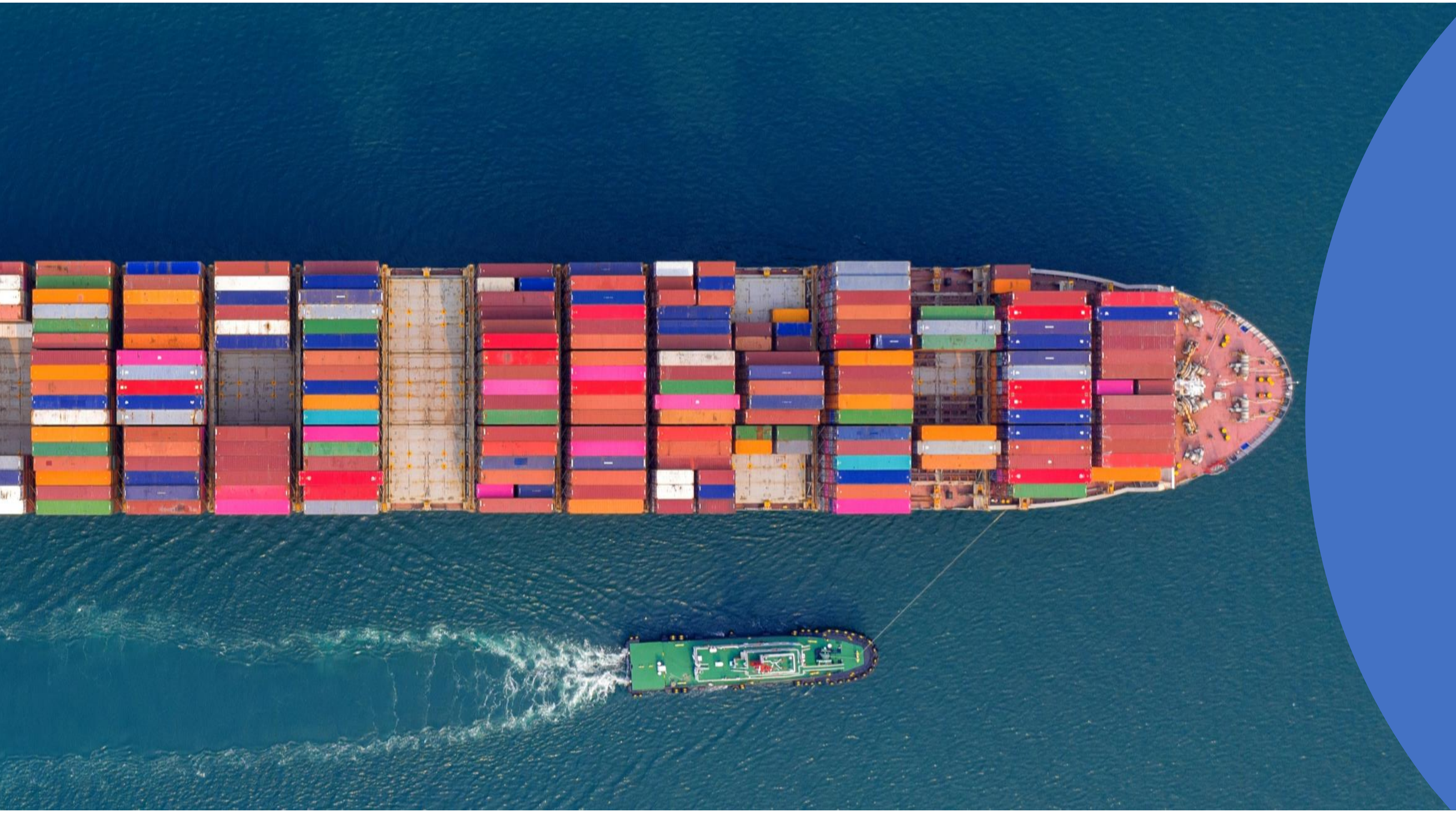
Universität Stuttgart
Analytic Computing



