



Projet IA A3

Analyse des données
maritimes dans le golfe
du Mexique

Besoin client 1

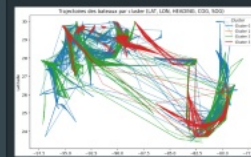
Adaption des données

```
col_names = [  
    'lon_min', 'lon_max',  
    'lat_min', 'lat_max',  
    'lon_ctr', 'lat_ctr',  
    'lon_rng', 'lat_rng',  
    'area', 'total_d'  
]
```

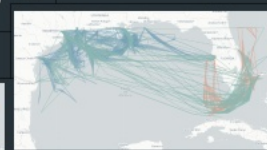
Calcul des clusters

Kmeans
2->10

Clustering 1.



Clustering 2.

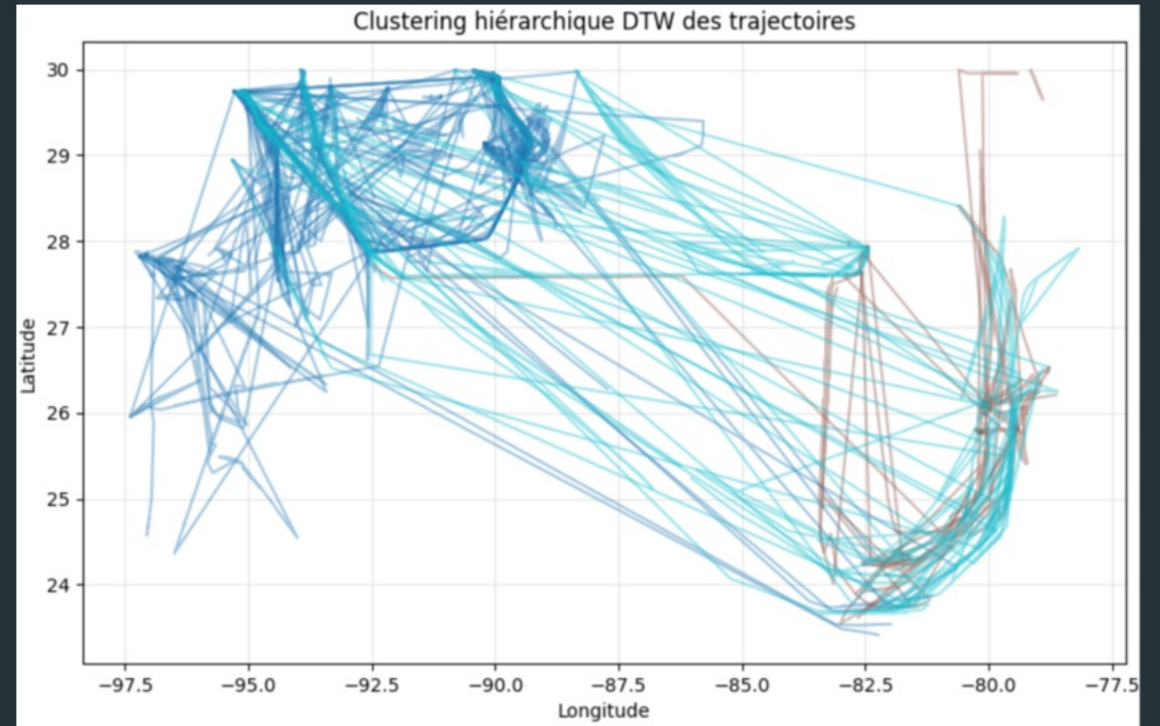
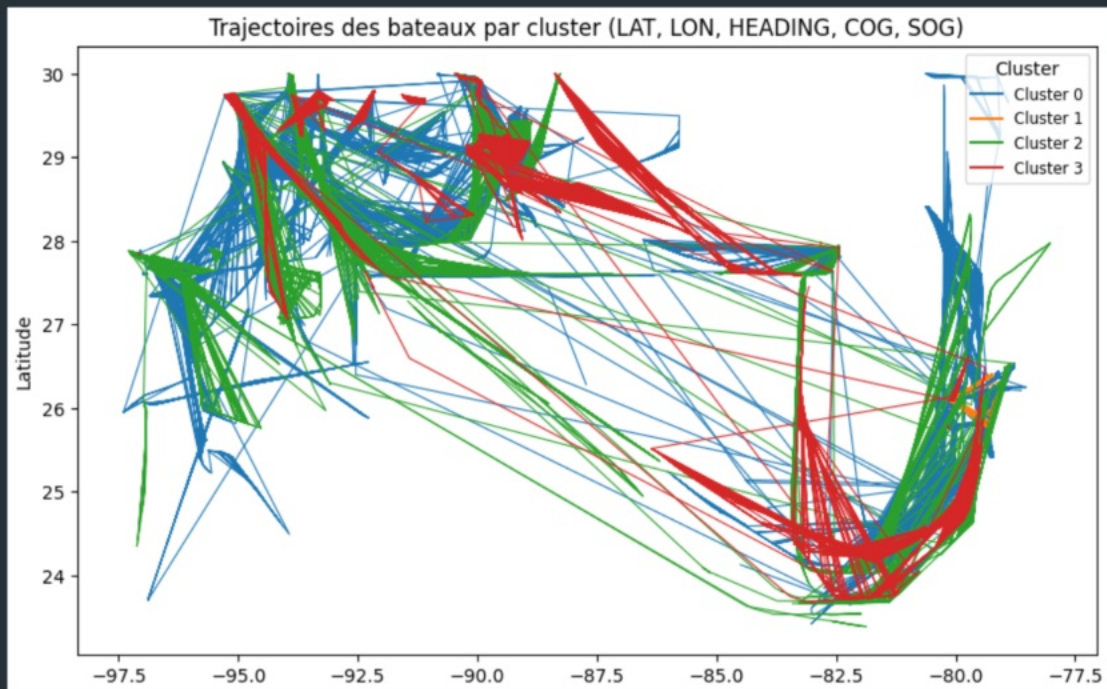


