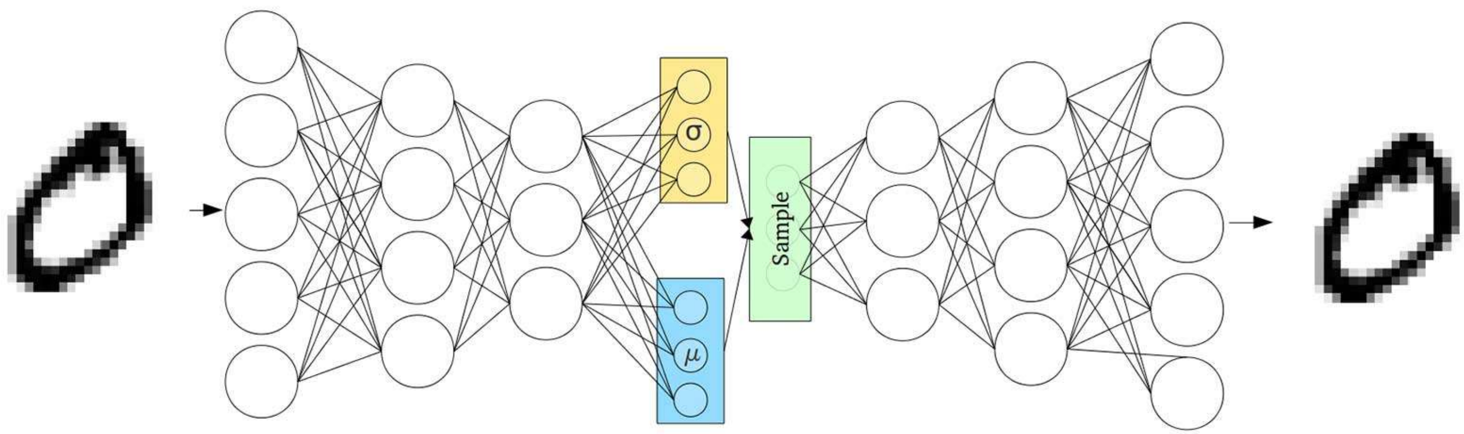
Variational Recurrent Neural Networks (VRNN)

- Described in article: *A Recurrent Latent Variable Model for Sequential Data (2015)*
- Combination of Recurrent Neural Network (RNN) and Variational Autoencoder (VAE).
- Introduce additional, latent stochastic variable $z_t \sim p(z_t \mid h_{t-1})$