Fachpraktikum

Maritime Anomaly Detection

08.02.2023

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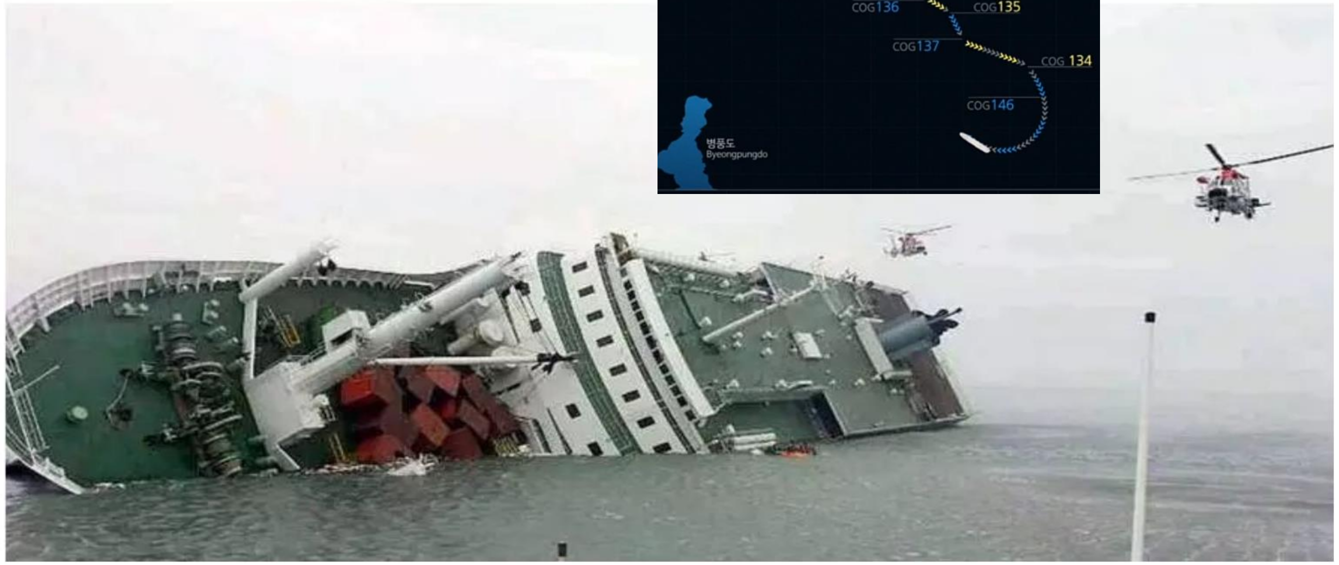
Motivation

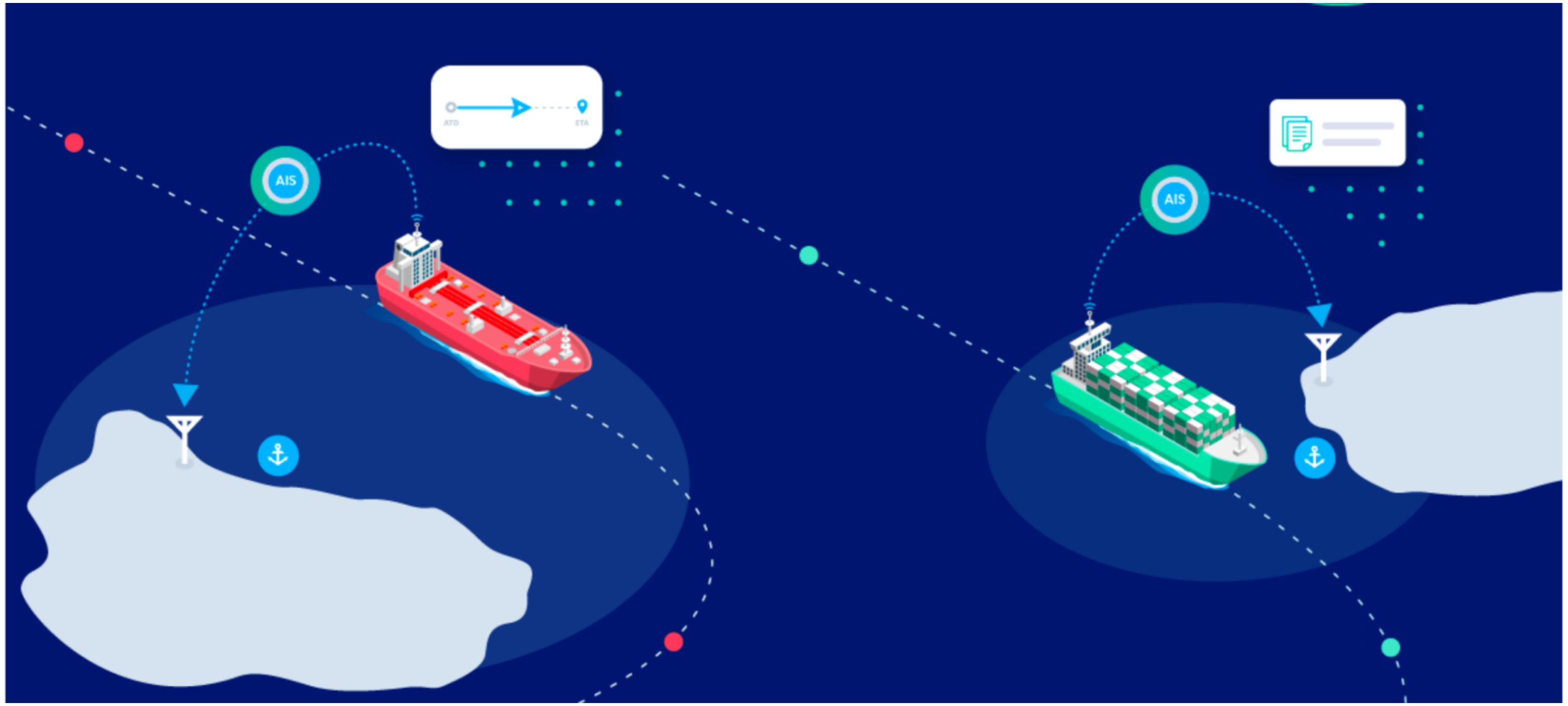
MV Golden Ray *capsized on 08.09.2019 within the Port of Brunswick's harbor*