Histogrammes

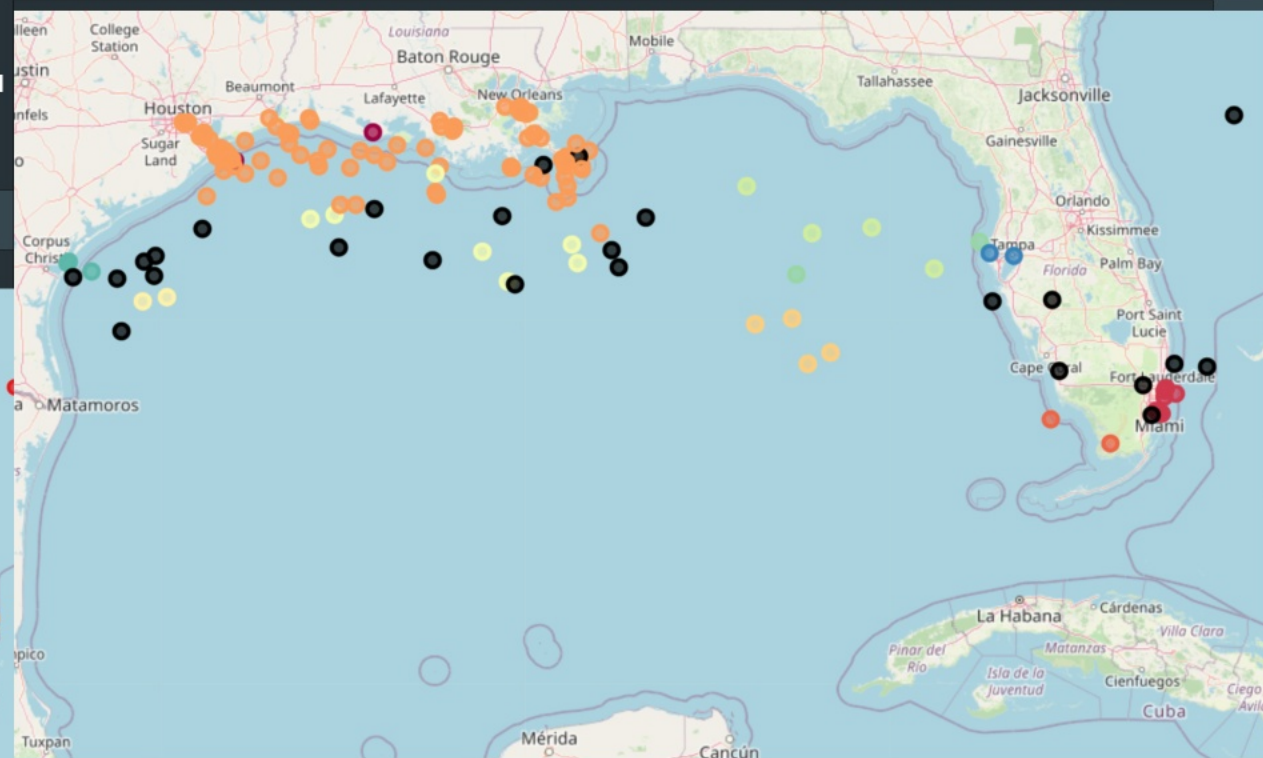
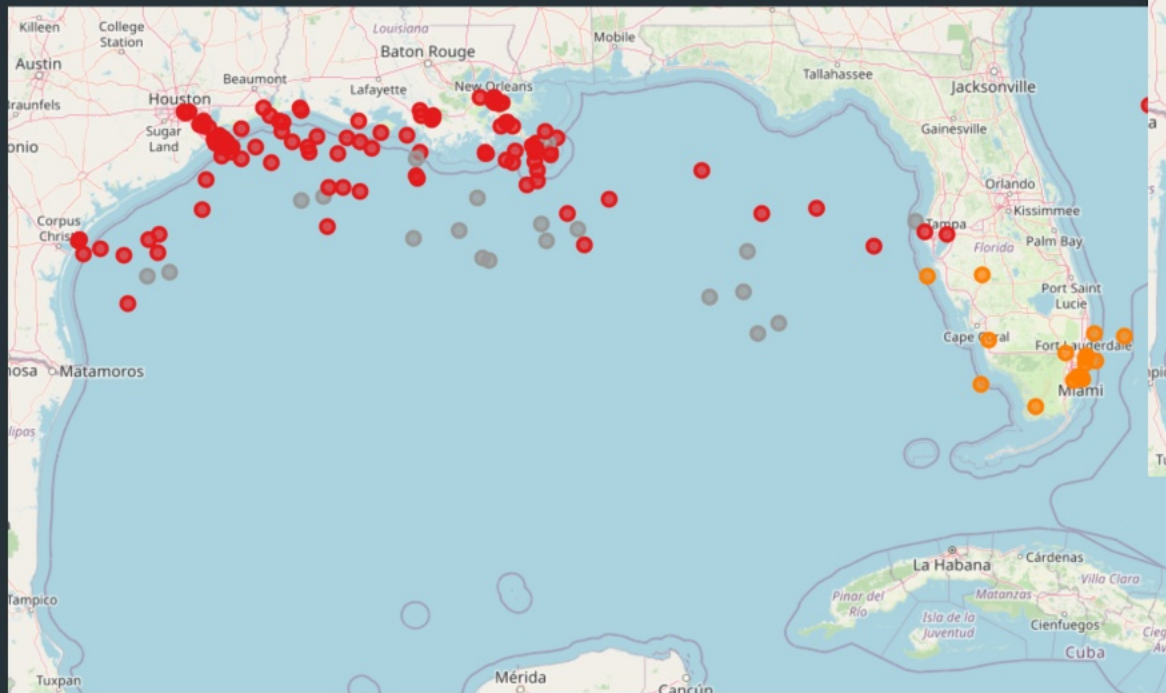
Script final

```
PROJECTION DE COORDONNÉES DES POINTS DE VUE  
POINTS DISPONIBLES:  
1. Miami (lat: 25.7617, lon: -80.1918)  
2. New Orleans (lat: 29.9511, lon: -90.0715)  
3. Houston (lat: 29.7604, lon: -95.3698)  
4. Savannah (lat: 32.0809, lon: -81.0991)  
5. Tampa (lat: 27.7661, lon: -82.5419)  
6. Tampa (lat: 27.7661, lon: -82.5419)  
7. Tampa (lat: 27.7661, lon: -82.5419)  
8. Tampa (lat: 27.7661, lon: -82.5419)  
9. Tampa (lat: 27.7661, lon: -82.5419)  
10. Tampa (lat: 27.7661, lon: -82.5419)  
11. Tampa (lat: 27.7661, lon: -82.5419)  
12. Tampa (lat: 27.7661, lon: -82.5419)  
13. Tampa (lat: 27.7661, lon: -82.5419)  
14. Tampa (lat: 27.7661, lon: -82.5419)  
15. Tampa (lat: 27.7661, lon: -82.5419)  
16. Tampa (lat: 27.7661, lon: -82.5419)  
17. Tampa (lat: 27.7661, lon: -82.5419)  
18. Tampa (lat: 27.7661, lon: -82.5419)  
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44. Tampa (lat: 27.7661, lon: -82.5419)  
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47. Tampa (lat: 27.7661, lon: -82.5419)  
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69. Tampa (lat: 27.7661, lon: -82.5419)  
70. Tampa (lat: 27.7661, lon: -82.5419)  
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78. Tampa (lat: 27.7661, lon: -82.5419)  
79. Tampa (lat: 27.7661, lon: -82.5419)  
80. Tampa (lat: 27.7661, lon: -82.5419)  
81. Tampa (lat: 27.7661, lon: -82.5419)  
82. Tampa (lat: 27.7661, lon: -82.5419)  
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88. Tampa (lat: 27.7661, lon: -82.5419)  
89. Tampa (lat: 27.7661, lon: -82.5419)  
90. Tampa (lat: 27.7661, lon: -82.5419)  
91. Tampa (lat: 27.7661, lon: -82.5419)  
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97. Tampa (lat: 27.7661, lon: -82.5419)  
98. Tampa (lat: 27.7661, lon: -82.5419)  
99. Tampa (lat: 27.7661, lon: -82.5419)  
100. Tampa (lat: 27.7661, lon: -82.5419)
```

Clustering 1.



Clustering 1.

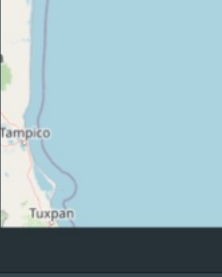


Adaption des données

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col_names = [  
    'lon_min', 'lon_max',  
    'lat_min', 'lat_max',  
    'lon_ctr', 'lat_ctr',  
    'lon_rng', 'lat_rng',  
    'area', 'total_d'  
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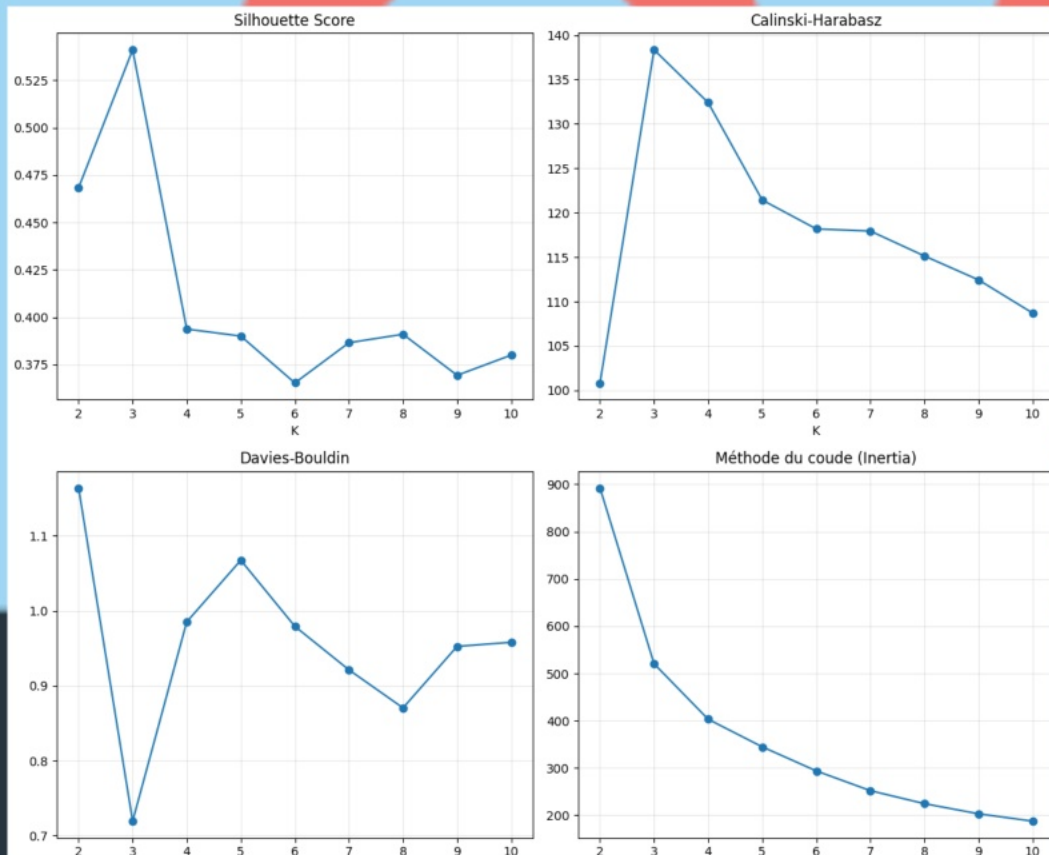
2