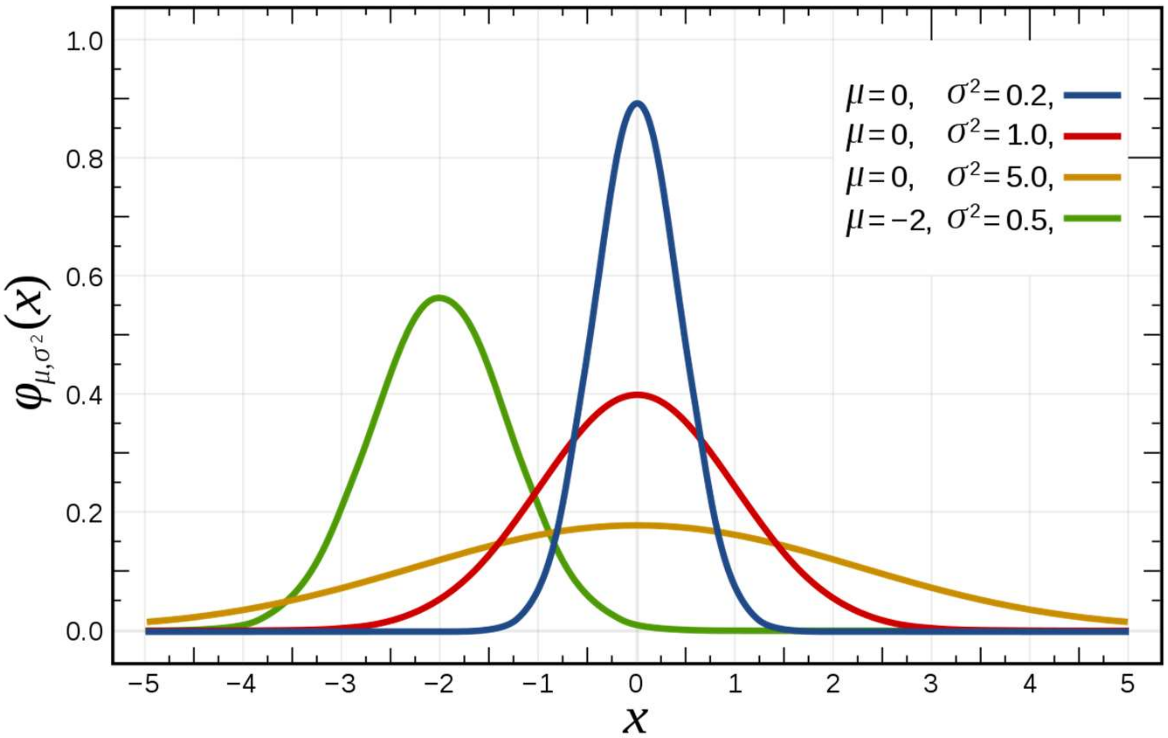
Autoencoder



Variational Autoencoder

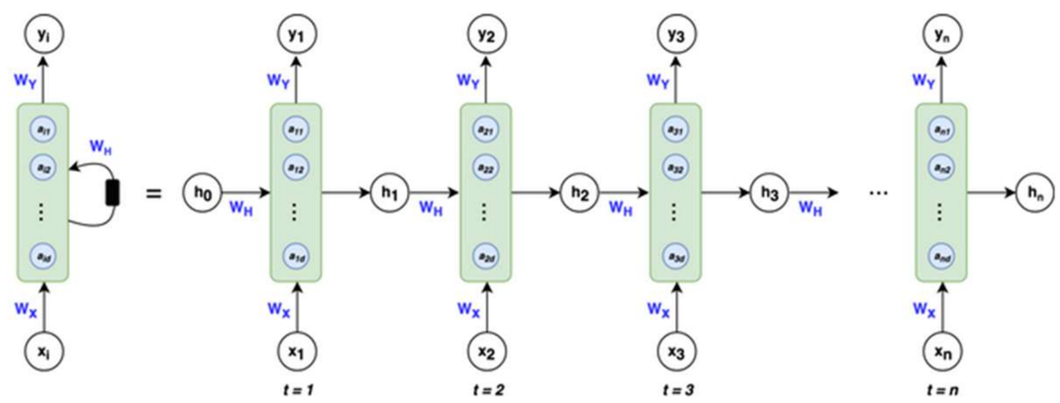


Normal distribution



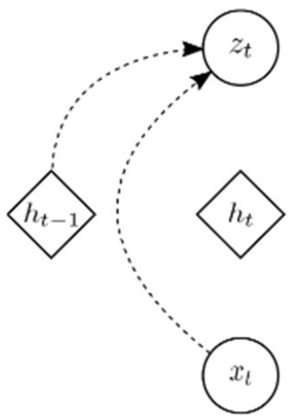
Recurrent Neural Network (RNN)

- RNN is a generalization of feedforward neural network that has an internal memory.
- Performs the same function for every input of the data while the output depends on current input and past computation.
- RNN can use their internal state (memory) (h_t) to proces sequences of inputs.



Variational Recurrent Neural Networks (VRNN)

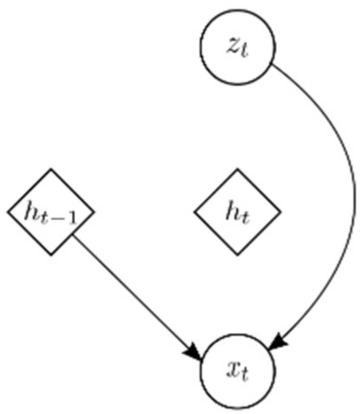
- Introduce stochastic variable z (latent state of variational autoencoder)



This is only used during the training,

A Recurrent Latent Variable Model for Sequential Data (https://arxiv.org/abs/1506.02216)