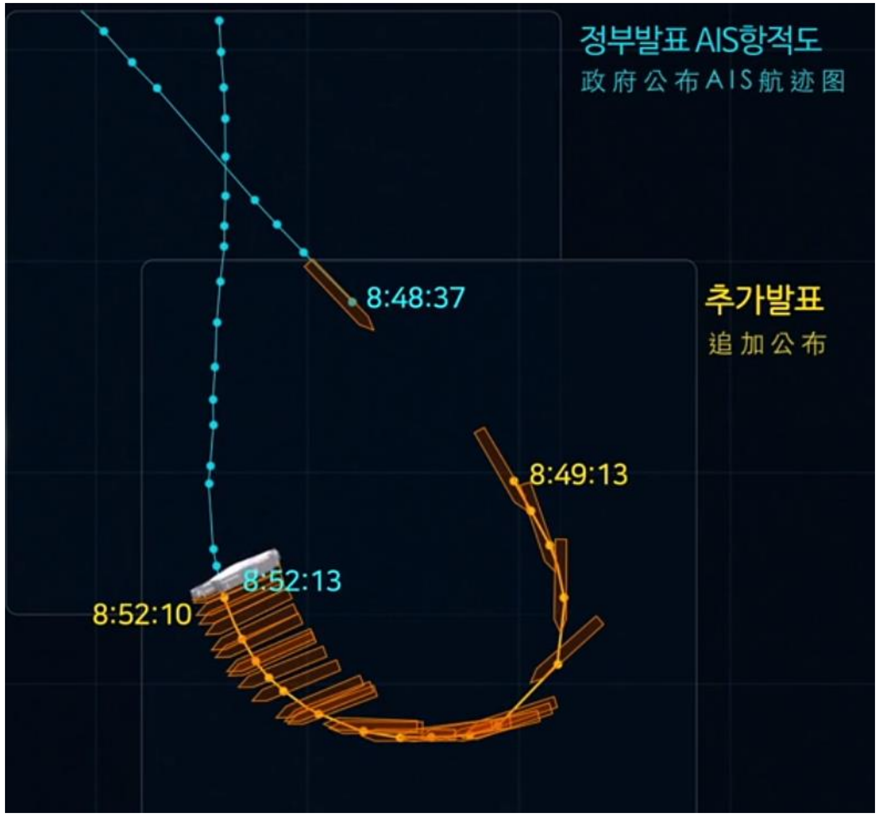


The ferry MV Sewol *sank on the morning of April 16, 2014, an route from Incheon towards Jeju in South Korea, 306 died in the disaster, including around 250 students.*

The automatic detection of abnormal behavior of vessels in ports and sensitive waters and the implementation of early warnings are of great importance in ensuring water traffic safety.

AIS: Automatic Identification System





MMSI	BaseDateTime	LAT	LON	SOG	COG
367369550	2019-09-08T00:00:06	31.14314	-81.49662	12.3	122.8

AIS is an automated, autonomous tracking system that tracks the location of vessels anywhere they are in the world.

MMSI: Maritime Mobile Service Identity, **LAT/LON**: latitude/longitude

SOG: Speed over Ground, **COG:** Course over Ground

What is our goal?

Our goal is to detect if this segment is anomalous!!