oul des clusters

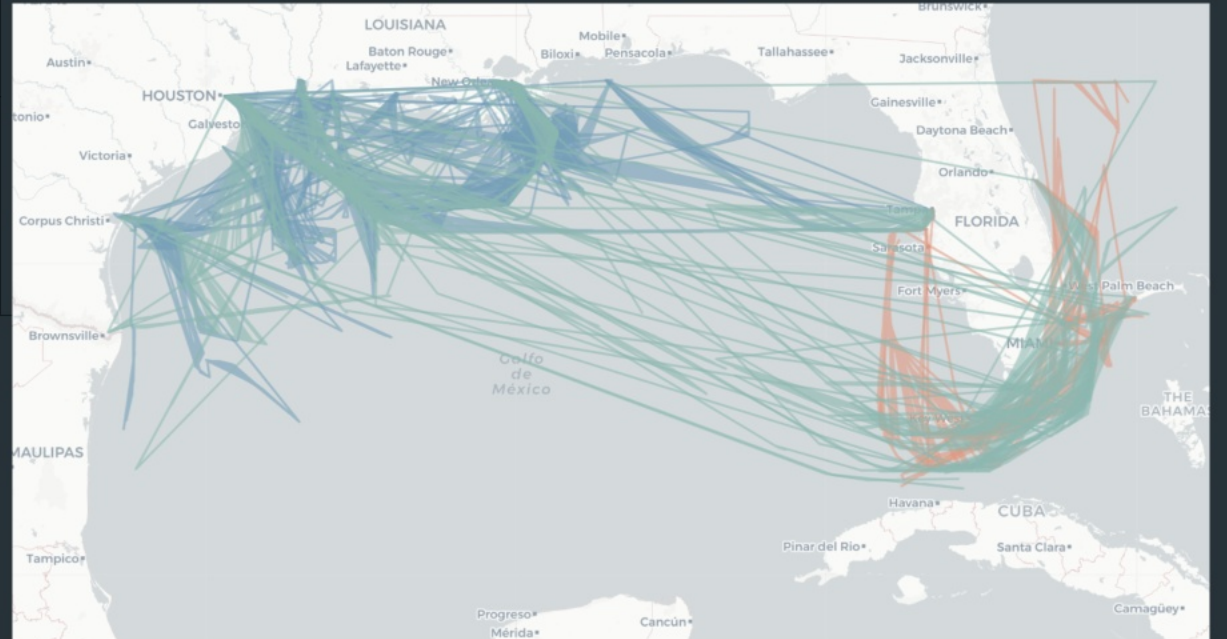
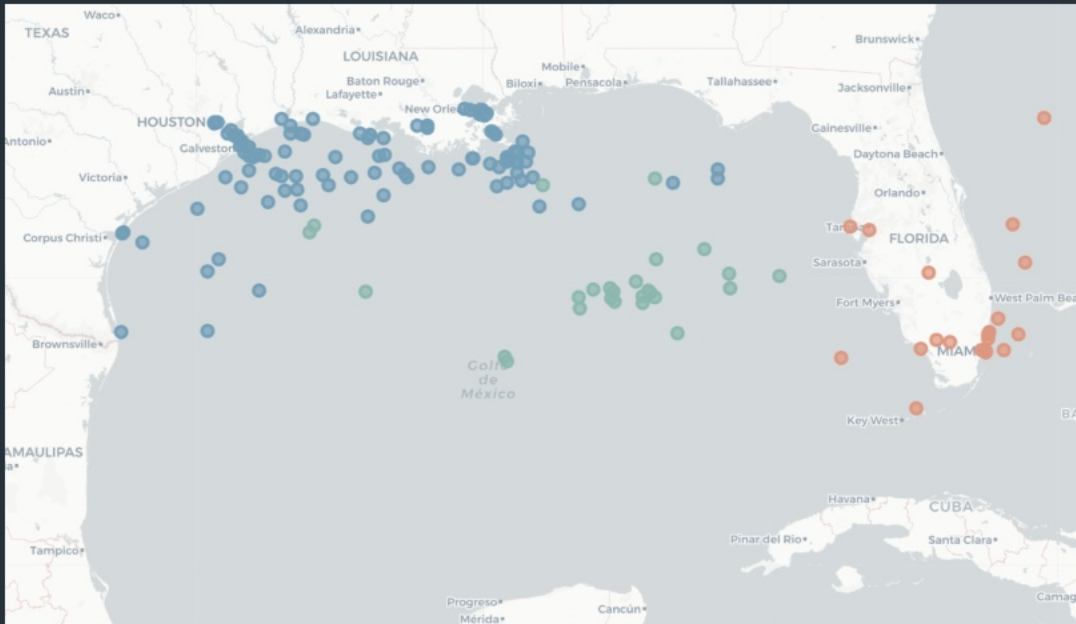


Calcul des clusters

Kmeans
2->10

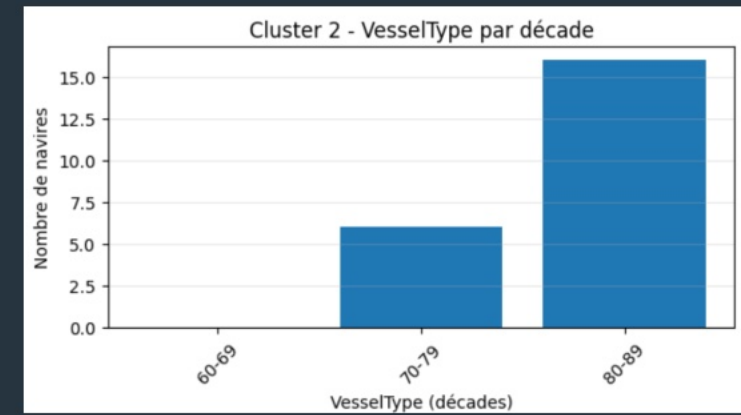
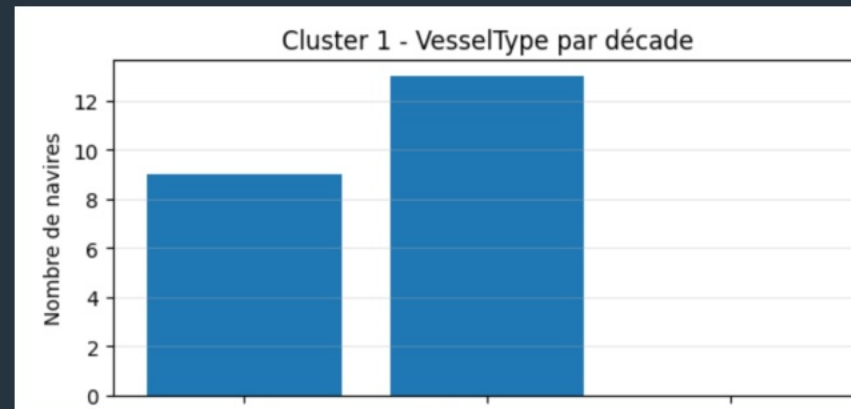
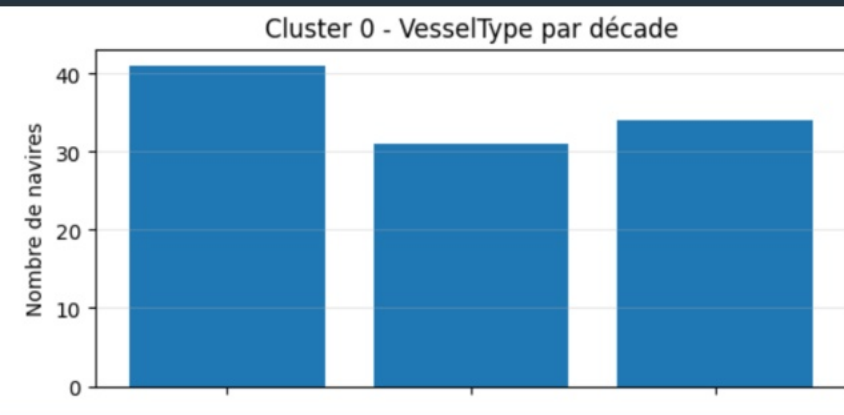


Clustering 2.