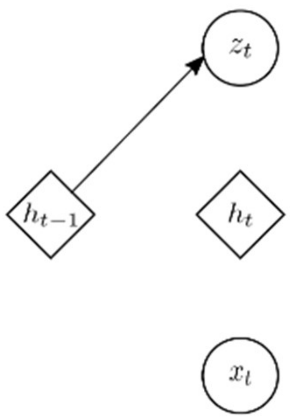
Variational Recurrent Neural Networks (VRNN)



Select randomly z_t from generated distribution and use it as parameter for generating x_t:

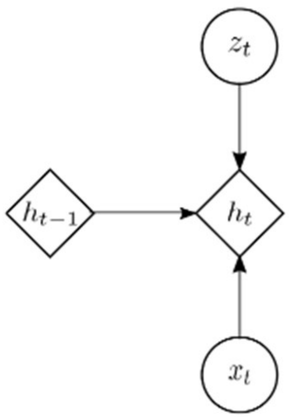
$$\mathbf{x}_t \mid \mathbf{z}_t \sim \mathcal{N}(\boldsymbol{\mu}_{x,t}, \mathrm{diag}(\boldsymbol{\sigma}^2_{x,t})) \text{ , where } [\boldsymbol{\mu}_{x,t}, \boldsymbol{\sigma}_{x,t}] = \varphi_\tau^{\mathrm{dec}}(\varphi_\tau^{\mathbf{z}}(\mathbf{z}_t), \mathbf{h}_{t-1})$$

Variational Recurrent Neural Networks (VRNN)



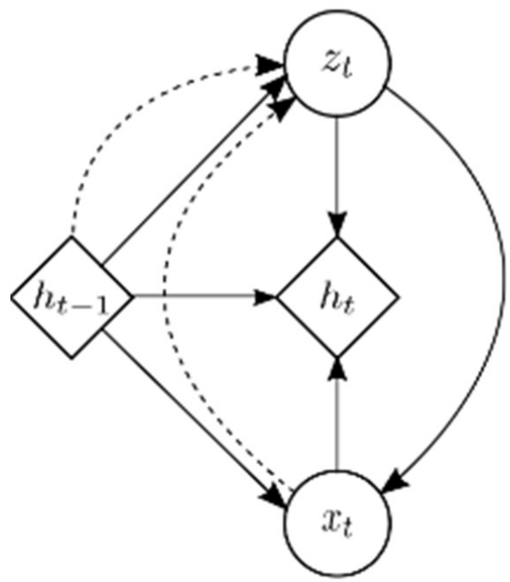
After training, previous hidden state is input for encoder to generate current latent variable

Variational Recurrent Neural Networks (VRNN)



$$\mathbf{h}_t = f_\theta\left(\varphi_\tau^{\mathbf{x}}(\mathbf{x}_t), \varphi_\tau^{\mathbf{z}}(\mathbf{z}_t), \mathbf{h}_{t-1}\right)$$

Variational Recurrent Neural Networks (VRNN)



A contrario detection

- Once the distribution $p(x_{1:T})$ is learned, we could simply apply a “global thresholding” rule to state the detection, i.e. AIS tracks whose $\log p(x_{1:T}) < e$ are flagged as abnormal, where:

$$\log p(\mathbf{x}_{1:T}) = \log p(\mathbf{x}_1) \sum_{t=1}^{T} \log p(\mathbf{x}_t | \mathbf{x}_{1:t-1}).$$

- In some areas, AIS tracks may involve multimodal but well-defined patterns, where in other areas, due to the variabilities of the AIS tracks, limited AIS datasets and/or a lower ability of the model to represent AIS tracks, the learned model may result in low probability values whatever the tracks.