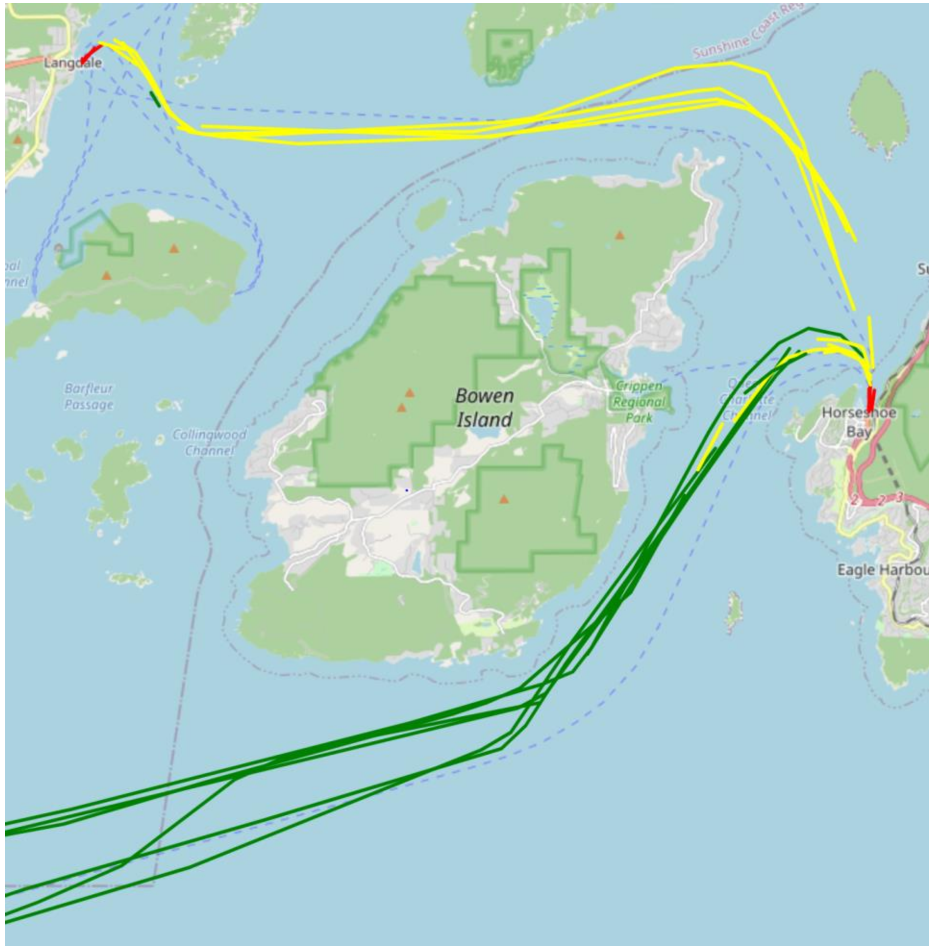
What is segment?

A **segment** contains the information about a ship's journey over **a 10-minute period**.

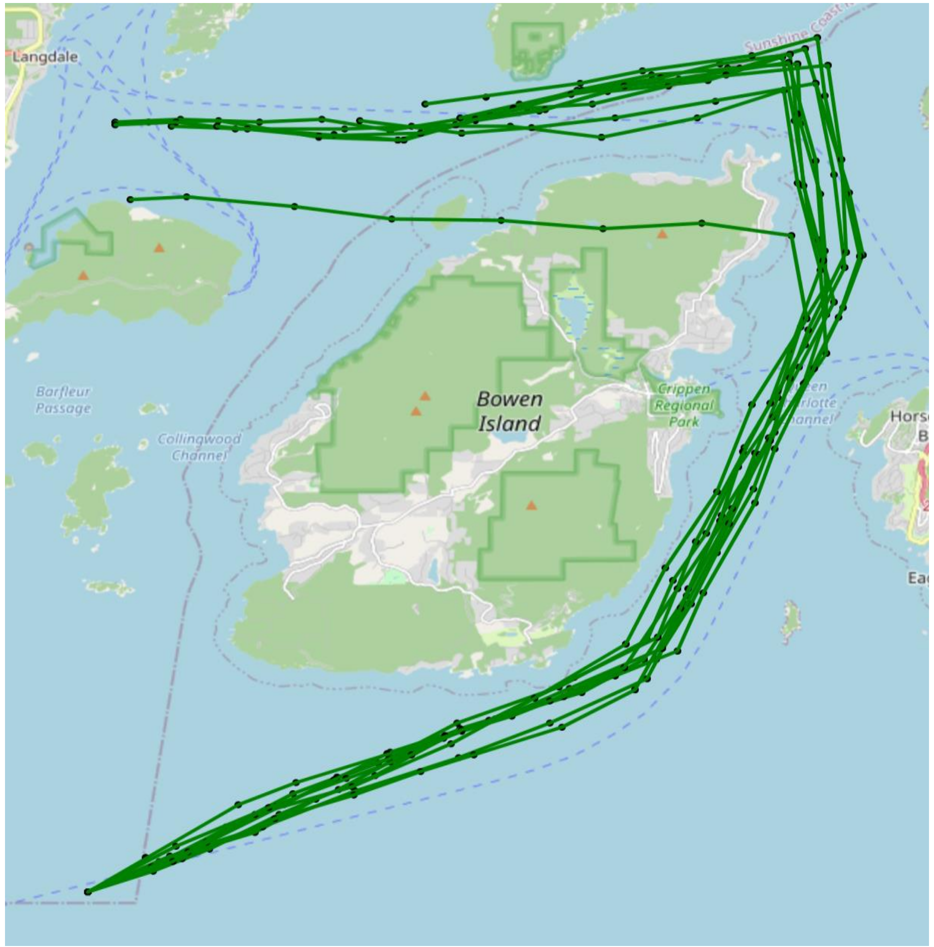
One AIS signal point of one ship per minute can be acquired, but sometimes some signal points may be lost. So in a ten-minute period, we can get up to 10 signal points of a ship.