Histogrammes

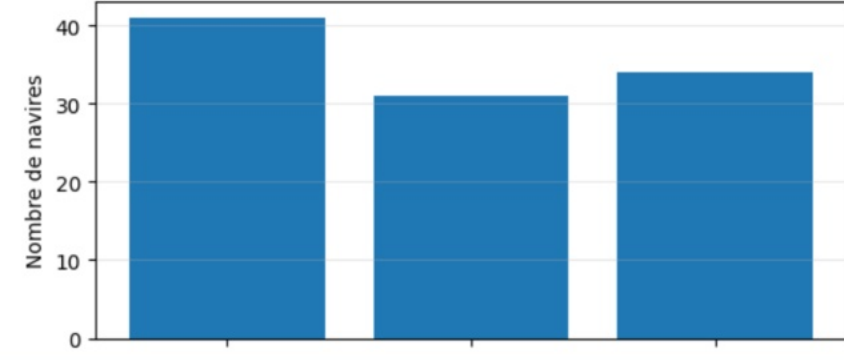
Histogrammes



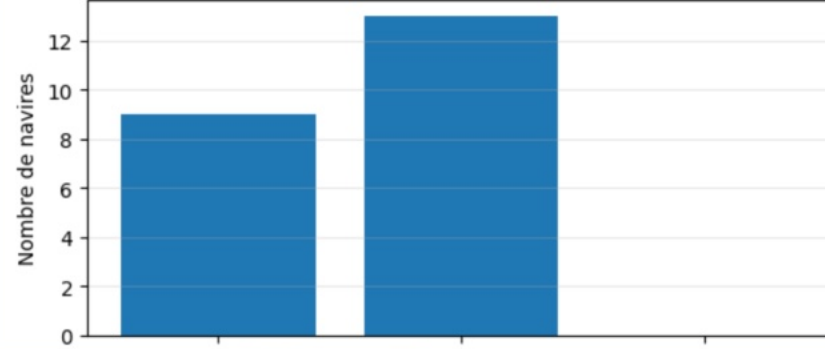
Histogrammes



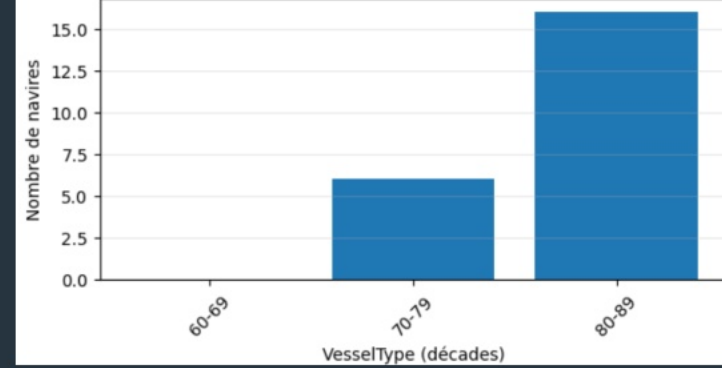
Cluster 0 - VesselType par décade



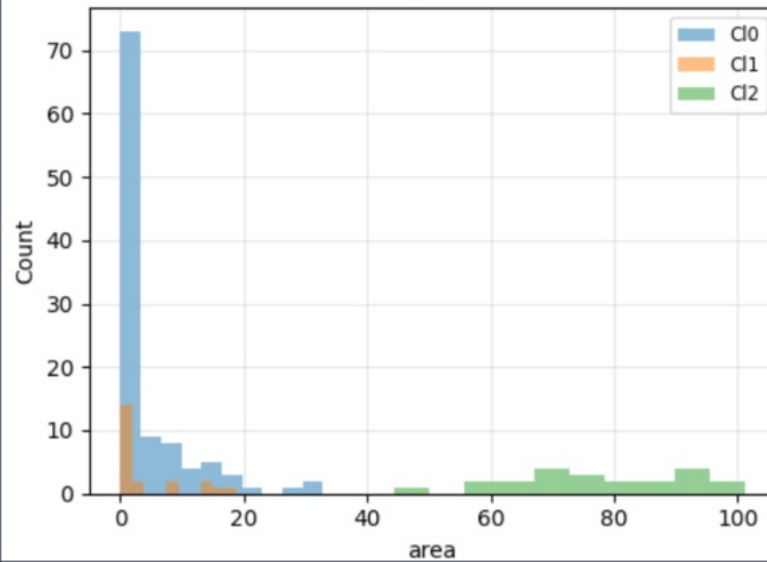
Cluster 1 - VesselType par décade



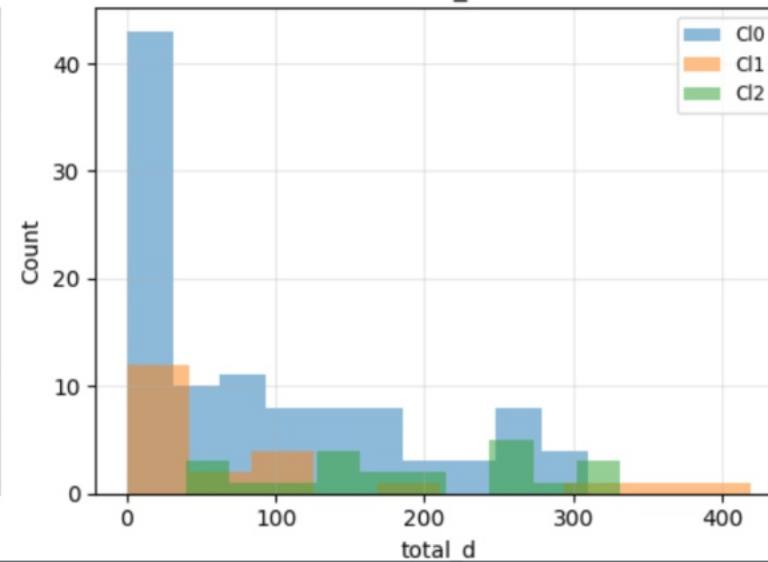
Cluster 2 - VesselType par décade



area



total_d



Script final

🚢 PRÉDICTION DE CLUSTER POUR TRAJETS MARITIMES 🚢

=====

PORTS DISPONIBLES:

=====

- | | |
|-------------------|-------------------------------|
| 1. Miami | (Lat: 25.7617, Lon: -80.1918) |
| 2. New Orleans | (Lat: 29.9511, Lon: -90.0715) |
| 3. Houston | (Lat: 29.7604, Lon: -95.3698) |
| 4. Beaumont | (Lat: 30.0860, Lon: -94.1018) |
| 5. Corpus Christi | (Lat: 27.7322, Lon: -97.0734) |
| 6. Tampa | (Lat: 27.9506, Lon: -82.4572) |
| 7. Key West | (Lat: 24.5551, Lon: -81.7821) |
- =====

❖ Choisissez le port de DÉPART:

Votre choix:

Script final

🚢 PRÉDICTION DE CLUSTER POUR TRAJETS MARITIMES 🚢

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- =====

❖ Choisissez le port de DÉPART:

Votre choix: tampa

🎯 Choisissez le port d'ARRIVÉE:

Votre choix:

Script final

🚢 PRÉDICTION DE CLUSTER POUR TRAJETS MARITIMES 🚢

=====

PORTS DISPONIBLES:

=====

1. Miami (Lat: 25.7617, Lon: -80.1918)
 2. New Orleans (Lat: 29.9511, Lon: -90.0715)
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 7. Key West (Lat: 24.5551, Lon: -81.7821)
- =====

🎯 Choisissez le port de DÉPART:

Votre choix: tampa

🎯 Choisissez le port d'ARRIVÉE:

Votre choix: miami

📍 TRAJET : Tampa -> Miami

Distance approximative : 3.1501°

🔄 Prédiction en cours...

🎉 RÉSULTAT : CLUSTER 1

Fin du script. Merci d'avoir utilisé le prédicteur ! 🐙

Script final

🚢 PRÉDICTION DE CLUSTER POUR TRAJETS MARITIMES 🚢

PORTS DISPONIBLES:

- | | |
|-------------------|-------------------------------|
| 1. Miami | (Lat: 25.7617, Lon: -80.1918) |
| 2. New Orleans | (Lat: 29.9511, Lon: -90.0715) |
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🎯 Choisissez le port de DÉPART:

Votre choix: tampa

🎯 Choisissez le port d'ARRIVÉE:

Votre choix: miami

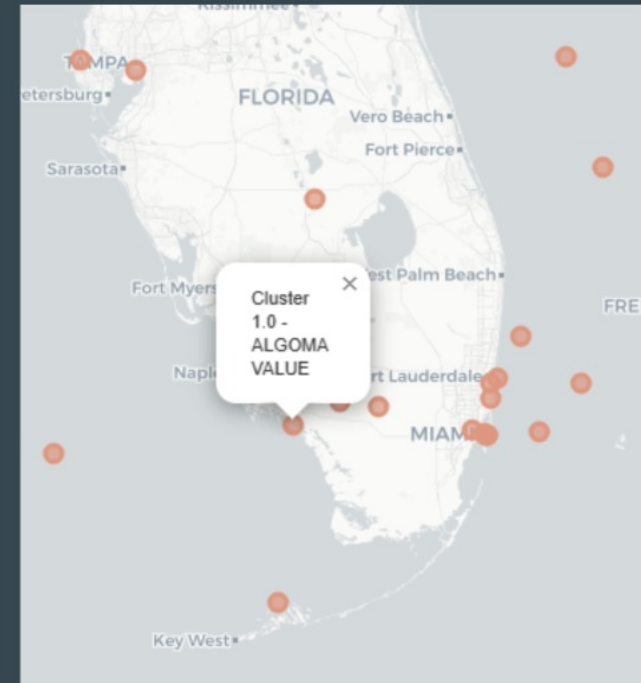
📍 TRAJET : Tampa -> Miami

Distance approximative : 3.1501°

🔄 Prédiction en cours...

