



# From AIS to routes: computing a Predicted Time of Arrival for vessels

2023



# Sinay - Maritime Data Solution

## WHAT WE DO?



### Monitor and predict your pollution

- Water
- Air
- Noise
- Underwater noise



### Mitigate your impact on biodiversity

- Marine mammals
- Birds
- Fishes
- Benthos



### Manage your business operation

- Metocean
- **ETA Predictions**
- Port Congestion
- Navigation and risk



# Presentation summary

Path  
processing

Route  
graph

Predicted  
Time of Arrival

# AIS data

## Automatic Identification System

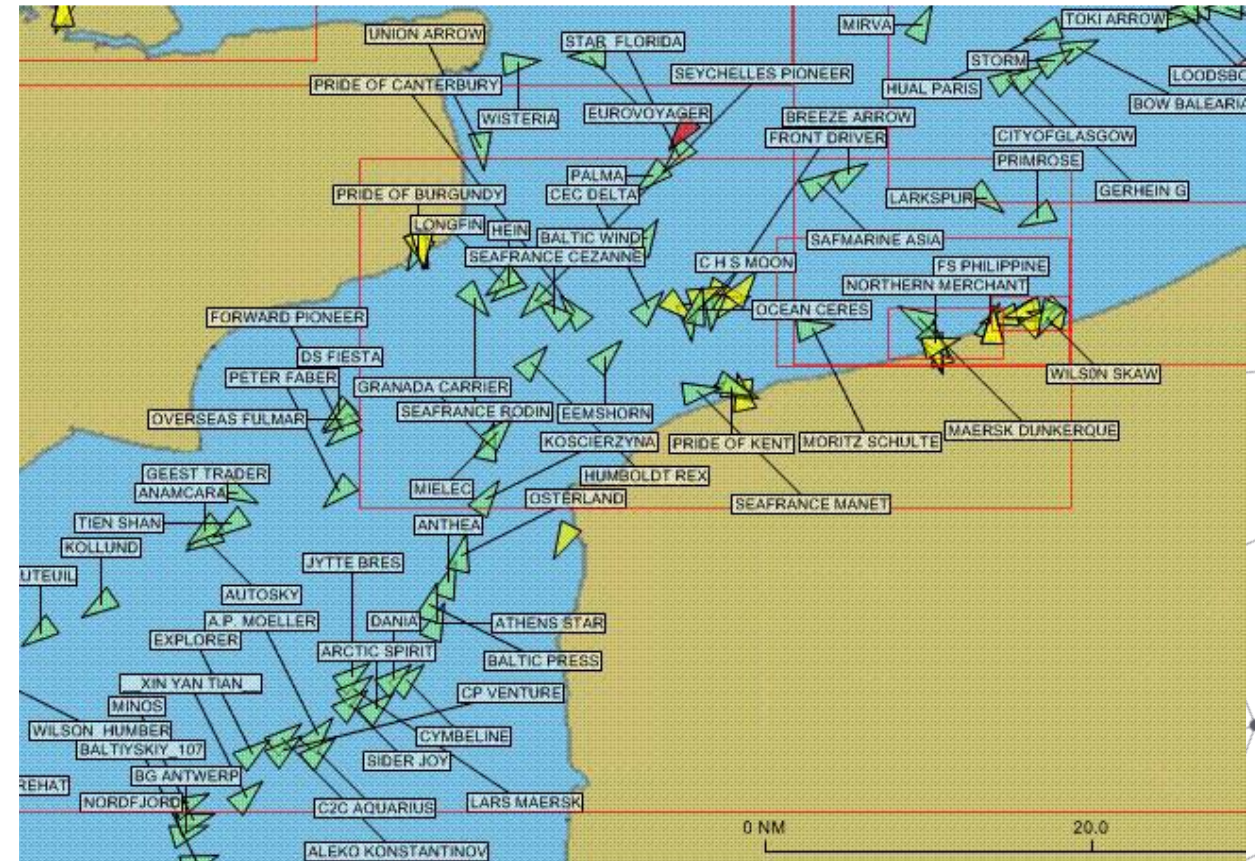
VHF frequencies  
Anti-collision system

### STATIC

MMSI/IMO  
Call sign  
Length/Width  
Type of ship

### DYNAMIC

Lat/Lon  
COG  
SOG  
Heading  
*Draught*  
*Destination*  
*ETA*



Mandatory for vessels > 300 gross tonnage, passenger ships and tankers

# AIS data

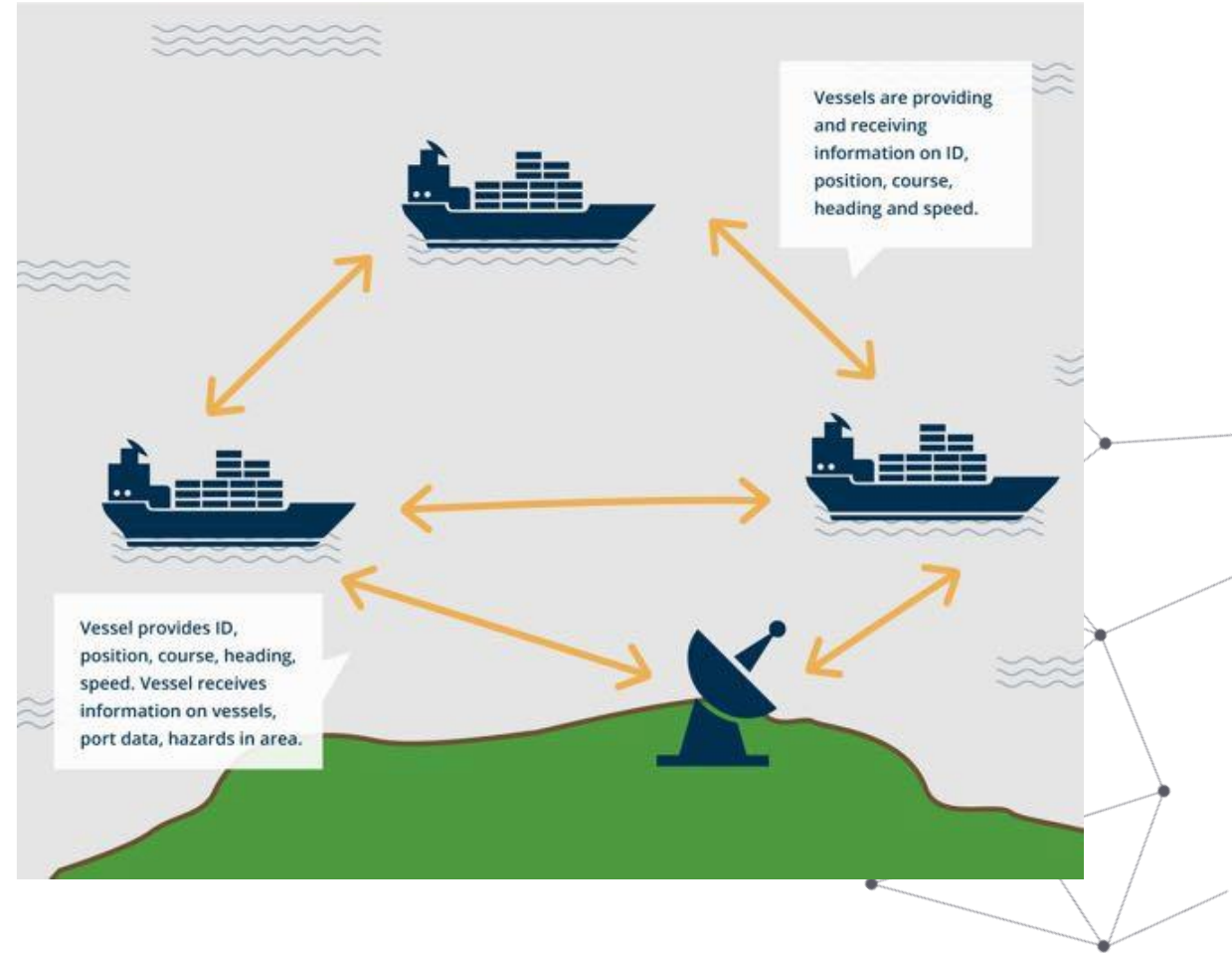
## Range

### Terrestrial

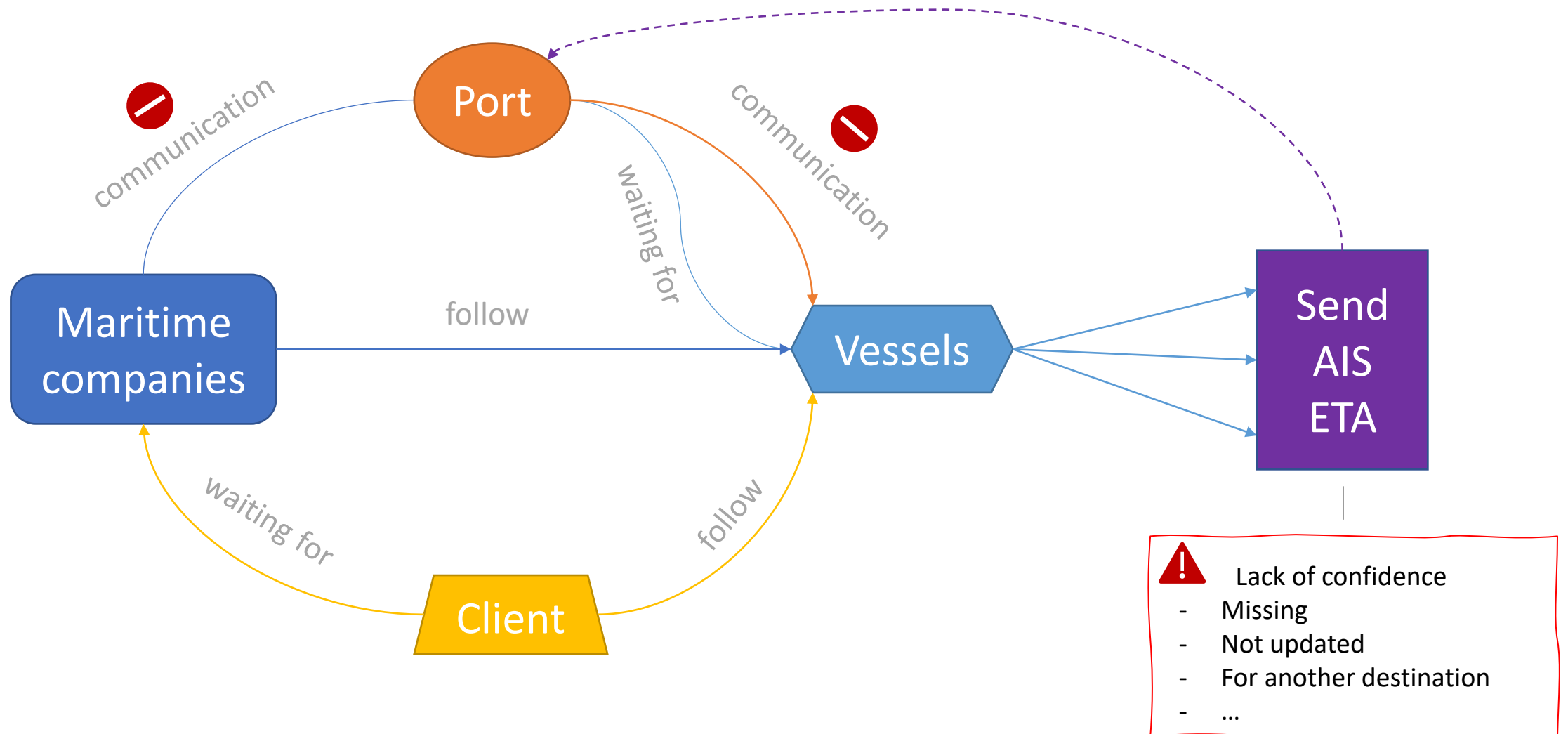