A contrario detection

- A contrario detection takes into account geographically-heterogeneous performance of the learned model.
- We divide area into *i* grids of cells C_i
- Let assume $l_{\mathbf{x}_t}^{C_i}$ the log probability $\log p(x_t|h_t)$ of AIS messages in a small geographical cell C_i ($x_t \in C_i$) and p^{C_i} the distribution of $l_{\mathbf{x}_t}^{C_i}$

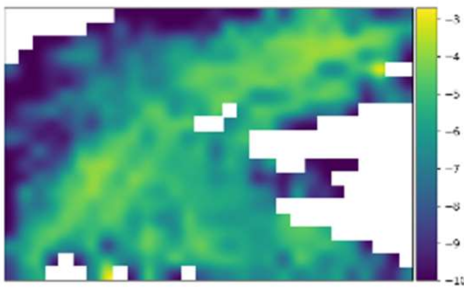
$$l_{\mathbf{x}_t}^{C_i} \sim p^{C_i}$$

A contrario detection

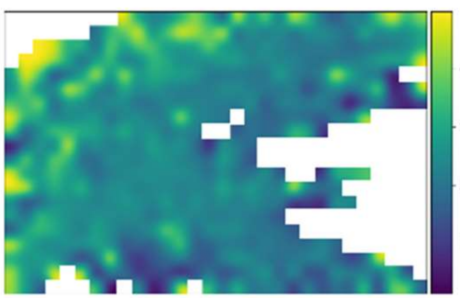
An AIS message in cell C_i is considered as abnormal if its log probability is smaller than the lowest $\frac{1}{p}$-quantile of p^{C_i}.

$$\mathbf{x}_t \textit{ is abnormal} \Leftrightarrow p^{C_i}(\mathrm{L} < l_{\mathbf{x}_t}^{C_i}) < p. \tag{10}$$

A contrario detection



(a)



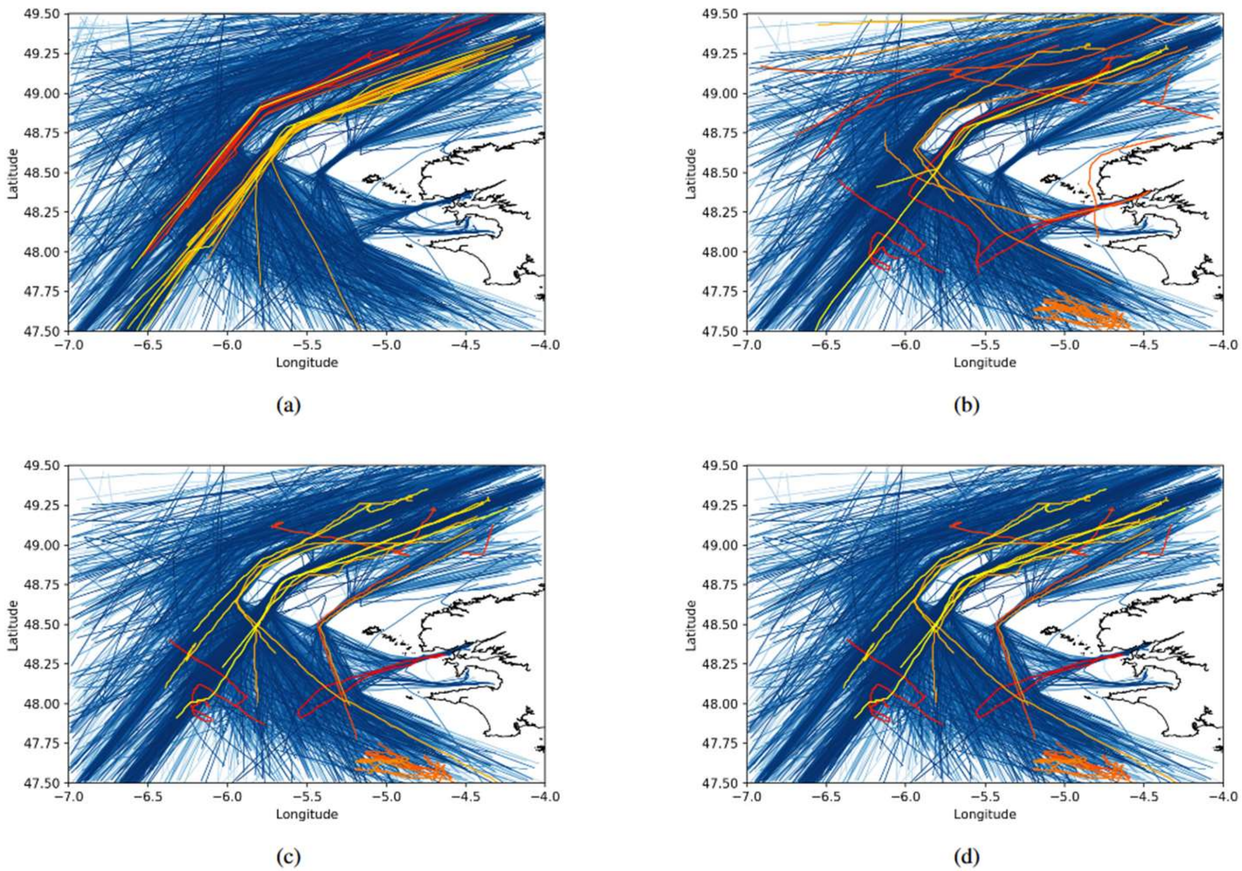
(b)