🎉 RÉSULTAT : CLUSTER 1

Fin du script. Merci d'avoir utilisé le prédicteur ! 🤖



Estimation des modèles :

LogisticRegression Accuracy: 0.886
GradientBoosting Accuracy: 0.864

Test avec Cargo

```
=== Test set performance ===  
Accuracy      : 0.909  
F1-score macro : 0.640
```

```
=== 5-fold CV performance ===  
Accuracy      : 0.863 ± 0.063  
F1-score macro : 0.630 ± 0.069
```

Interpréteur

Interpréteur (dalex)

```
A new explainer has been created!  
Instance 3 | Vrai : 70 → Prédit : 70  
<dalex.predict_explanations_break_down.object.BreakDown object at 0x7083377e090>  
Instance 9 | Vrai : 69 → Prédit : 60  
<dalex.predict_explanations_break_down.object.BreakDown object at 0x70833c289650>  
Instance 20 | Vrai : 89 → Prédit : 80  
<dalex.predict_explanations_break_down.object.BreakDown object at 0x708337f8f650>  
Instance 42 | Vrai : 80 → Prédit : 70  
<dalex.predict_explanations_break_down.object.BreakDown object at 0x70833c33e810>  
Modèle et LabelEncoder enregistrés dans /content/drive/MyDrive
```

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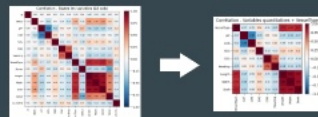
12

Besoin Client 2

Script

```
● Pipeline et LabelEncoder chargés depuis "/content/drive/MyDrive"  
# Entrez les caractéristiques du navire à prédire :  
# Largeur (width) : 28  
# Tirant d'eau (Draft) : 10  
# Longueur (Length) : 183  
# Type de cargo (numérique, ex: 70, 80, 90, etc.) : 83  
# Résultat de la prédiction :  
# Type de navire prédit : 80  
# Confiance du modèle : 90.67%
```

Matrices de corrélation



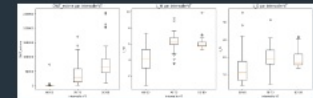
Début des prédictions

```
9 features →  
== Modèle 1 : features d'étendue ==  
Accuracy (test) : 1.000  
3 features (Length, Width, Draft) →  
== Modèle 2 : features statiques seulement ==  
Accuracy (test) : 1.000
```

Solution 1 : 70% MMSI en train/30% MMSI en test (gourmand)

Solution 2 : Premier signal par bateau (perte d'info)

Feature ingeneering



DWT, estime = CB * Length * Width * Draft * g
L, W = Length / Width
B, D = Length / Draft

13

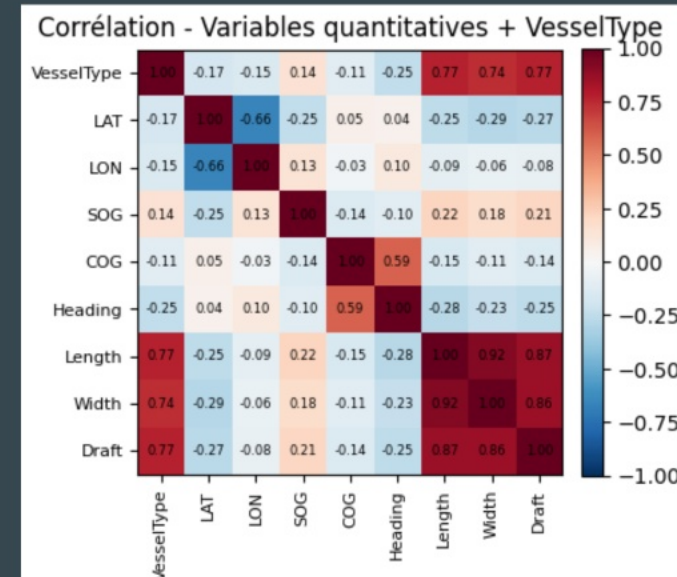
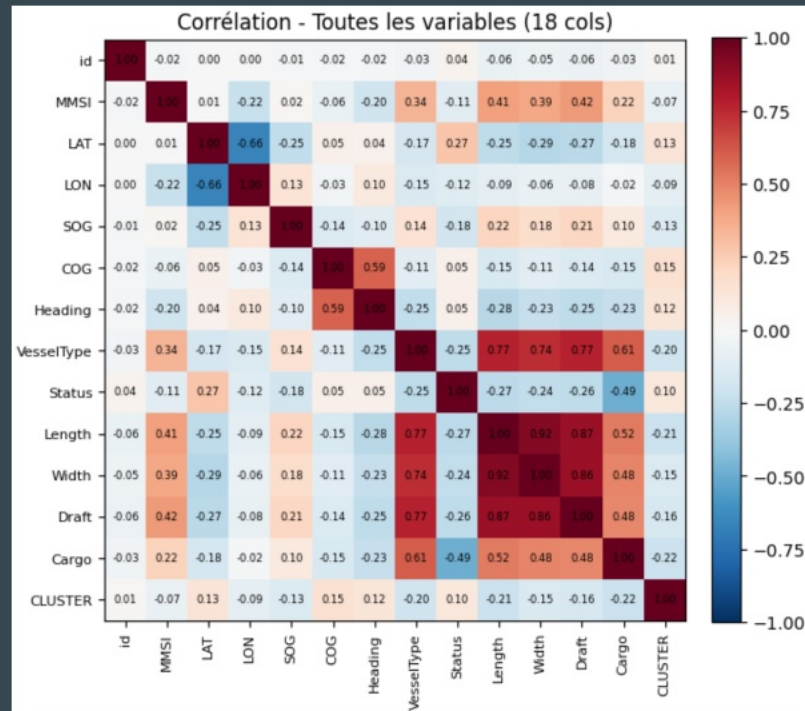
7

8

9

10

Matrices de corrélation



Début des prédictions

9 features ->

```
=== Modèle 1 : features étendues ===  
Accuracy (test)      : 1.000
```

3 features (Length, Width, Draft)->

```
=== Modèle 2 : features statiques seulement ===  
Accuracy (test)      : 1.000
```

Début des prédictions

9 features ->

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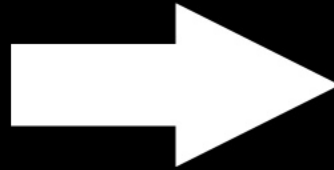
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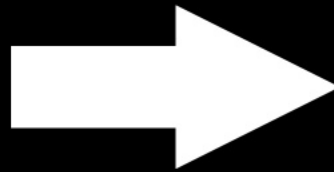
Début des prédictions

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Fuite de données car
signaux réptitifs



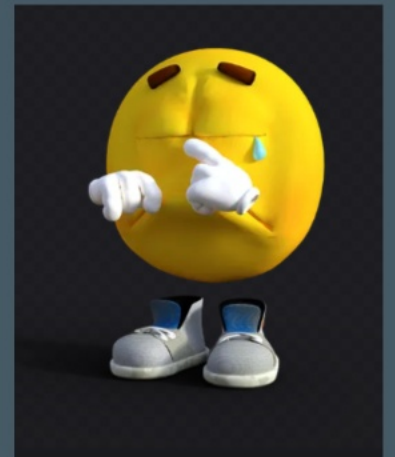
Solution 1 : 70% MMSI en train/30% MMSI en test (gourmand)



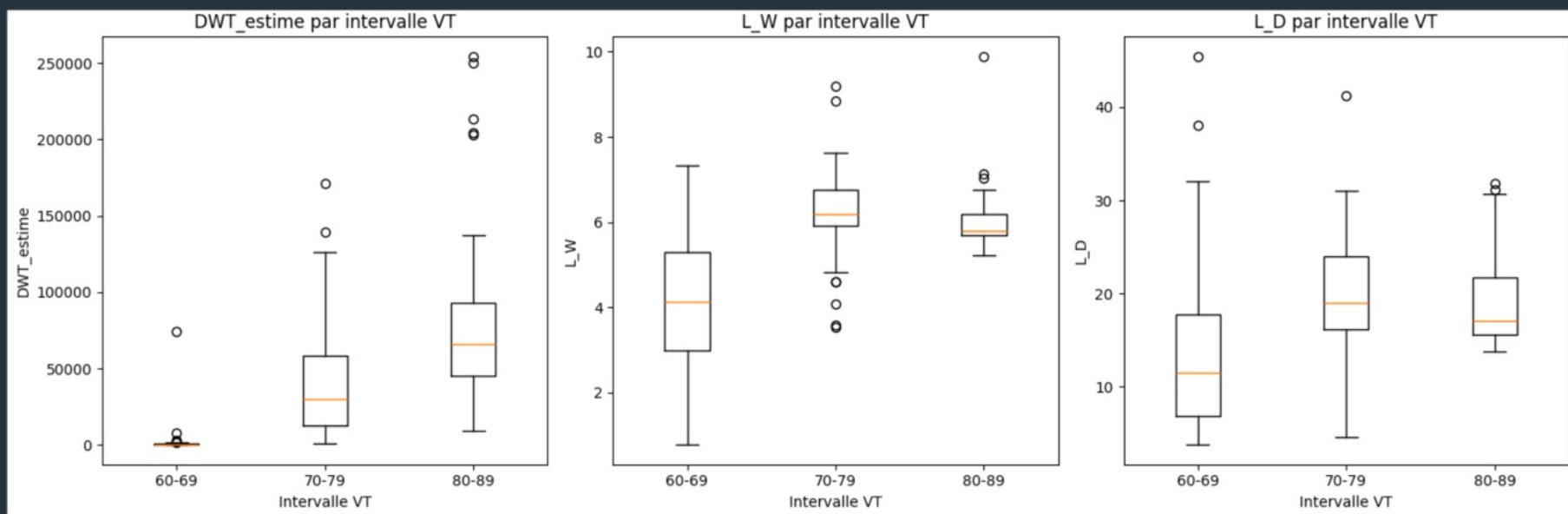
Solution 2 : Première signal par bateau (perte d'info)