Coastal stations  
37-74km

### Satellite

5000km at 750km  
altitude  
Less precise  
Message collisions



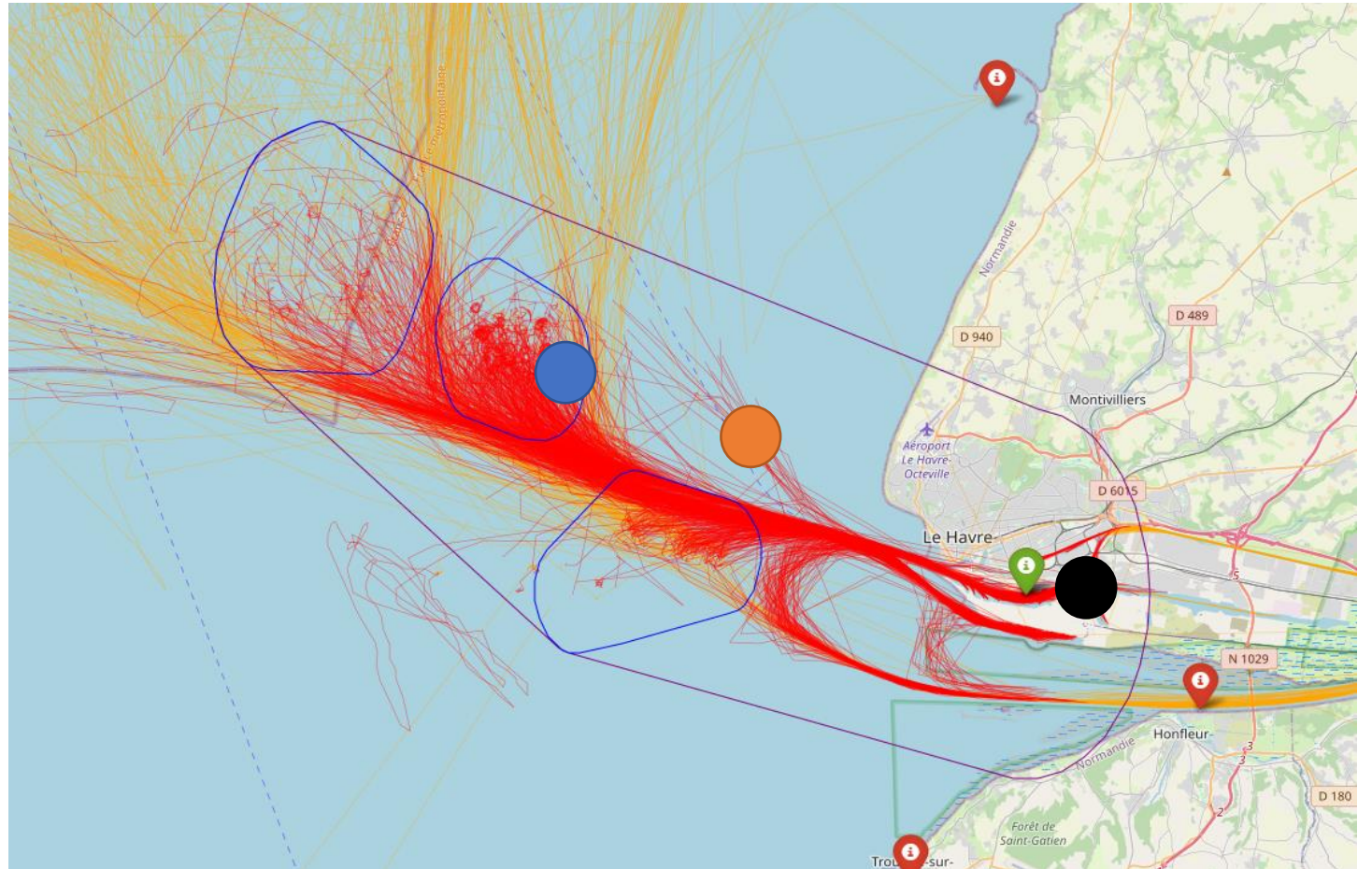
# Why compute an Estimated Time of Arrival ?





# What is an ETA?

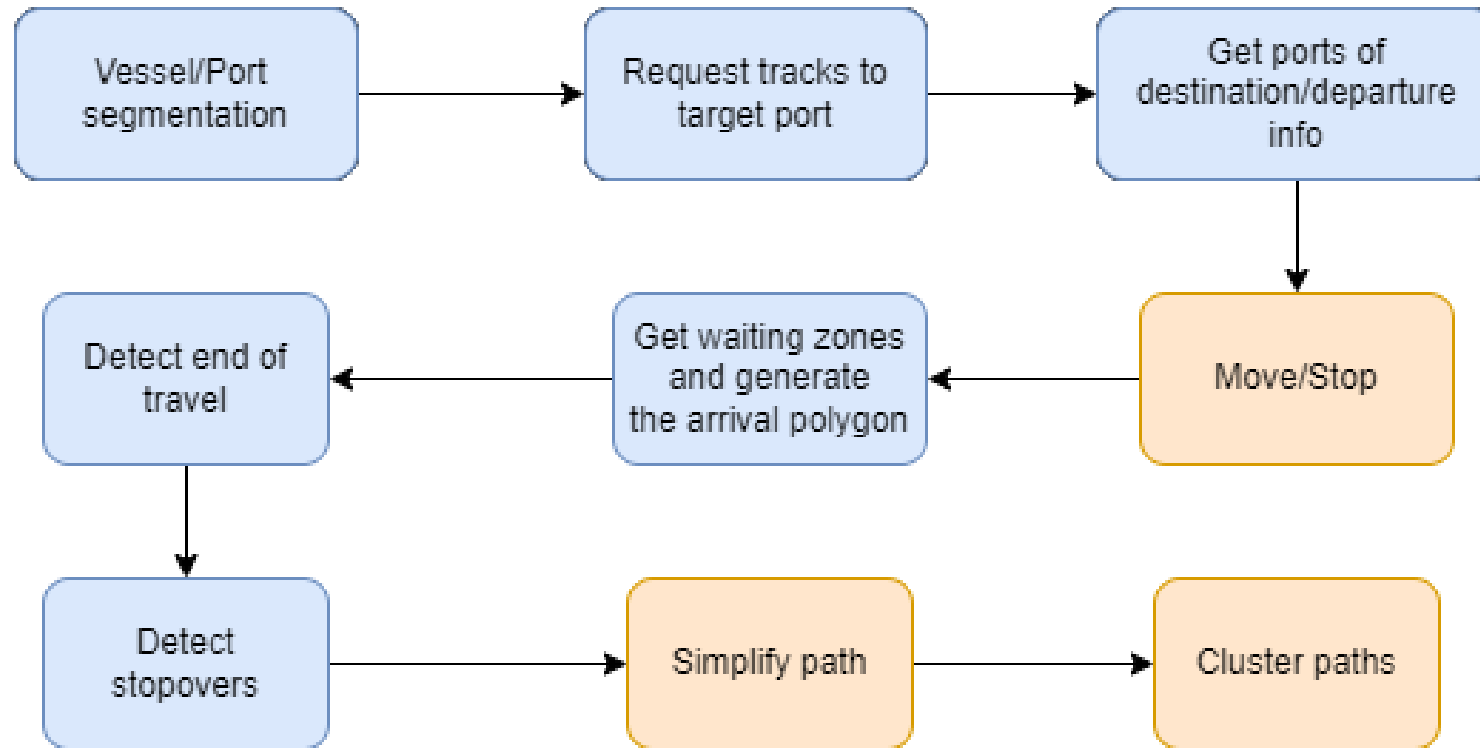
- ETA, PTA, ATA ●
- Estimated Time to Berth (ETB) ●
- End of Sea Passage ●
- Objective: PTA to waiting zone



# 1. Path processing



## Preprocessing pipeline





## Move/Stop segmentation

*"A probabilistic stop and move classifier for noisy GPS trajectories" Bermingham et Lee 2018*

- Parameters defined for each trajectory
- Index displacement:  $\Delta_{i,j} = \frac{|i - j|}{h_i}$
- $h_i$  decides how large the sampling window is.
- Spatial displacement:  $\omega_{i,j} = \frac{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{h_d}$
- $h_d$  controls how strict is the stop probabilities computation (low  $h_d$  = positions must be close)