Method: Supervised learning

We use supervised learning to train the model, so we need to set labels for the dataset to distinguish between abnormal and normal data.



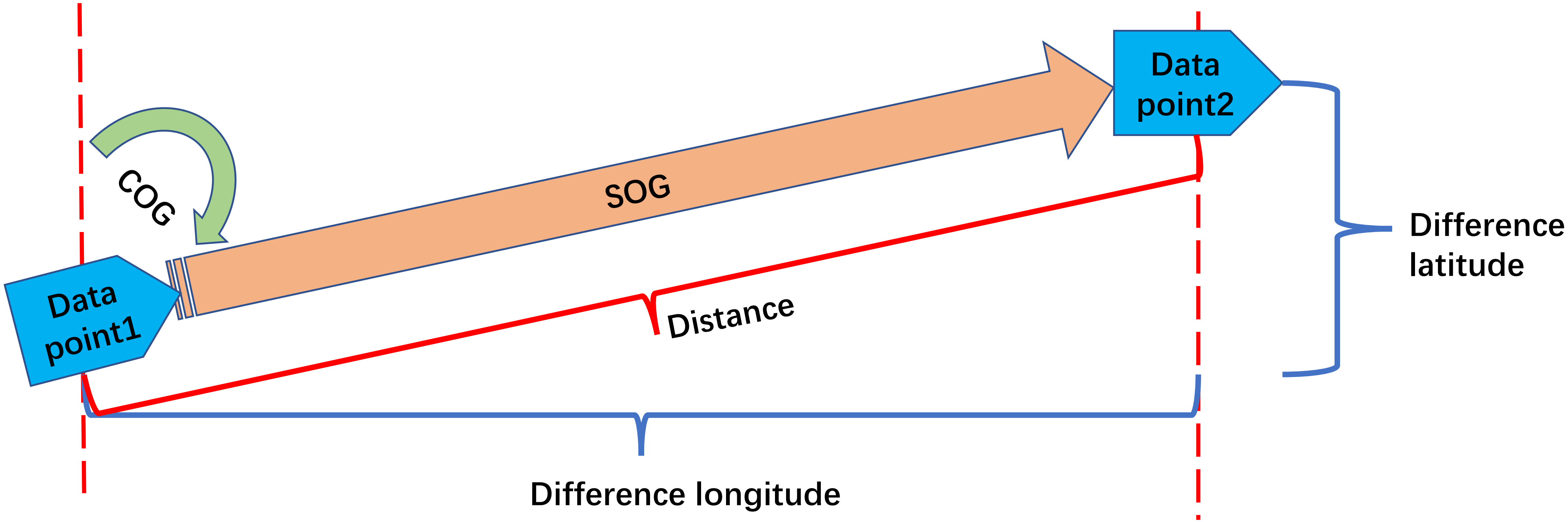
Treat all real data as normal



Set up abnormal scenarios and **simulate** abnormal data
Treat all simulated data as anomalous

Feature Selection

1. **SOG**: Speed over Ground
2. **COG**: Course over Ground
3. **Distance**: Distance between coordinates of two subsequent measurements.