↗ Solution 1 : 70% MMSI en train/30% MMSI en test (gourmand)

→ Solution 2 : Première signal par bateau (perte d'info)



Feature ingeenering

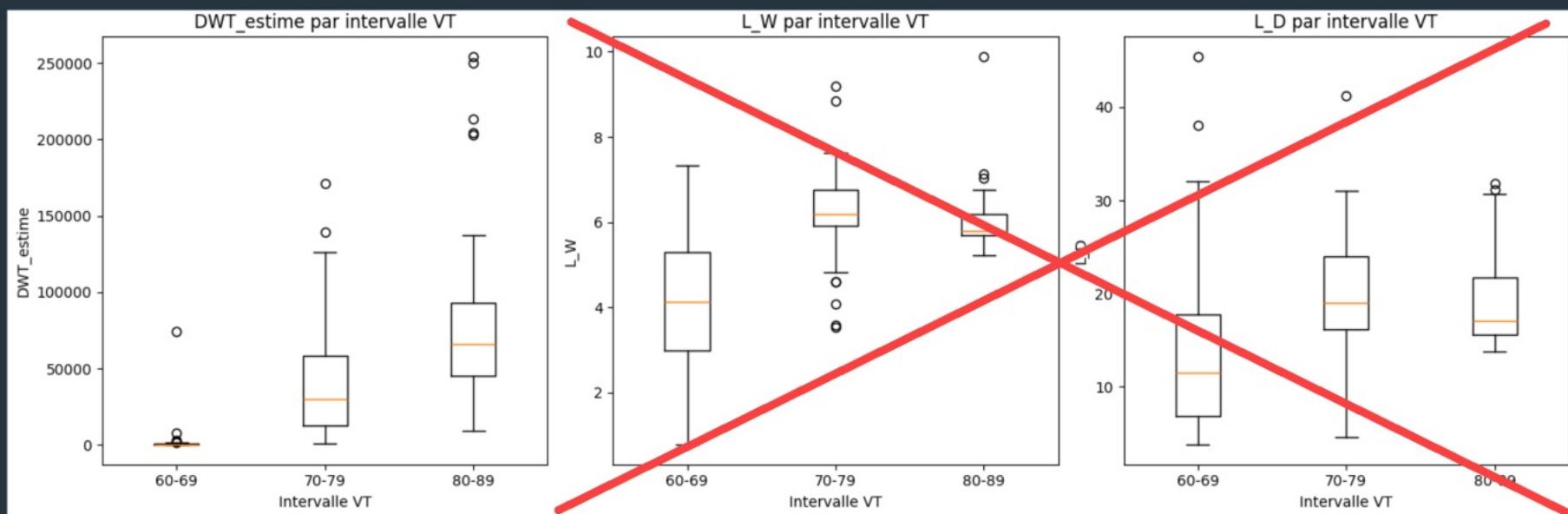


$DWT_estime = CB \times Length \times Width \times Draft \times \rho$

$L_W = Length / Width$

$L_D = Length / Draft$

Feature ingeenering



$DWT_estime = CB \times Length \times Width \times Draft \times \rho$

$L_W = Length / Width$

$L_D = Length / Draft$


$$L_W = \text{Length} / \text{Width}$$
$$L_D = \text{Length} / \text{Draft}$$

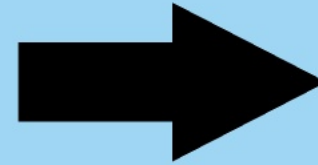
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Interpréteur

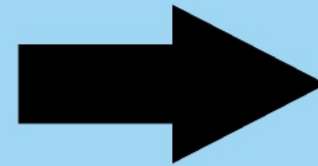
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Interpréteur

Test sans Cargo

```
=== Test set performance ===  
Accuracy           : 0.818  
F1-score macro    : 0.366
```

Interpréteur (dalex)

A new explainer has been created!

Instance 3 | Vrai : 70 → Prédit : 79
<dalex.predict_explanations._break_down.object.BreakDown object at 0x7b8337f7e090>

Instance 9 | Vrai : 69 → Prédit : 60
<dalex.predict_explanations._break_down.object.BreakDown object at 0x7b833c289650>

Instance 20 | Vrai : 89 → Prédit : 80
<dalex.predict_explanations._break_down.object.BreakDown object at 0x7b8337f8fb50>

Instance 42 | Vrai : 80 → Prédit : 70
<dalex.predict_explanations._break_down.object.BreakDown object at 0x7b833c33e810>
Modèle et LabelEncoder enregistrés dans /content/drive/MyDrive

A new explainer has been created!

Instance 3 | Vrai : 70 → Prédit : 79
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Modèle et LabelEncoder enregistrés dans /content/drive/MyDrive

Interpréteur (dalex)

Erreur 3 — Instance 20 | Vrai : 89 → Prédit : 80

Break Down



A new explainer has been created!

Instance 3 | Vrai : 70 → Prédit : 79

<dalex.predict_explanations._break_down.object.BreakDown object at 0x7b8337f7e090>

Instance 9 | Vrai : 69 → Prédit : 60

<dalex.predict_explanations._break_down.object.BreakDown object at 0x7b833c289650>

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Instance 42 | Vrai : 80 → Prédit : 70

<dalex.predict_explanations._break_down.object.BreakDown object at 0x7b833c33e810>

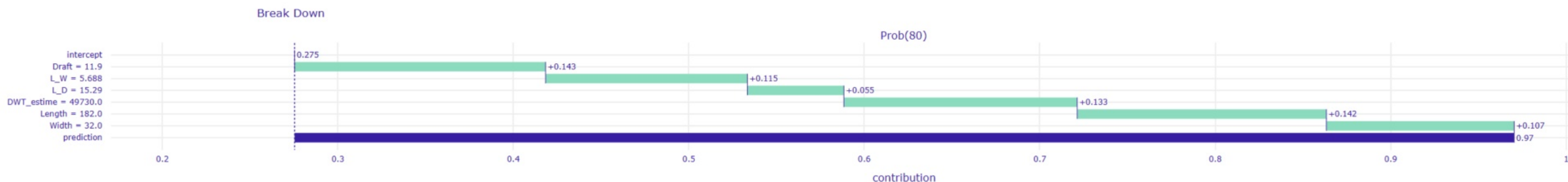
Modèle et LabelEncoder enregistrés dans /content/drive/MyDrive

Interpréteur (dalex)

Erreur 3 — Instance 20 | Vrai : 89 → Prédit : 80



✓ Succès — Instance 0 | Vrai : 80 → Prédit : 80 (97.0%)



Script

 Pipeline et LabelEncoder chargés depuis `~/content/drive/MyDrive``

 Entrez les caractéristiques du navire à prédire :

 Largeur (Width) : 28

 Tirant d'eau (Draft) : 10

 Longueur (Length) : 183

 Type de cargo (numérique, ex: 70, 80, 90, etc.) : 83

 Résultat de la prédiction :

 Type de navire prédit : 80

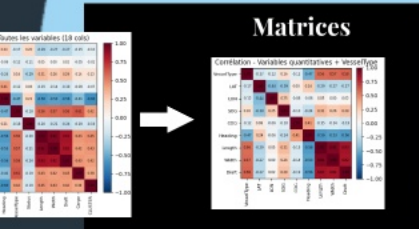
 Confiance du modèle : 69.67%



Projet IA A3

Analyse des données
maritimes dans le golfe
du Mexique

Besoin client 3



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Choix du modèle

Prédire la position future (LAT, LONG) d'un sardine à partir de ses données historiques.
→ Machine Learning (ML) et LLM
→ Capture des relations complexes
RandomForest/Regressor

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Amélioration du modèle

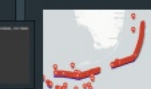
Modèle	MAE	RMSE	R2	Score
ML	0.0000	0.0000	0.0000	0.0000
ML	0.0000	0.0000	0.0000	0.0000
ML	0.0000	0.0000	0.0000	0.0000
ML	0.0000	0.0000	0.0000	0.0000

BUT :

Enrichir le modèle pour mieux capturer la dynamique des sardines.