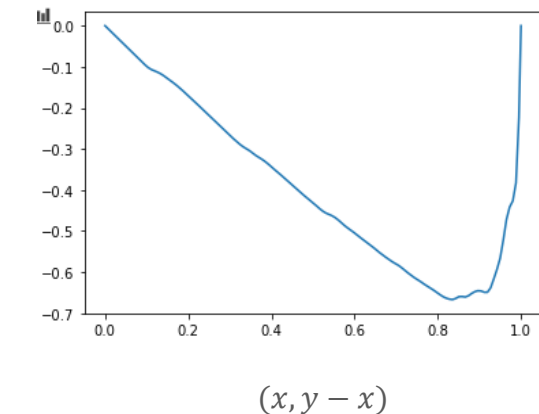
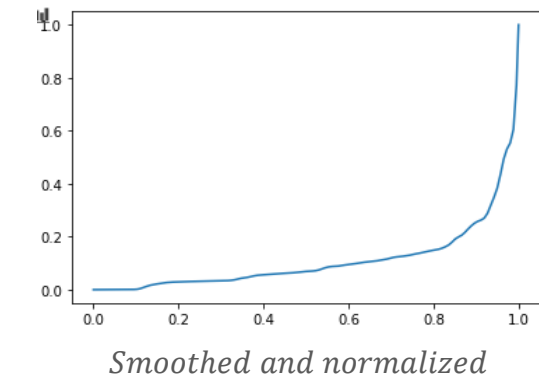
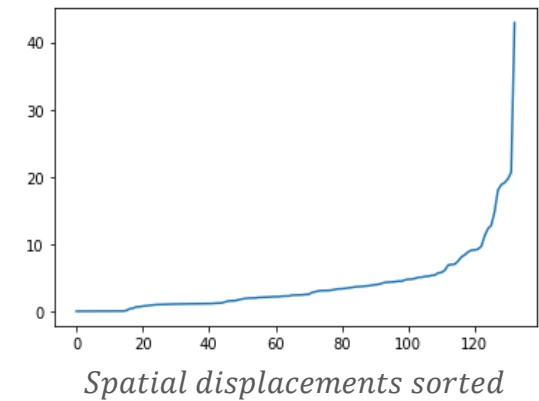
# Move/Stop segmentation

Parameter:  $h_d$

Finding a “Kneedle” in a Haystack, Satopää et al. 2011

$h_d$ : find the elbow point of the spatial displacements sorted in ascending order (where the distance between points dramatically changes)

- $(x, y-x)$ : spot where the most dramatic changes are
- Local minima are candidates



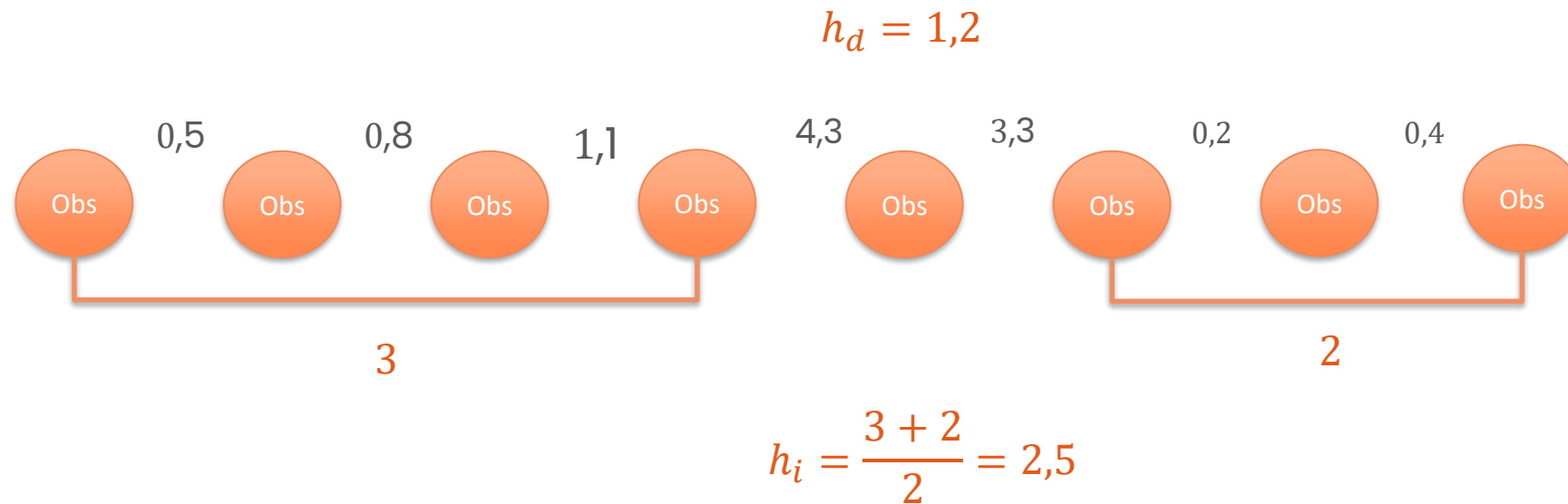
# Move/Stop segmentation

## Parameters: $h_i$

$h_i$ : find groups of contiguous positions with spatial displacement  $< h_d$

$h_i$  = half mean size of these groups.

= the size the Stop sequence is likely to have





## Move/Stop segmentation

### Stop probability

$$L(\text{Stop}|x_i, y_i) = \frac{\sum_{j=l}^u \{K(\omega_{i,j})K(\Delta_{i,j})\}}{\sum_{j=l}^u K(\Delta_{i,j})}$$

Compute a Stop probability for each position

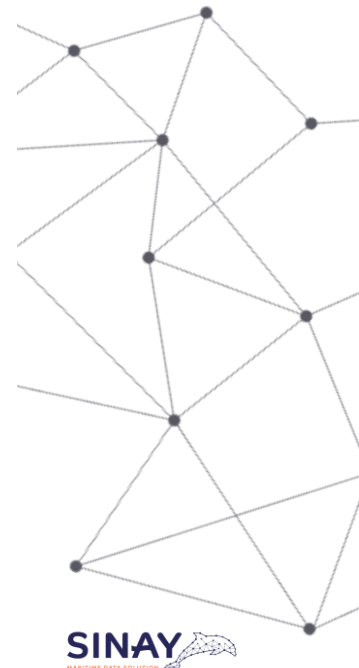
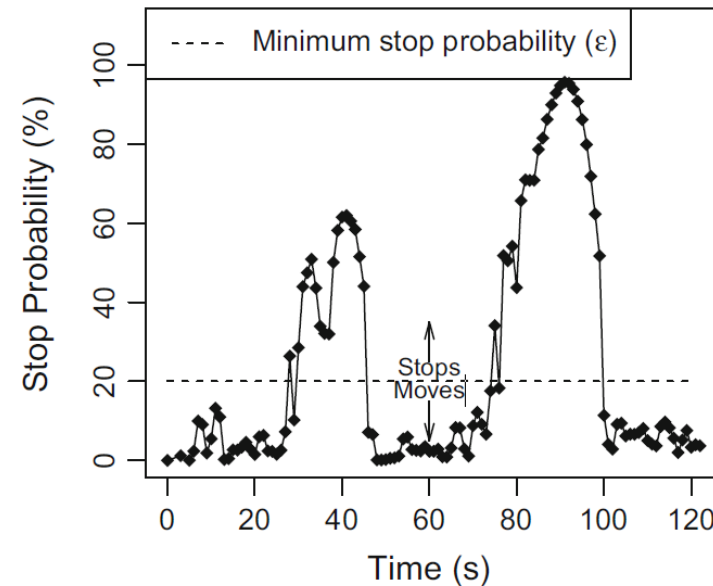
Perform Kmeans with  $k = 2$  on probabilities