The “performance” map displaying the mean (a) and the standard deviation (b) of the Gaussian approximation of distributions pCi from AIS messages in the validation set from January to March, 2017

Experiments and results

Neural network architecture

- Resolutions of the latitude, longitude, SOG and COG were set to 0.01◦(about 1km), 0.01◦, 1 knot and 5◦,respectively.
- *f* as LSTM with one single hidden layer of size 100 for cargo and tankers dataset, 120 for all types of vessel
- z_t is a real-valued variable of the same size of the hidden layer of LSTM.
- $p(x_t|h_t,z_t)$is a multivariate Bernoulli distribution parameterized by a fully connected network with one hidden layer of size 100

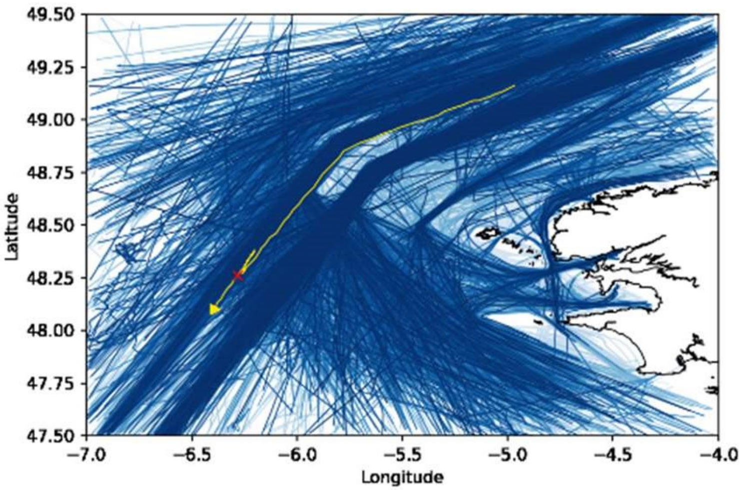


(a)TREAD (a DBSCAN-based method)

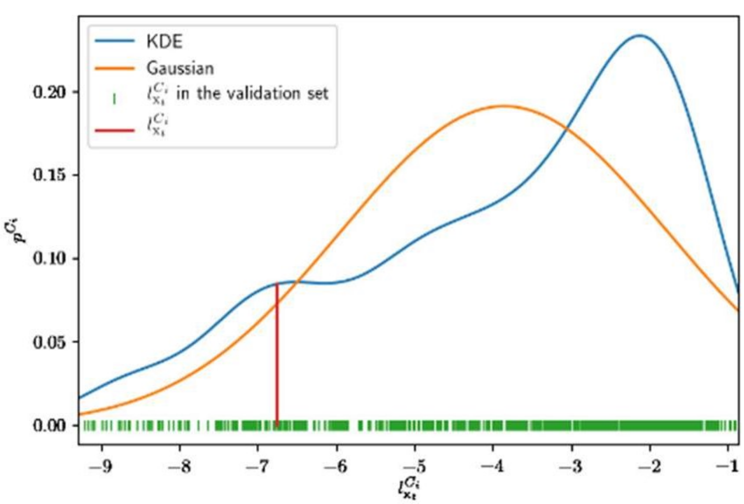
(b)Using a VRNN to learn the distribution of AIS tracks then applying a “global threshold”