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Visualisation des résultats



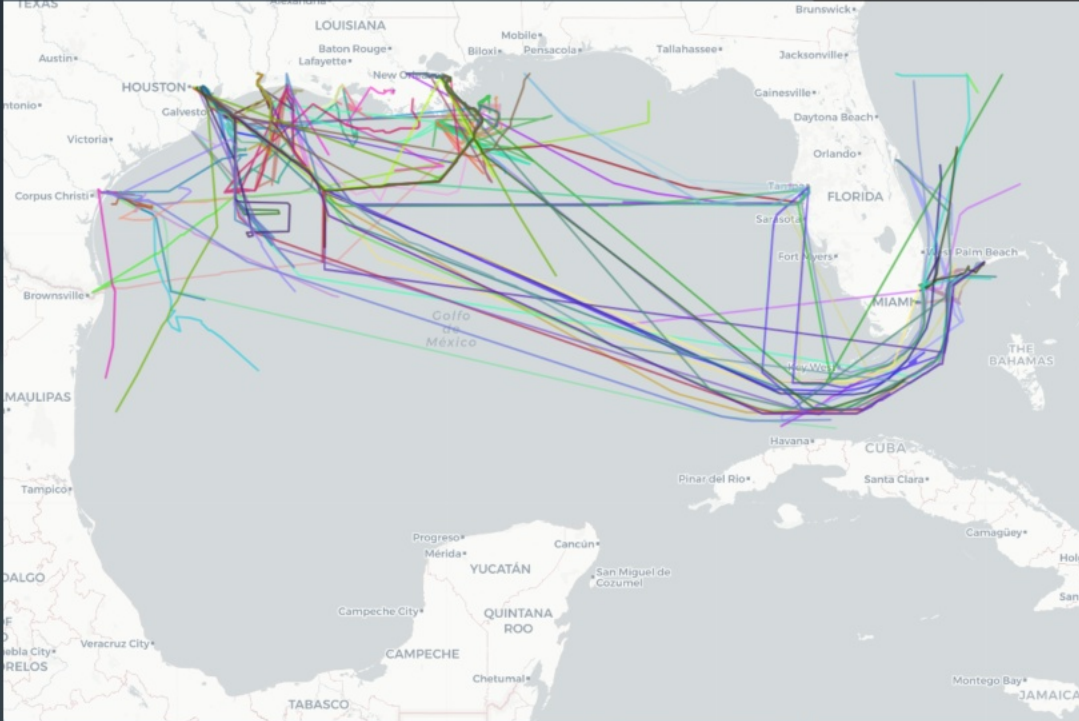
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Choix du modèle

Prédire la position future (LAT, LON) d'un navire à partir de ses données historiques.

- > MultiOutput : LAT et LON
- > Capture des relations complexes

RandomForestRegressor



Amélioration du modèle

	MAE_lat	MAE_lon	RMSE_lat	RMSE_lon	Dist_mean_km
features					
dynamiques	0.4936	1.9143	0.8870	3.3448	199.7484
statiques	0.2949	0.7366	0.6305	1.7556	84.0805
dyn+stat	0.0345	0.0810	0.1455	0.4006	9.8189
dyn+stat+oh	0.0334	0.0772	0.1425	0.4055	9.4337
enrichi_roll5	0.0309	0.0710	0.1301	0.3839	8.7871
full_features	0.0205	0.0429	0.0984	0.2698	5.7047

	MAE_lat	MAE_lon	RMSE_lat	RMSE_lon	Dist_mean_km
tolerance					
30s	0.049270	0.095587	0.194374	0.508255	12.528254
45s	0.035207	0.055706	0.151667	0.306607	8.014220
1min	0.020467	0.042943	0.098445	0.269807	5.704652
2min	0.015108	0.041026	0.090610	0.277474	4.999919
3min	0.015108	0.036221	0.081960	0.225794	4.576238
5min	0.015195	0.039404	0.087968	0.257217	4.865440

BUT :

Enrichir le modèle pour mieux
capter la dynamique des
manœuvres

Visualisation des résultats

Exemples de MMSI : 538003366, 215583000, 311000808, 636021151, 311070400, 636022111, 244561000, 309587000, 369390000, 241770000
Entrez le MMSI : 538003366

Navire : ALGOMA VALUE (MMSI 538003366)

Horizons disponibles : [5, 10, 15]

Choisissez un horizon (min) : 5

Modèle chargé.

Stats pour +5 min :

MAE LAT : 0.0147°

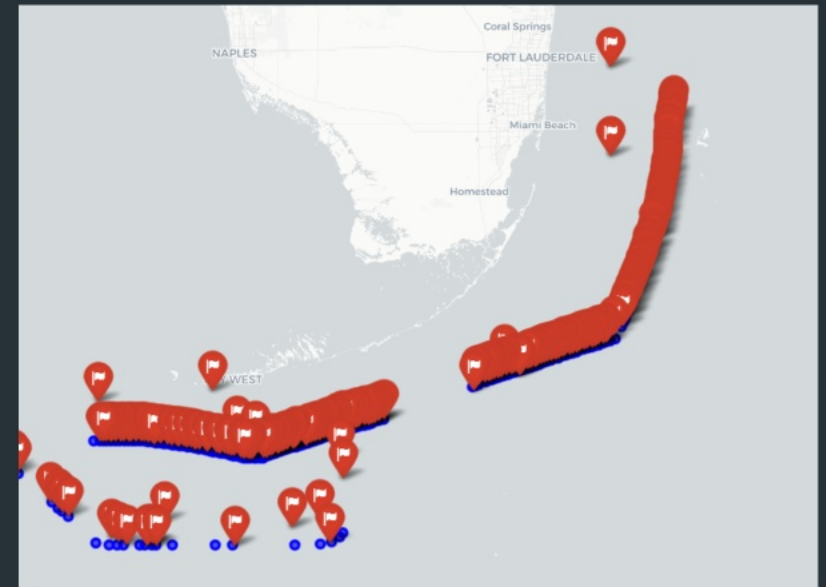
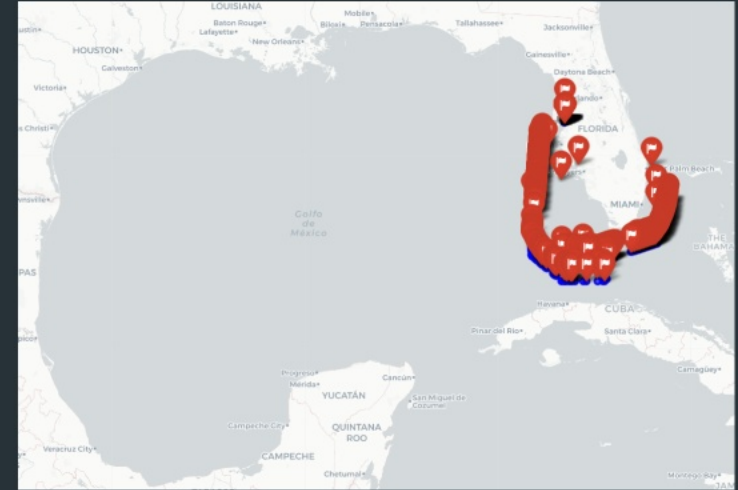
MAE LON : 0.0058°

Méd dist : 0.180 km

Q3 dist : 0.431 km

Moy dist : 1.999 km

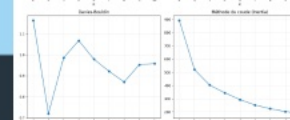
Affichage pour des prédictions à 5 minutes





Projet IA A3

Analyse des données
maritimes dans le golfe
du Mexique



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Histogram



Prédictions

Avec Cargo : `=== Test set performance ===`
 Accuracy : 0.908
 F1-score macro : 0.818

Sans Cargo : `=== Test set performance ===`
 Accuracy : 0.611
 F1-score macro : 0.170

Variation de SOG/COG

Accuracy globale : 0.637

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Bonus

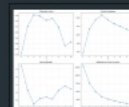


Eurêka

- recherche des données sur le site d'AIS
- téléchargement des csv jour par jour
- concaténation des csv
- nettoyage du merge_csv



Partie 1 -> DB AIS

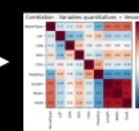


Importation des données
 Cluster 0 (1000 points)
 Cluster 1 (1000 points)
 Cluster 2 (1000 points)
 Cluster 3 (1000 points)

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Matrices



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AIS Data for 2024

Below are links to the CSV files that make up the AIS data for 2024. This HTML file is provided to emulate the access you would have through an ftp site.

The total size to download all the files is 116.7GB.