Threshold =  $(\max(\text{minCluster}) + \min(\text{maxCluster})) / 2$

$$K(z) = e^{-0.5z^2}$$

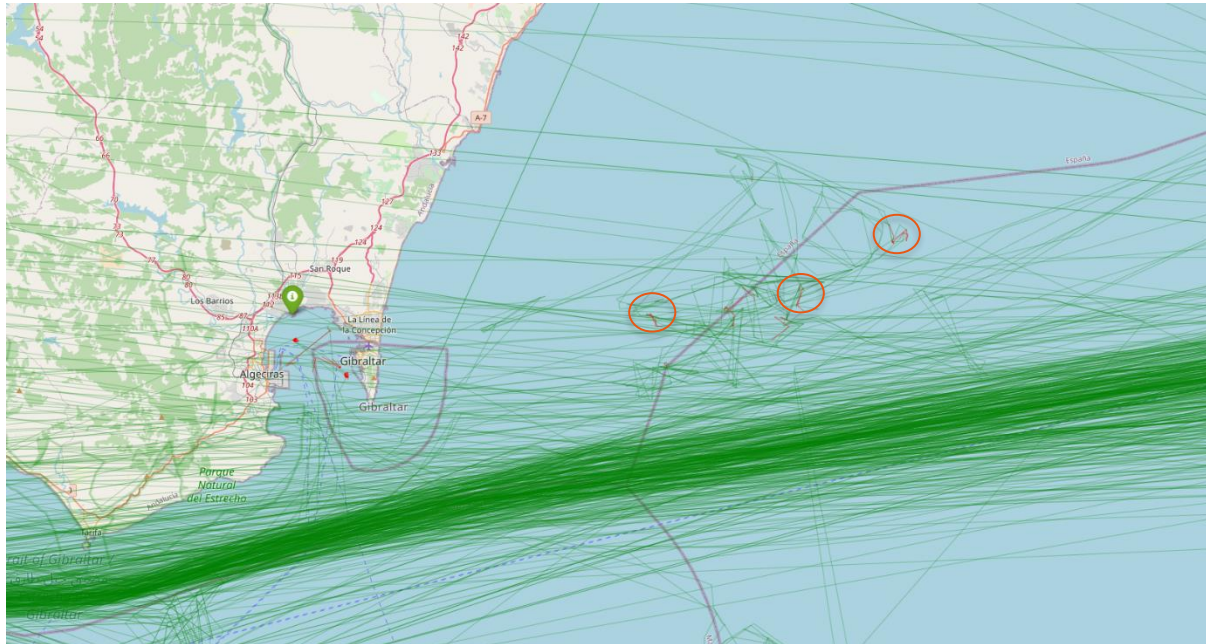
$$l = \max(0, i - 3 * h_i).$$

$$u = \min(n, i + 3 * h_i).$$

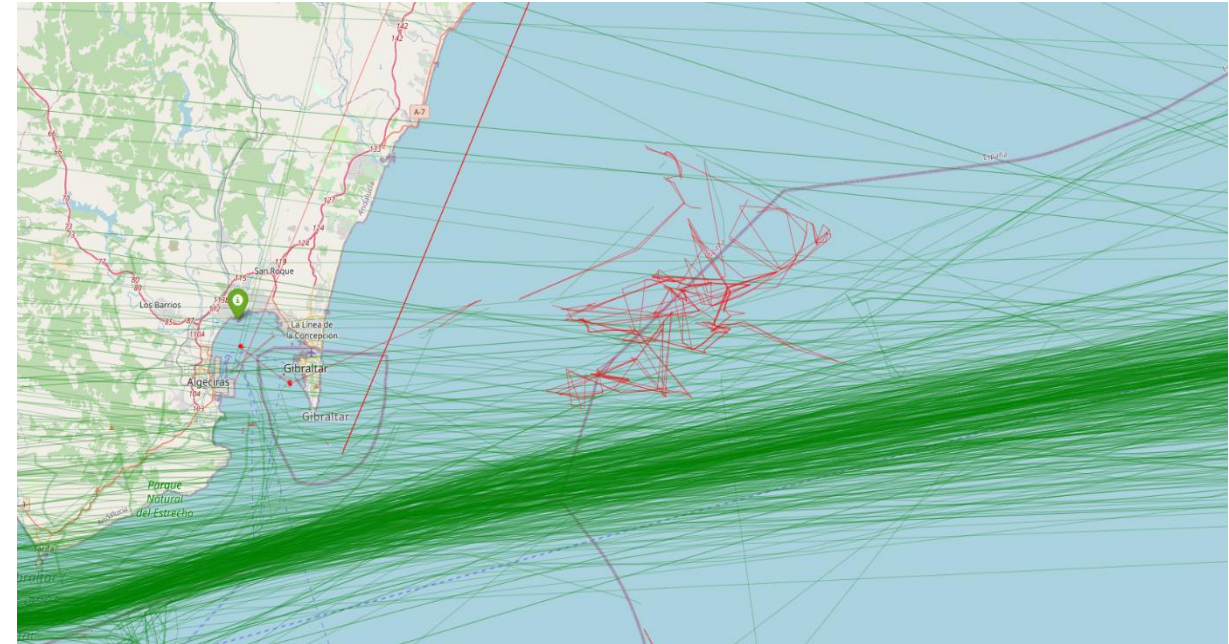


# Comparison with baseline

Baseline: speed  $\leq 2$



*Probabilistic*



*Baseline*



# Simplify Moves

Extracting Shipping Route Patterns by Trajectory Clustering Model Based on Automatic Identification System Data, Sheng et Yin 2018 - modified

Parameters for each Trajectory:

- Course change threshold:  $\alpha$
- Speed change threshold:  $\beta$
- Distance from characteristic traj:  $\lambda$

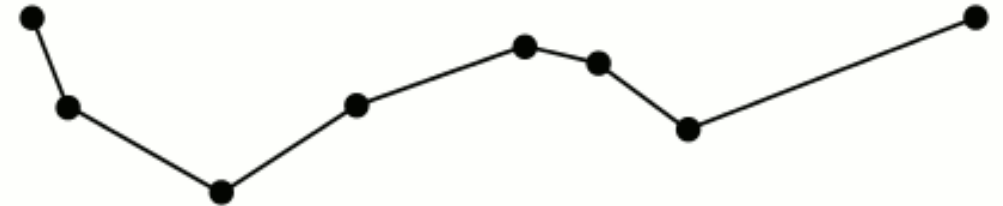
$\alpha, \beta$ : originally mean over dataset  $\rightarrow$  Kneedle

$\lambda$  set manually  $\rightarrow$  Kneedle:

- Start  $\lambda = 0,001$ , generate characteristic trajectory
- Use Kneedle on distance distribution to find  $\lambda$
- Generate track with new  $\lambda$

$$CRC = \frac{|\omega_{P_{t_m}} - \omega_{P_{t_n}}|}{t_m - t_n}$$

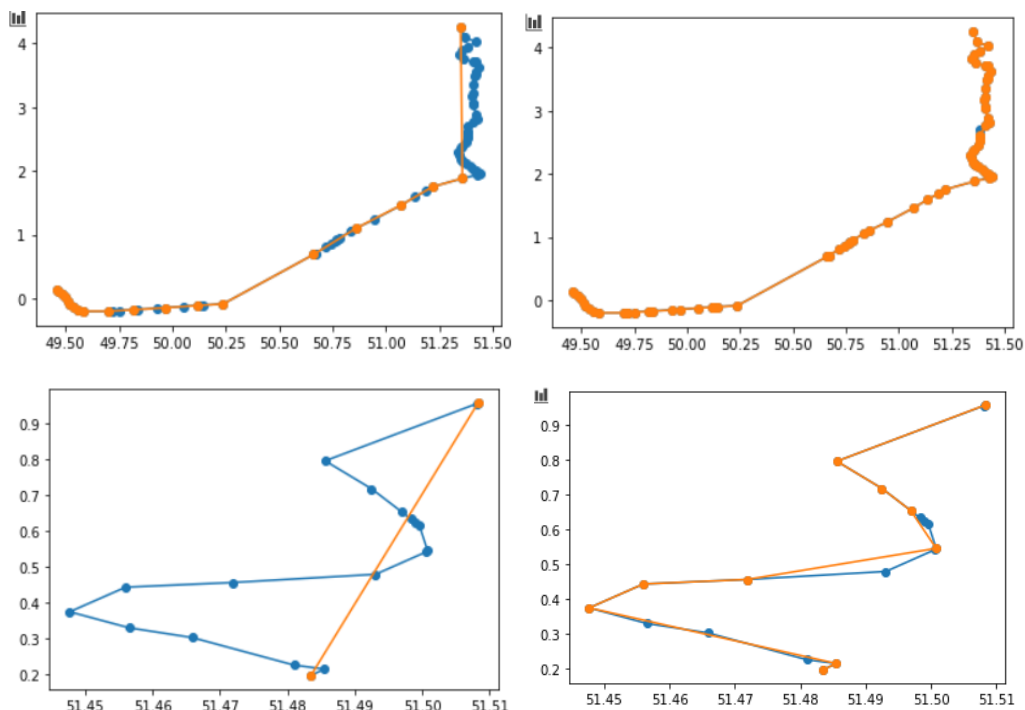
$$CRS = \frac{|v_{P_{t_m}} - v_{P_{t_n}}|}{t_m - t_n}$$



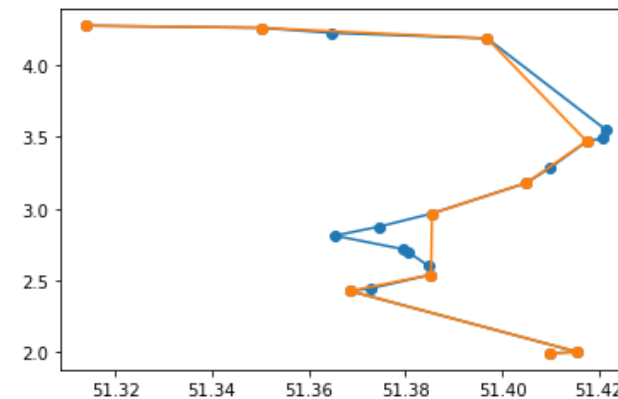
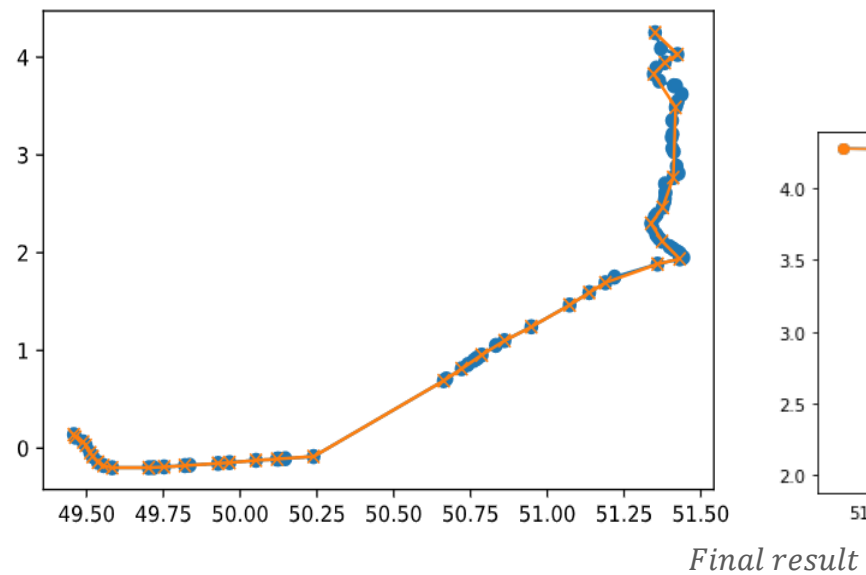
*Get characteristic trajectory*

# Simplify Moves

## $\lambda$ comparison and final results



$\lambda = 0.1$  (left) and  $\lambda = 0.001$  (right)