(c)GeoTrackNet, approximating each pCi by a Gaussian distribution;

(d)GeoTrackNet, approximating each pCi by KDE (Kernel Density Estimation)



(a)



(b)

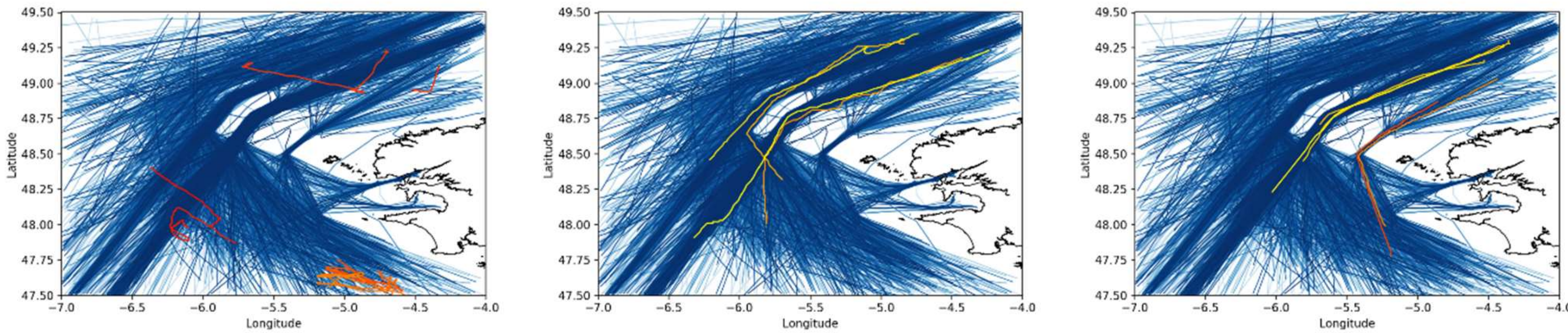
Comparison between the Gaussian approximation and KDE for distribution p^Ci.

(a) a track detected as abnormal by KDEGeoTrackNet, andnot by GaussianGeoTrackNet.

(b) p^Ci of the area around the point “x” in (a).

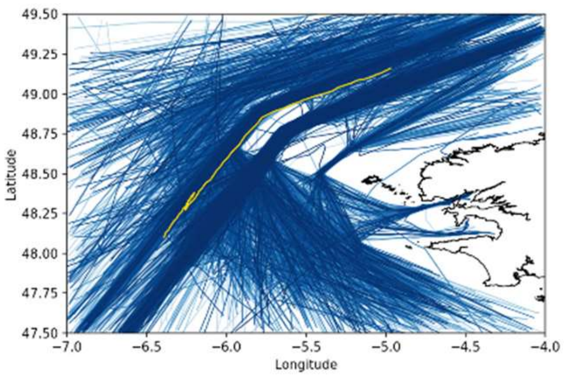
(a). $p^{C_i}_{KDE}(\mathrm{L} < l^{C_i}_{\mathbf{x}_t}) = 0.128$ while $p^{C_i}_{Gauss}(\mathrm{L} < l^{C_i}_{\mathbf{x}_t}) = 0.082$.

Overall,when the data comprises all types of vessels, p^Ci is not unimodal and KDE shall be preferred.

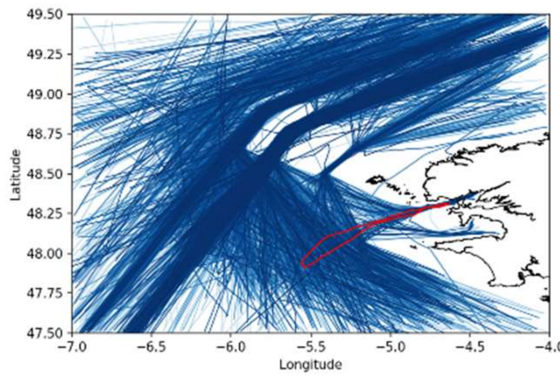


(a) (b) (c)