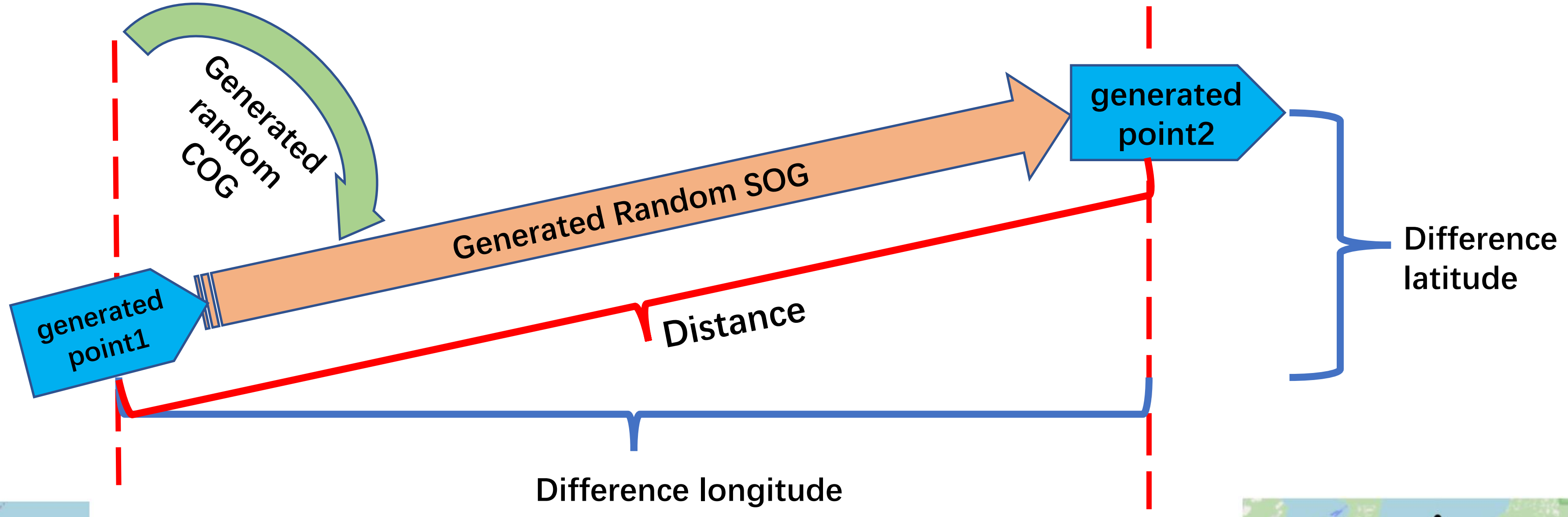


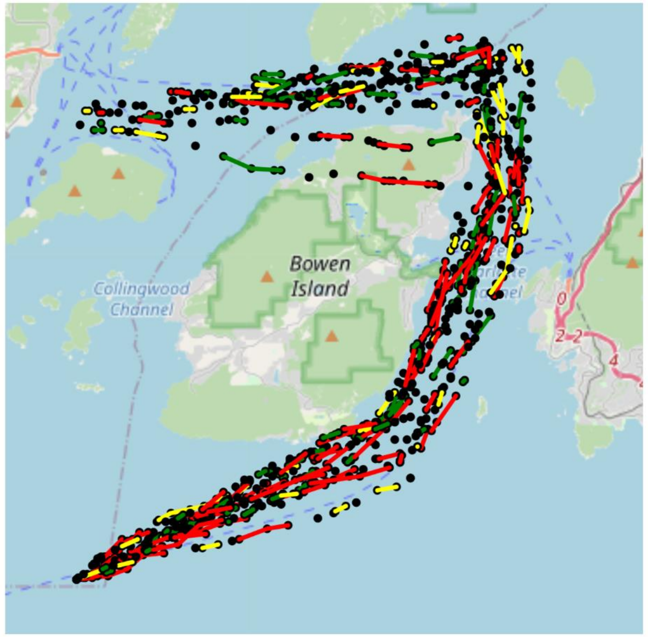
So we select 3 Features for each time points, and each segment have max. 10 time points.

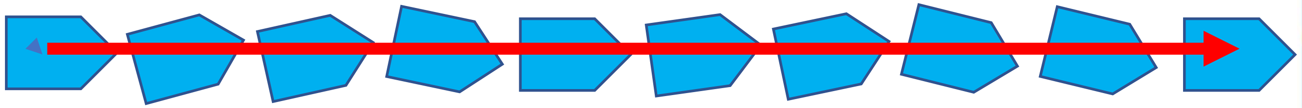
Each segment is represented as an array of shape 10 x 3.

Data Generation

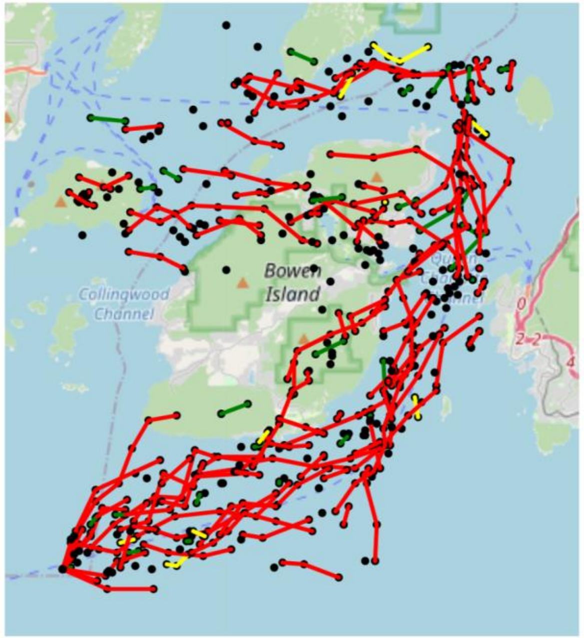
Firstly generate points and then make segments:



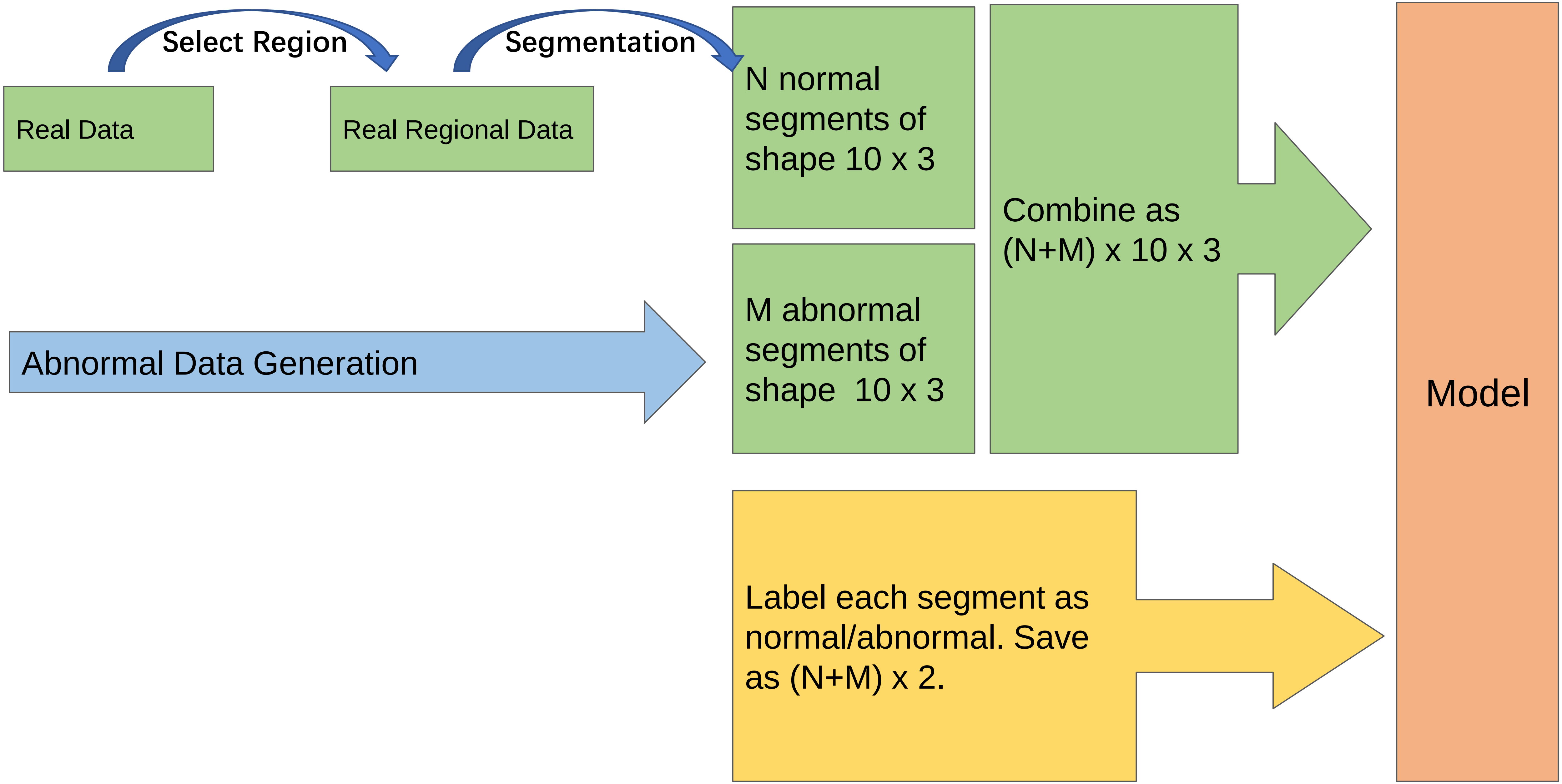




Combine 10 generated points to get a segment



Data preprocessing



Model: 1D Convolutional Neural Network

Why 1D-CNN Model?