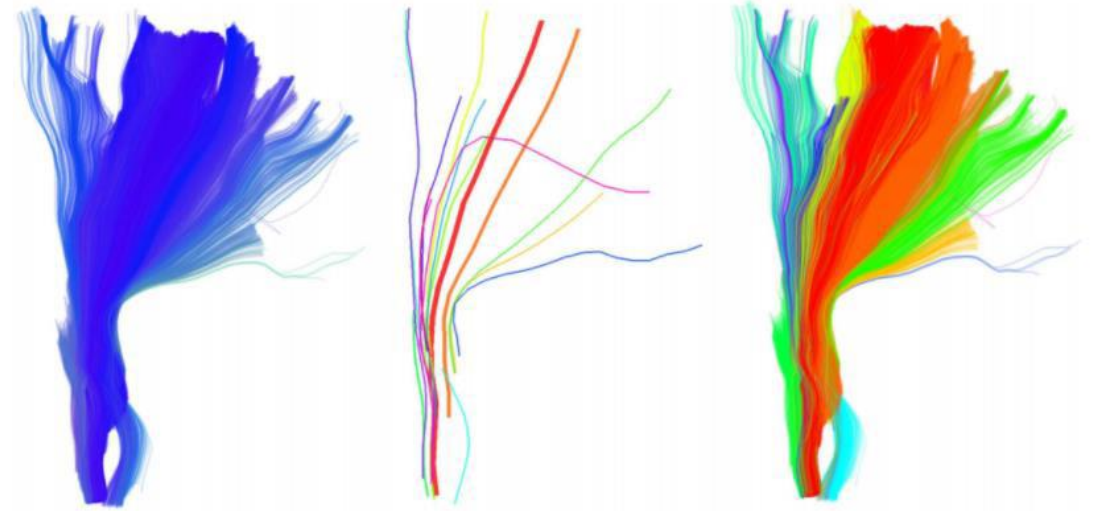


# QuickBundle – Garyfallidis et al. 2016

- Développé pour le clustering des liaisons nerveuses, similarité avec les positions (latitude, longitude)
- Trajectory = « StreamLine »
- Point to point distance with previous trajectories
- Threshold: add to current cluster or new cluster

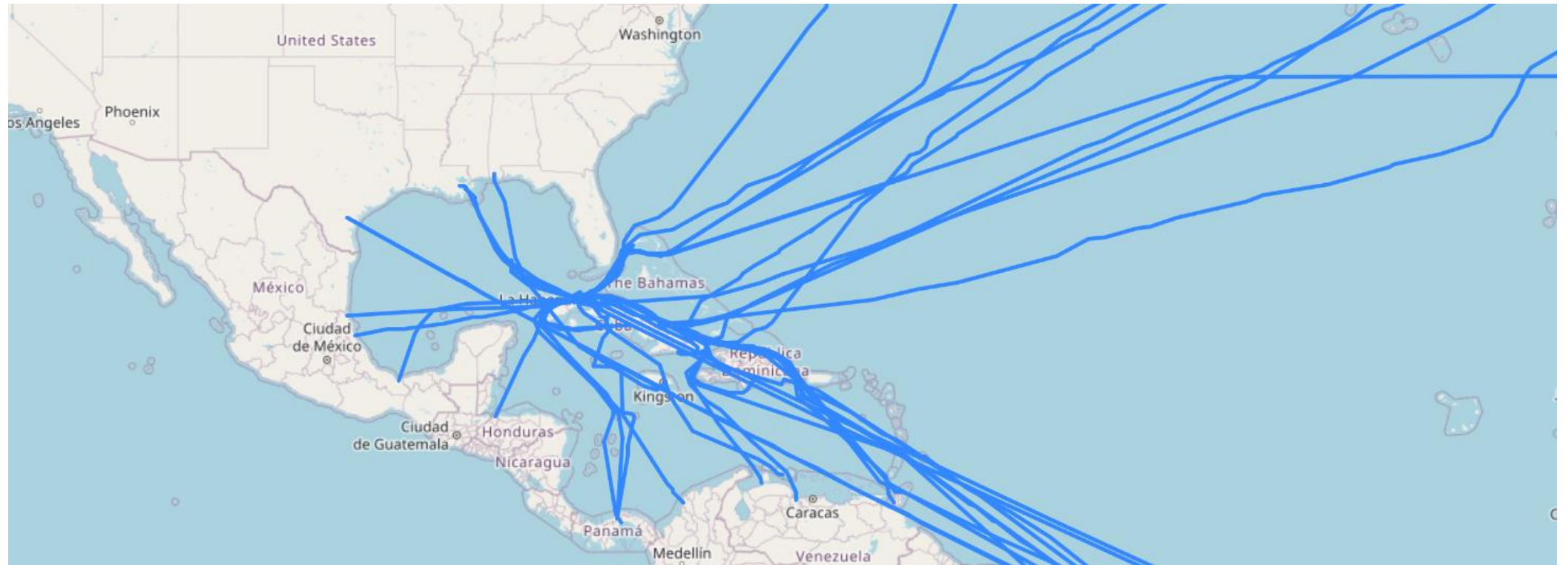
Adaptation: Haversine distance + sampling to get same number of points for all trajectories

Python library



*Frontiers In Neuroscience, vol 6, 2016. Example of white matter fibers after applying QB – Garyfallidis et al.*

# QuickBundle



*Routes to La Havane*



## Route stats

id	departure_port	arrival_port	coords	mean_speed	std_speed	min_speed	max_speed	path_length	mean_dist
1	BEANR	RUBNK	[(51.2846, 4.3087), (51.35016, 4.2536564), (5...	11.509351145038169	2.3095131961998505	1.9	14.9	1299.894208153229	1313.8625076459757
2	BEANR	RUBNK	[(51.30414, 4.27202), (51.383385, 4.20984), (...	15.524662060678883	2.213824112473036	3	20.5	1457.7063680791682	1476.541090667727
3	DEBRV	RUBNK	[(53.569, 8.5401), (53.63149, 8.451109), (53....	14.564954682779456	2.1350780237226656	5.9	17.8	1243.8554140497076	1274.9031417821288
4	DEBRV	RUBNK	[(53.572395, 8.536526), (53.62793, 8.455355...	17.661016949152543	3.5864109034550435	4	102.3	1133.2204356635443	1144.0144170785832
5	DEHAM	RUBNK	[(53.539978, 9.90682), (53.55505, 9.802417),...	15.2886781268524	2.5861945908060053	0.1	21.3	1303.13422543429	1326.3876377186018
6	DEKEL	RUBNK	[(54.366154, 10.158263), (54.43094, 10.2293...	14.306719826023922	3.3661489128053748	0.1	102.3	744.9658161156524	752.6692760373314
7	DKAAR	RUBNK	[(56.151997, 10.2415), (56.14278, 10.342525...	16.44380032206119	2.1136990322120344	4	18.1	771.0879001604093	774.4352544875742
8	EEPLA	RUBNK	[(59.372803, 24.014648), (59.440613, 24.046...	15.964173228346455	2.9741866901553182	8	19.9	167.1955081156978	169.29492582831102

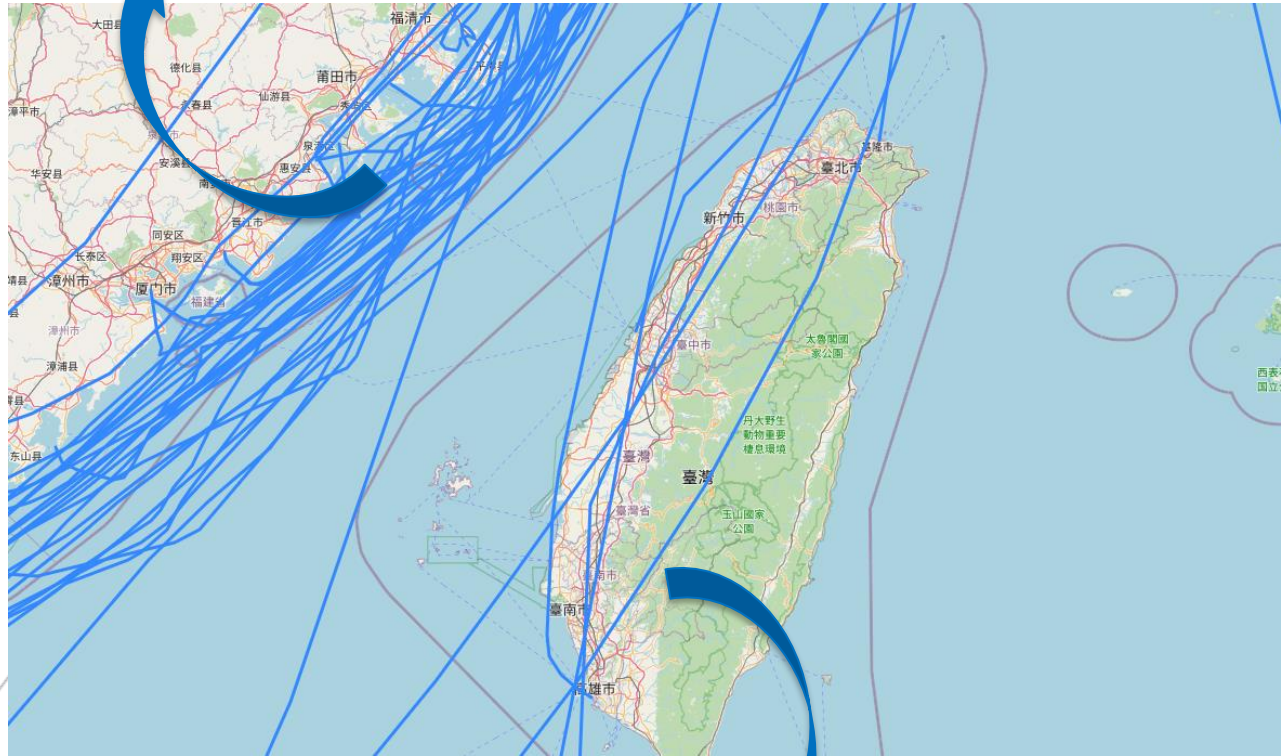
std_dist	min_dist	max_dist	mean_time	std_time	min_time	max_time	n_paths
0.2733858123203845	1313.589121833655	1314.135893458296	413.225	0.383	412.842	413.608	2
7.978960912740735	1456.0162060673797	1484.7975374413531	342.62	27.42192542473996	316.635	415.494	10
15.079087829992318	1259.8240539521364	1289.982229612121	324.8805	17.6945	307.186	342.575	2
14.822036378716891	1118.4920661669123	1154.846462784914	232.61575	11.107744671511856	213.41	239.567	4
13.108360581084112	1294.1996455507574	1352.096731388126	316.57689473684206	27.299296383635077	279.991	421.226	38
9.264302453373888	729.0967490925351	792.3961961554892	192.56747407407408	39.14212202953813	137.959	349.39	135
0.5001326325180707	774.081607311628	775.1425488394666	169.90233333333333	1.2605356885952188	169.011	171.685	3
6.620511074802813	158.3441869761673	176.11433003627957	57.59625	14.232180777642618	35.006	74.419	4