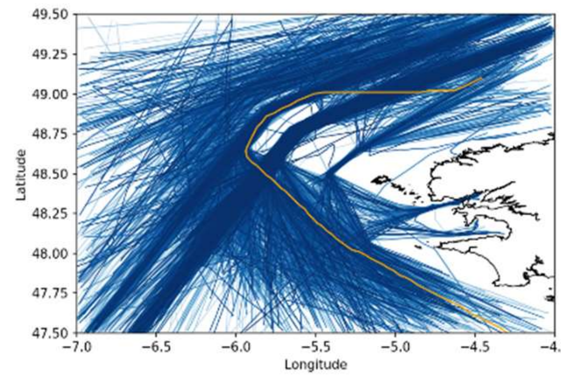
a) Vessels following abnormal routes. DBSCAN-based methods can not apply to these tracks because they can not be assigned to any common maritime route.
b) Geometrically or geographically abnormal tracks (e.g., deviating from maritime routes, unusual turns, etc.).
c) Abnormal speed tracks (e.g. suspiciously slowing down in a maritime route)



(d)

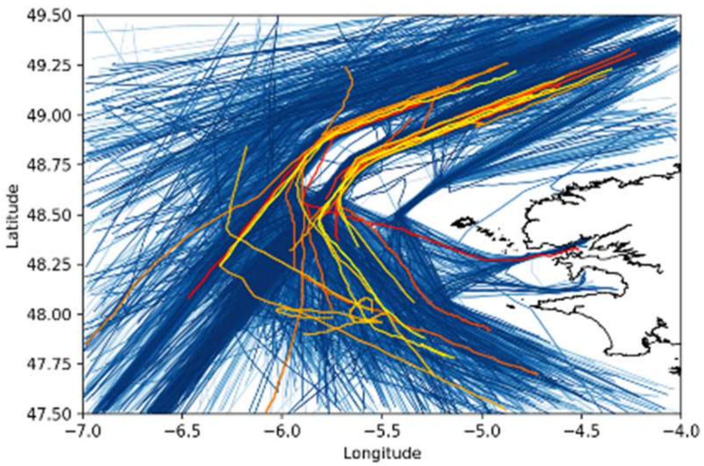


(e)

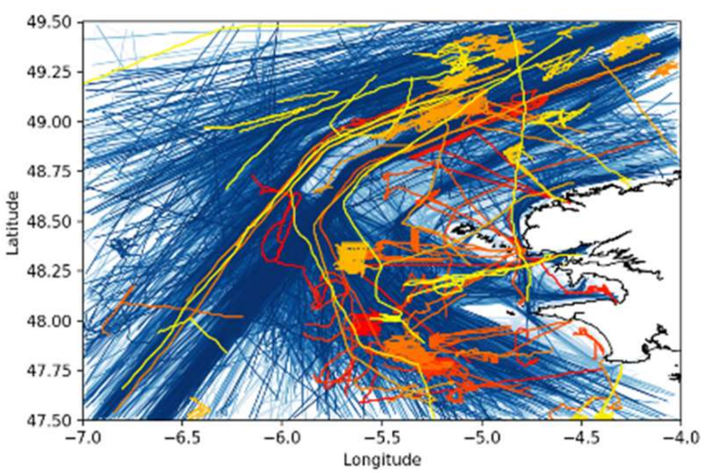


(f)

(d) Double U-turns.
(e) A cargo vessel steamed to sea then went back.
(f) Each segment of this track is normal, however, it is unusual that a vessel follows this path. GeoTrackNet can detect this track because it has a memory (the memory of its LTSM).



(a)



(b)

Anomaly detection examples for the model trained on data from January to March 2017 and tested on data from July 21 to September 30, 2017.

(a)When the data comprise only cargo and tanker vessels.

(b) When the data comprise all kind of vessels

Conclusions

- DBSCAN-based models cannot monitor AIS tracks that do not follow maritime routes. Our method applies to all AIS tracks in the Region of interest.
- The proposed model can detect detect both geometric/geographic and speed-related anomalies.
- The nature of VRNN provides additional means to condition the output onto external control inputs or other sources of information. Hence, our model could further benefit from complementary information such as weather conditions, ocean current situations, etc.

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