All Files

[AIS_2024_01_01.zip](#)
[AIS_2024_01_02.zip](#)
[AIS_2024_01_03.zip](#)
[AIS_2024_01_04.zip](#)
[AIS_2024_01_05.zip](#)
[AIS_2024_01_06.zip](#)
[AIS_2024_01_07.zip](#)
[AIS_2024_01_08.zip](#)
[AIS_2024_01_09.zip](#)
[AIS_2024_01_10.zip](#)
[AIS_2024_01_11.zip](#)

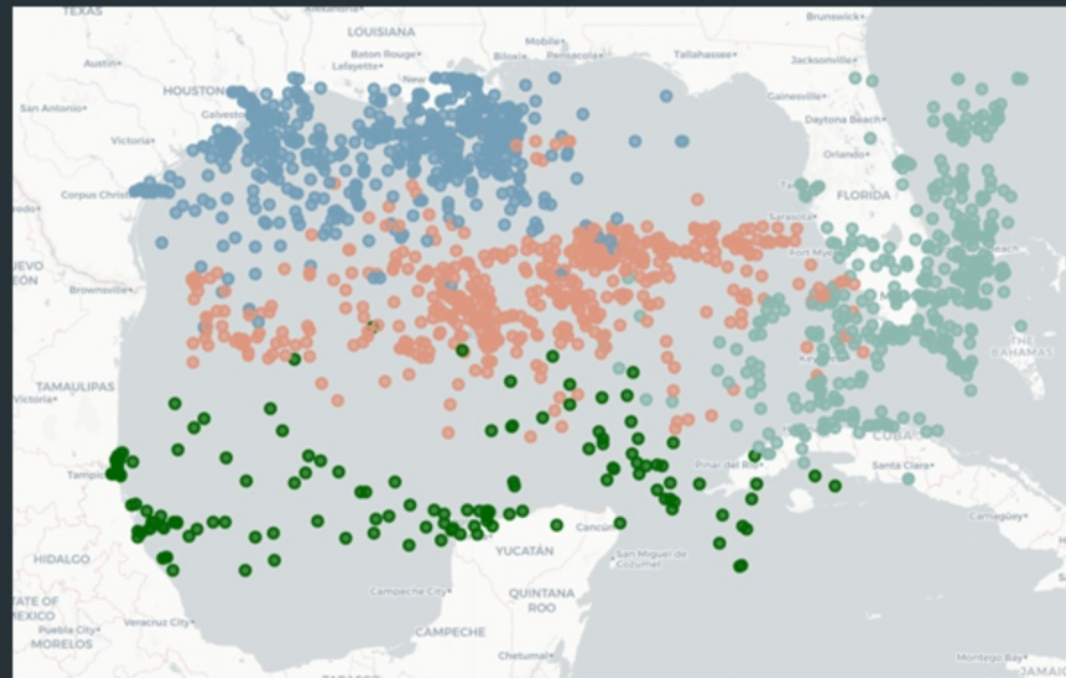
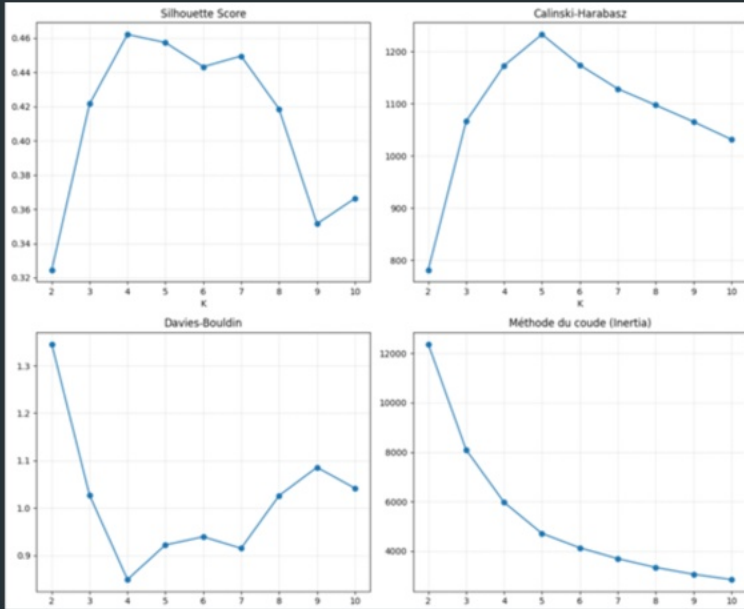
Eurêka

- recherche des données sur le site d'AIS
- téléchargement des csv jour par jour
- concaténation des csv
- nettoyage du merge_csv

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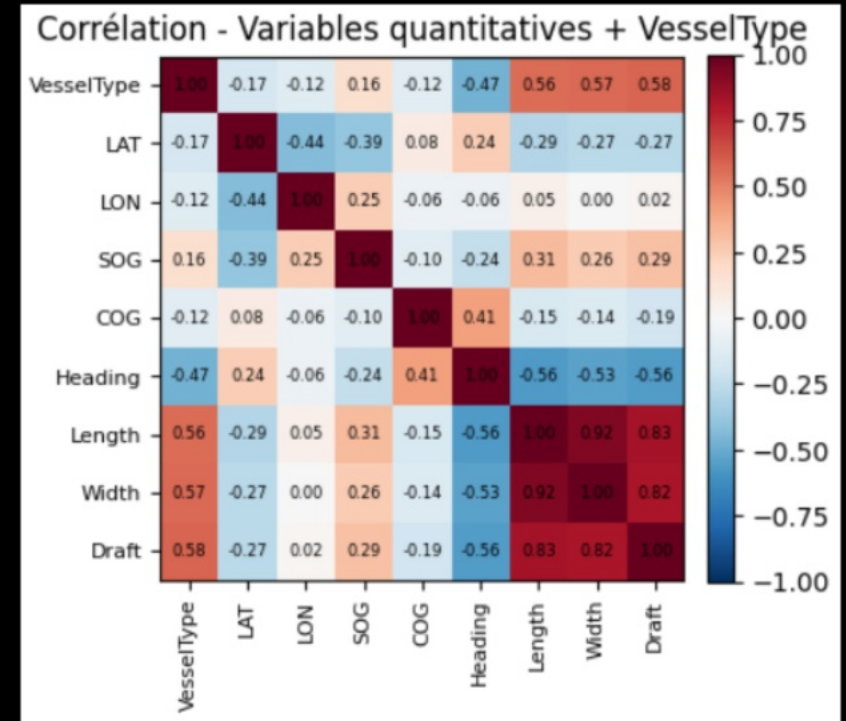
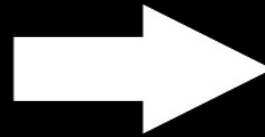
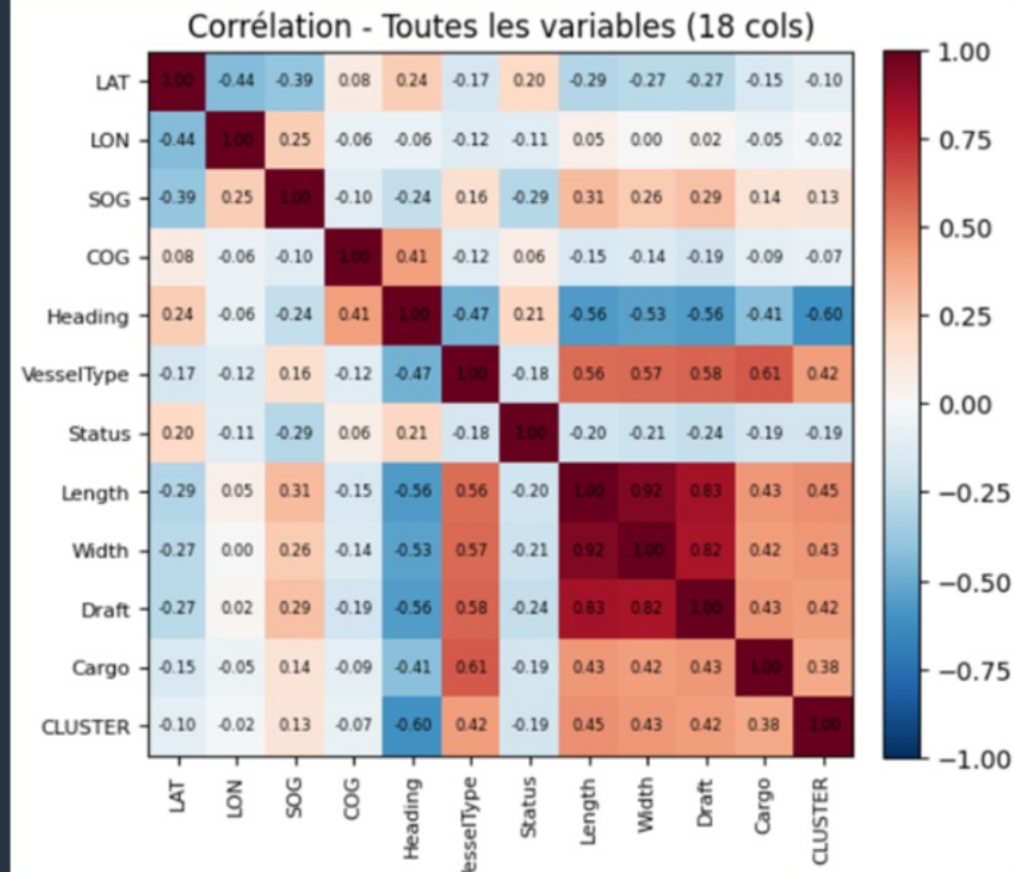


Partie 1 ➤ DB AIS



Composition des clusters
Cluster 0 (690 bateaux):
Cluster 1 (511 bateaux):
Cluster 2 (430 bateaux):
Cluster 3 (150 bateaux):

Matrices



Prédictions

Avec Cargo :

```
=== Test set performance ===  
Accuracy          : 0.908  
F1-score macro    : 0.818
```

Sans Cargo :

```
=== Test set performance ===  
Accuracy          : 0.611  
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