## 2. Route graph



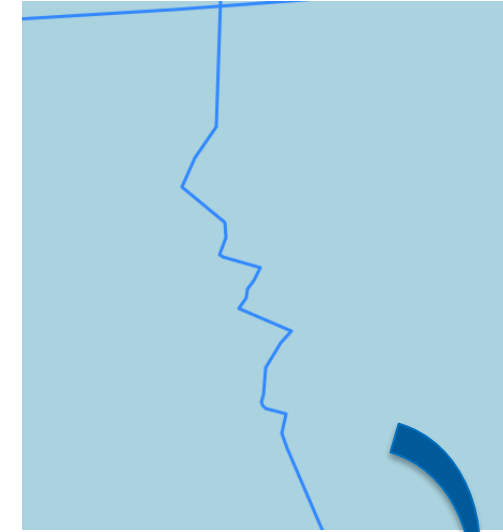
## Port to port routes

Many are actually the same



Some goes through land

More than 33.000, hard to add new information



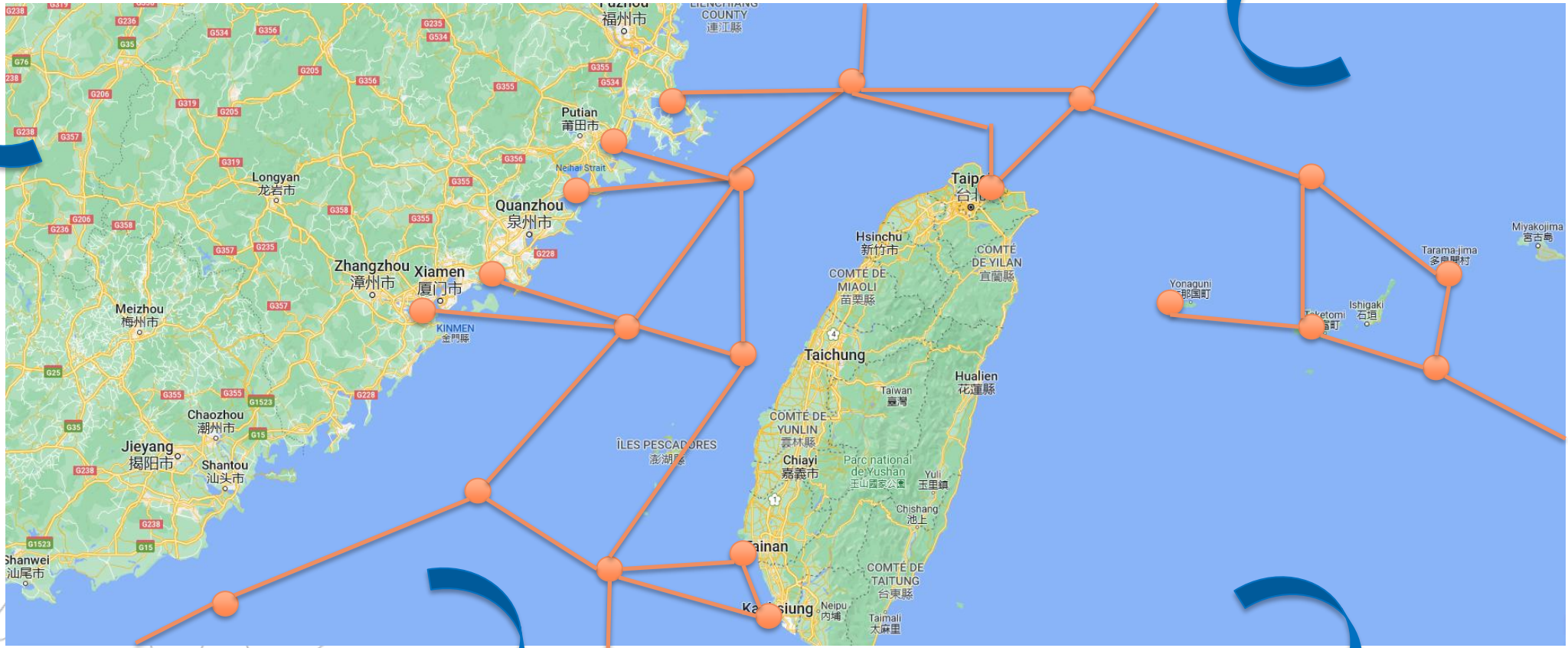
Weird shapes  
(low number of  
vessels)



One visualization for all ports

## Route graph

Faster to find the right route by approximation if port not in the routing system



Clean up the previous set of paths

Nodes and edges can store many types of information

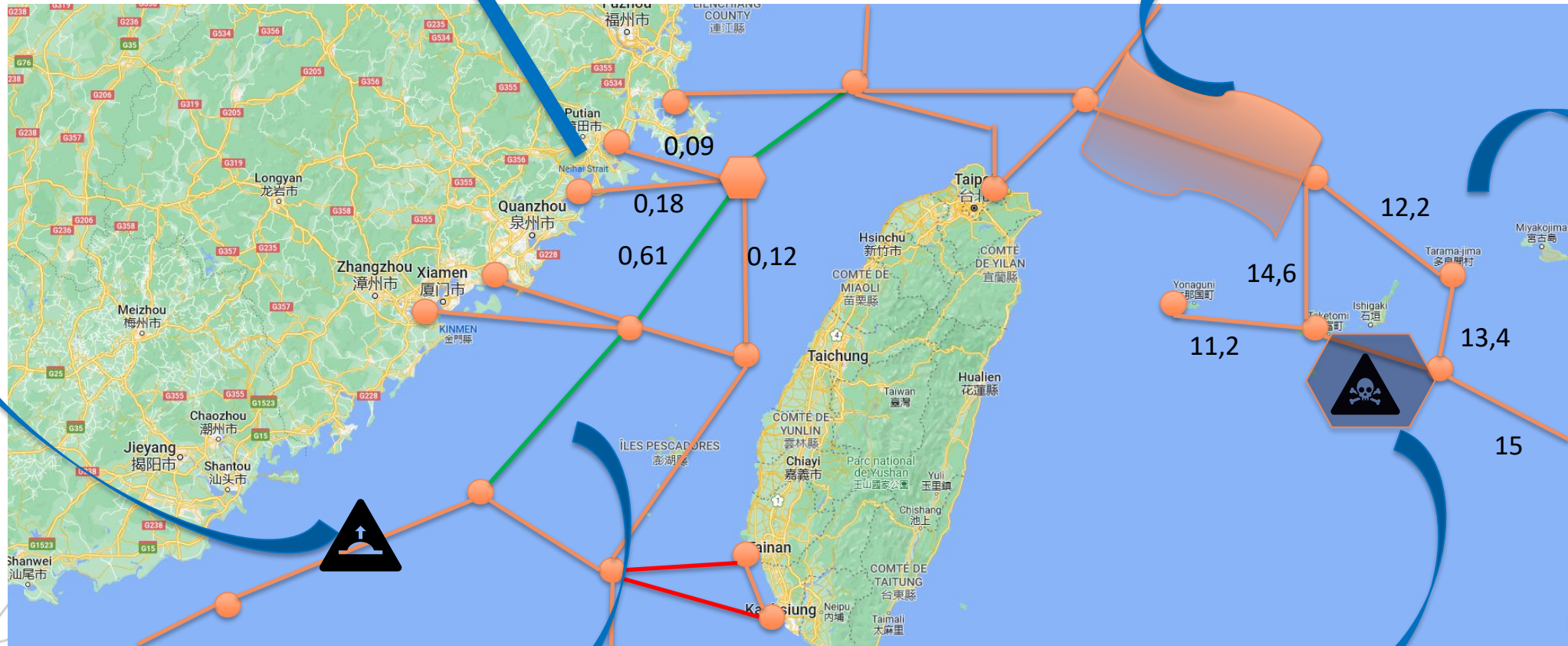


Transition matrices

## Examples

Normalcy patterns  
w.r.t. position, speed, course...

Adverse  
weather



Speed  
along edges

Real-time congestion

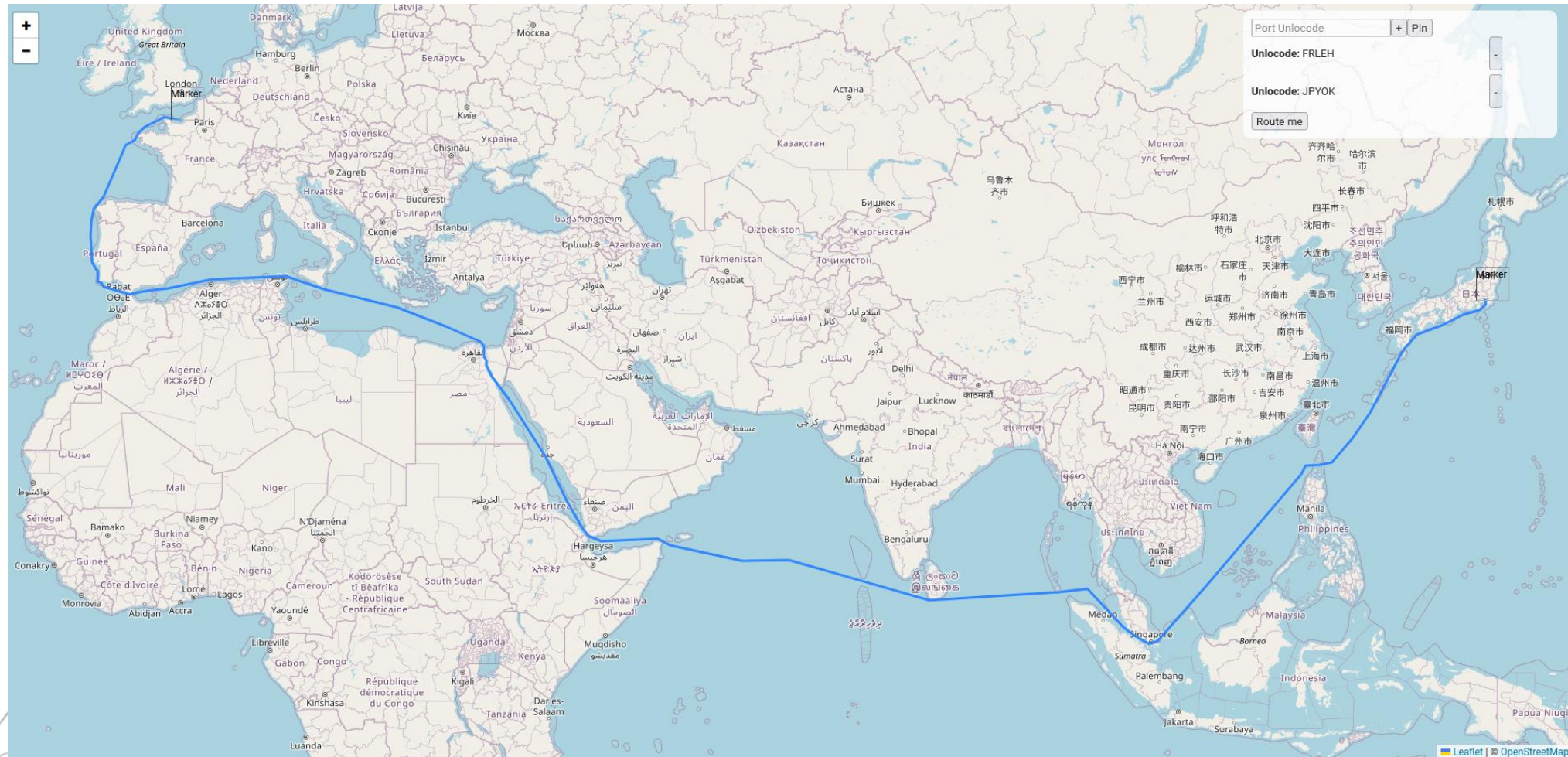
Avoid edges (pirates,  
protected areas...)



## Demo routing (based on the european project Searoute)



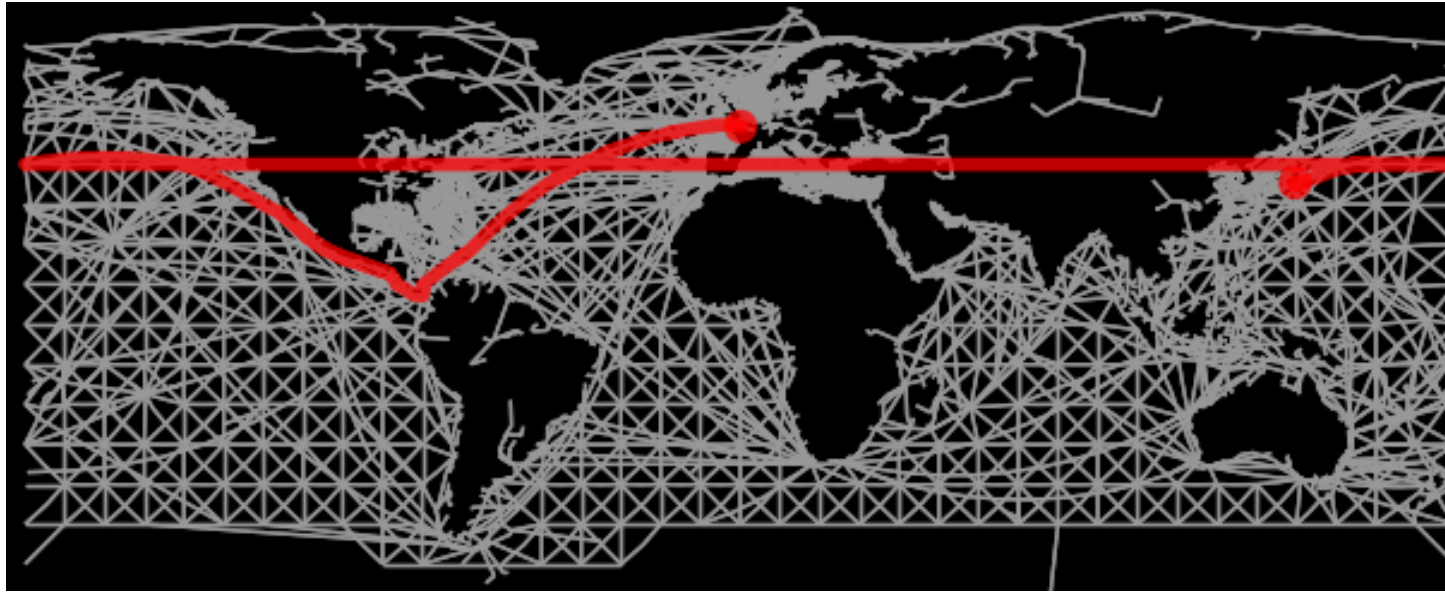
# Demo routing



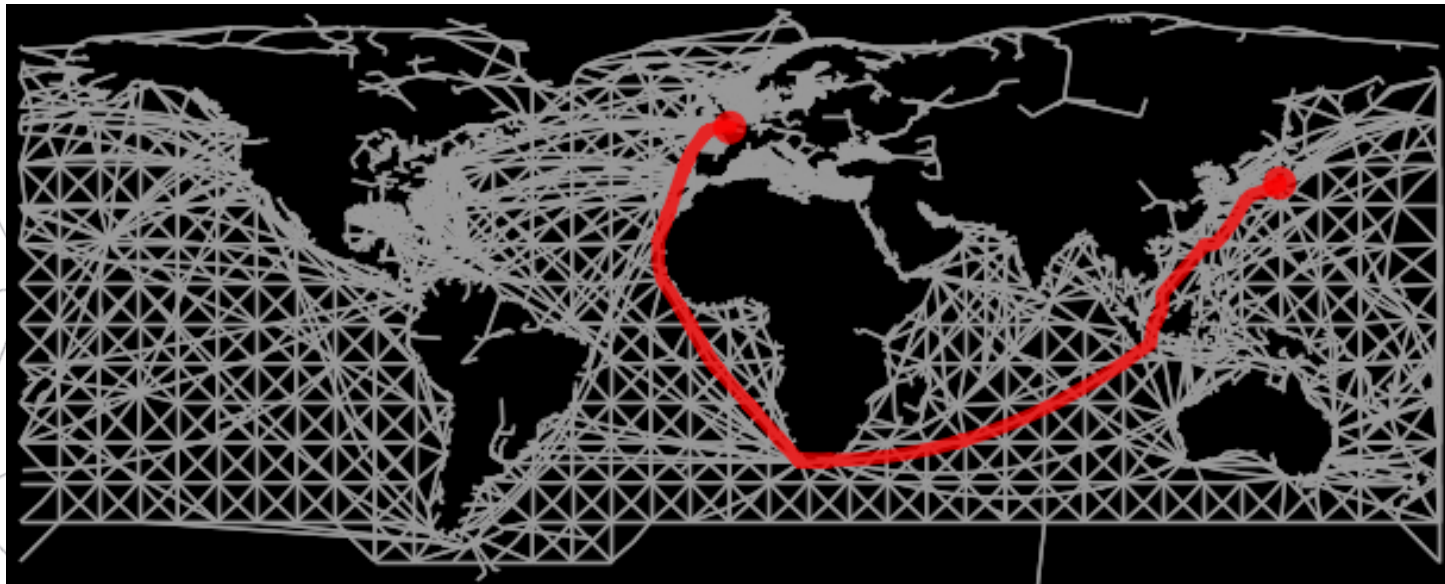
*FRLEH – JPYOK through Suez canal*

## Demo routing

*FRLEH – JPYOK  
through Panama*



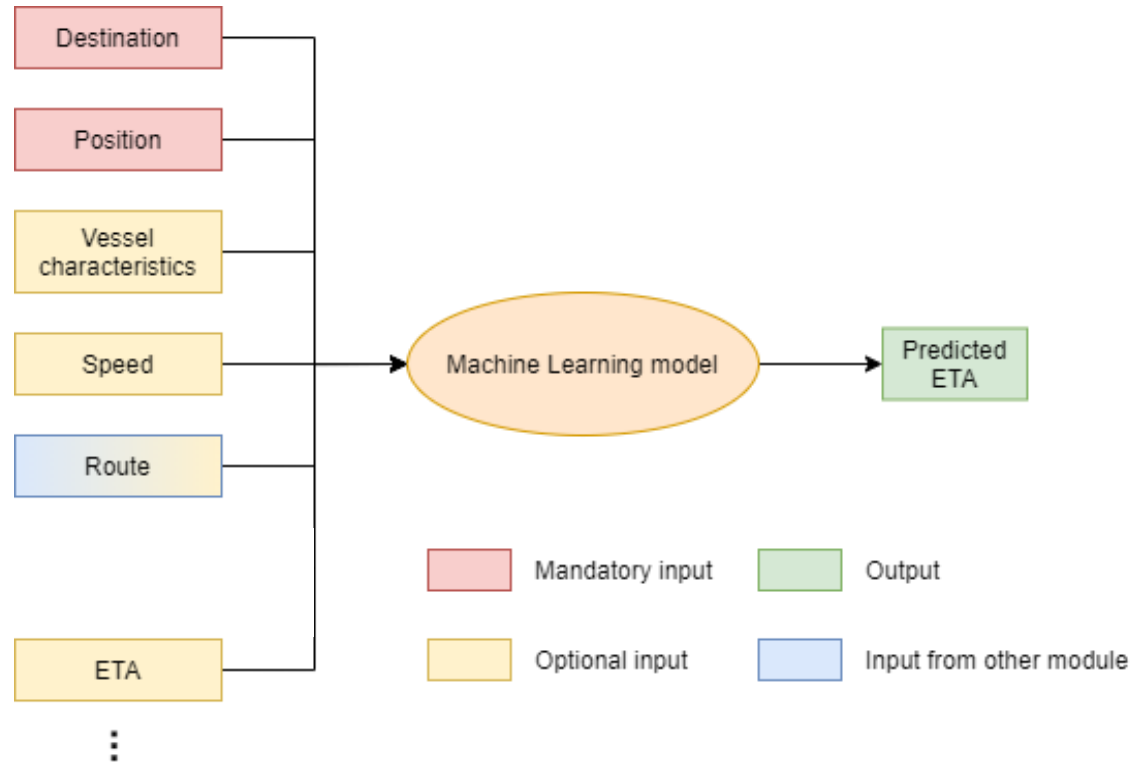
*FRLEH – JPYOK  
through cape of  
Good Hope*





# 3. Predicted Time of Arrival

# Predicted Time of Arrival (PTA)

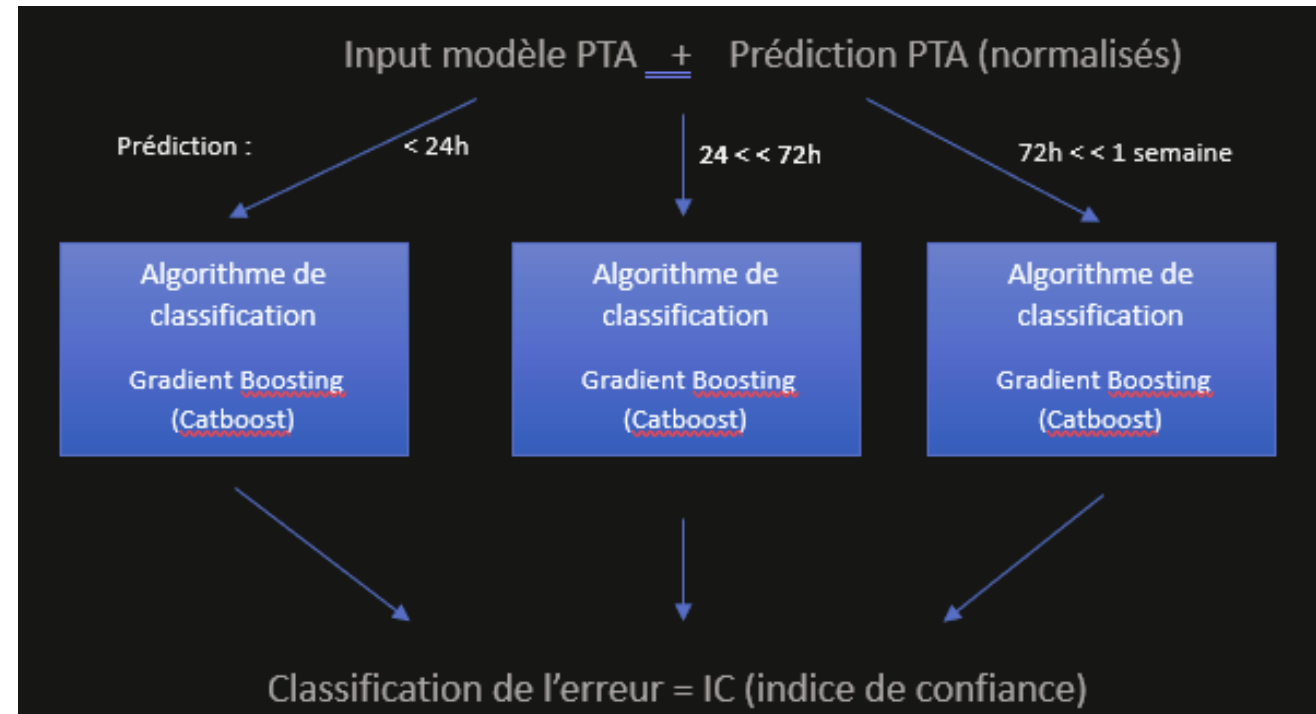


## Important variables for PTA:

- Vessel size makes it sensitive to weather
- ETA from the captain provides guidance
- Depends on the chosen route

## Confidence index – Machine learning

- Users need to know if they can trust the prediction
- Try to predict the error between the PTA and the ATA
- Uses the same input as the PTA API + the predicted time
- Error range → confidence index



1 2 3 4 5



*The higher the index is, the more confidence in the result*



# Confidence index – Expert system

## Approximation quality

AngleQuality: [GOOD: 0, POOR: 1]

VesselToRoute: [GOOD: 0, POOR: 1]

RouteToPort: [GOOD: 0, POOR: 1]

**ApproximationQuality: [GREAT: 0, GOOD: 1, POOR: 2]**

## Route quality

RouteDensity: [DENSE: 0, MEDIUM: 1, LIGHT: 2]

RouteStability: [STABLE: 0, UNSTABLE: 1]

VesselToRoute: [GOOD: 0, POOR: 1]

**RouteQuality: [GREAT: 0, GOOD: 1, POOR: 2]**

## Prediction quality

InputQuality: [COMPLETE: 0, INCOMPLETE: 1]

RemainingTime: [SHORT: 0, MEDIUM: 1, LONG: 2]

**PredictionQuality: [GREAT: 0, GOOD: 1, POOR: 2]**

```
[VARIABLE_IMPORTANCE]
MEAN_SPEED = 1.75
SHIP_TYPE = 1
CAPTAIN_REMAINING_TIME = 0.5
LENGTH = 0.25
WIDTH = 0.25
DRAUGHT = 0.25
```

SINAY  
APIs

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**Powerful APIs for precise maritime insights**

Whether your activity is focused on ocean freight and issues regarding vessel tracking and ETA, port congestion, GHG emissions or ocean analytics and biodiversity, our APIs will help you build the best tools specially tailored to your needs.

**Container Tracking API**  
  
 Track your container over its voyage. **Get its status, location, ETA and all events of the journey.** Search by container number, booking number or Bill of Lading number.  
  

Logistics
START FREE PLAN

**ETA API**  
  
 Get **automated ETA Predictions for any vessel to any port worldwide.** Based on AI and machine learning algorithms combining real-time situational awareness and decades of historical data, Sinay's ETA predictions are highly reliable and accurate.  
  

AI
Logistics
START FREE PLAN

**Ports and Vessels API**  
  
**Retrieve vessel IMO/MMSI or port UNLOCODE** Search for a Port or a Vessel using its name or partial identifier, and retrieve its correct name, IMO, MMSI and UNLOCODE.  
  

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**CO2 API**  
  
 Monitor CO2 Emissions per TEU. **Monitor carbon emissions of any sea voyage per TEU.** Get an estimation for a voyage ahead of time or calculate emissions post voyage.  
  

Green shipping
Logistics
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**Port Congestion API**  
  
 Get a **real-time status of Port Congestion worldwide,** filter Port Congestion per Vessel Type and characteristics and compare Port Congestion Status with average port congestion.  
  

Logistics
AI
START FREE PLAN

**Noise API**  
  
 Monitor Sound Exposure Level. **Monitor SEL for any vessel type or journey worldwide.** Compare with LLOYDS and Bureau Veritas standards.  
  

Green shipping
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CONTACT

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# ETA Calculator



## ETA Calculator

ETA predicted  
May 13, 2023 5:51 PM UTC



Route duration 5d 2h Interval +/- 13h ⓘ

Confidence interval

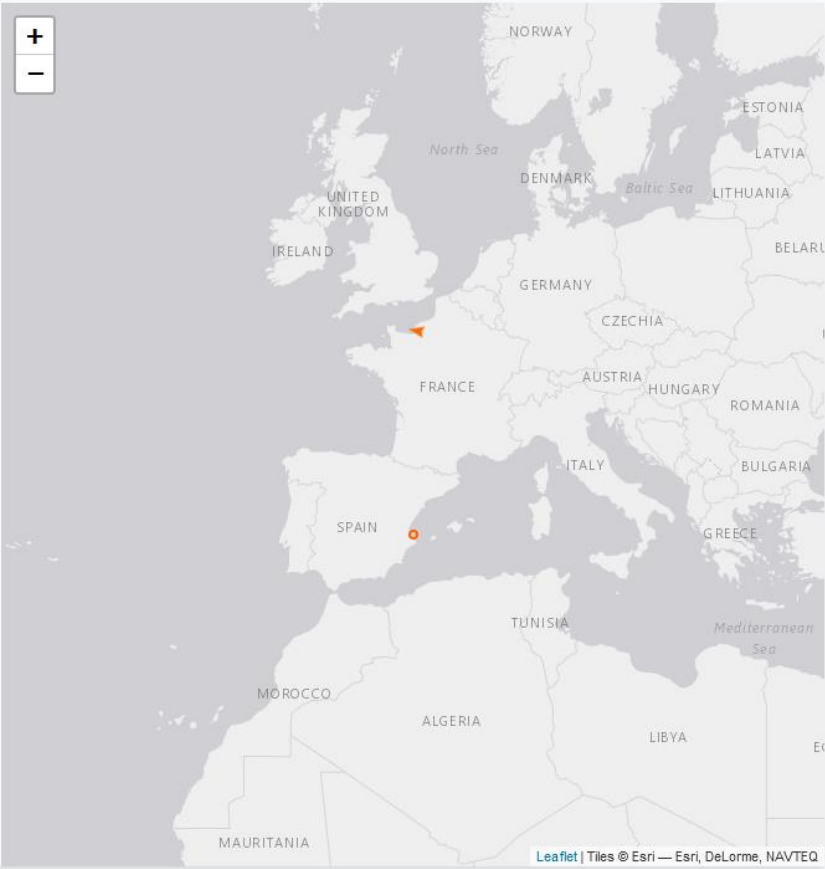
Minimum arrival date May 13, 2023 4:27 AM

Maximum arrival date May 14, 2023 7:16 AM

 SHARE THIS ETA

CALCULATE ANOTHER ETA

Rate this calculated ETA ★★★★★



CREATE AN API KEY

HELP CENTER ?

### Summary

Vessel [CHANGE](#)

Vessel name CMA CGM ZHENG HE

IMO 9706906

Departure [CHANGE](#)

Location Current position

Date May 8, 2023

Time 3:56 PM UTC

Arrival [CHANGE](#)

Location VALENCIA (ESVLC)

### History

 ACCESS ETA HISTORY

 How does it work ?

Our calculation are based on historical AIS data and vessels details.





# SINAY

MARITIME DATA SOLUTION

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