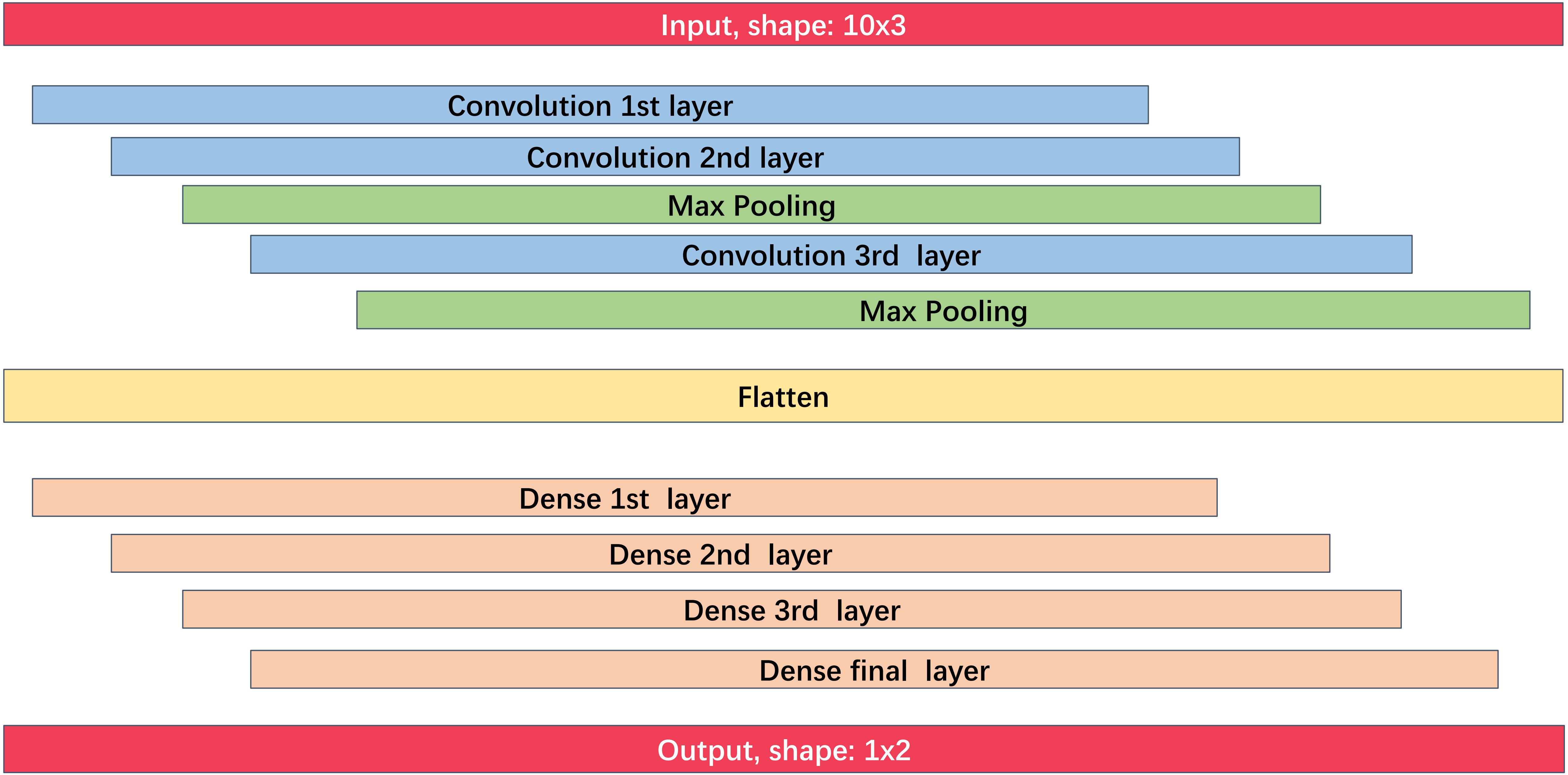
“A 1D-CNN Based Deep Learning Technique for Sleep Apnea Detection in IoT Sensors, (ISCAS) 2021”

“Classification of ECG Signals Based on 1D Convolution Neural Network, (Healthcom) 2017”

- The 1D-CNN model is widely used for anomaly detection of **time-series data** like **ECG signals**, and **AIS signals** are also time-series data, so we think it is very appropriate to use the 1D-CNN model

- Compared to models such as RNN-based LSTMs, 1D CNNs have the advantage of **being fast to train** and **can be computed in parallel**.

CNN-Model structure



Train/Test Dataset

Train Dataset:

->317 segments from real normal data in 2019_01_01 in selected area

->132 segments from random generation abnormal data in selected area

Test Dataset:

->211 segments from real normal data in 2019_06_01 in selected area

->112 segments from random generation abnormal data in selected area

Dataset for real accident test:

->537 segments from real normal and abnormal data in 2019_09_08 in the area the accident happens

->443 segments from real normal and abnormal data in 2019_09_07 in the area the accident happens

Evaluation

Confusion Matrix		Predicted results	
		Negative	Positive
Ground Truth	Negative	True Negative(TN)	False Positive(FP)
	Positive	False Negative(FN)	True Positive(TP)

For example:

```
[[ 90  22]
 [  5 206]]
```

$$Precision = \frac{TP}{TP+FP}$$

$$Recall = \frac{TP}{TP+FN}$$

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

For example:

	precision	recall	f1-score
Abnormal	0.9474	0.8036	0.8696
Normal	0.9035	0.9763	0.9385

Precision reflects the ability of the model to discriminate between **negative samples.**
Recall reflects the ability of the model to discriminate between **positive samples.**
F1 score is a **combination** of both

Results analysis and optimization of models and datasets

We did **7 tests** with different **models and datasets pairings**

Result_1(D1-M1) and Result_2 (D1-M2)

	Dataset_1
CNN-Model_1	D1-M1
CNN-Model_2	D1-M2

CNN-Model1

- use **2** features: SOG COG

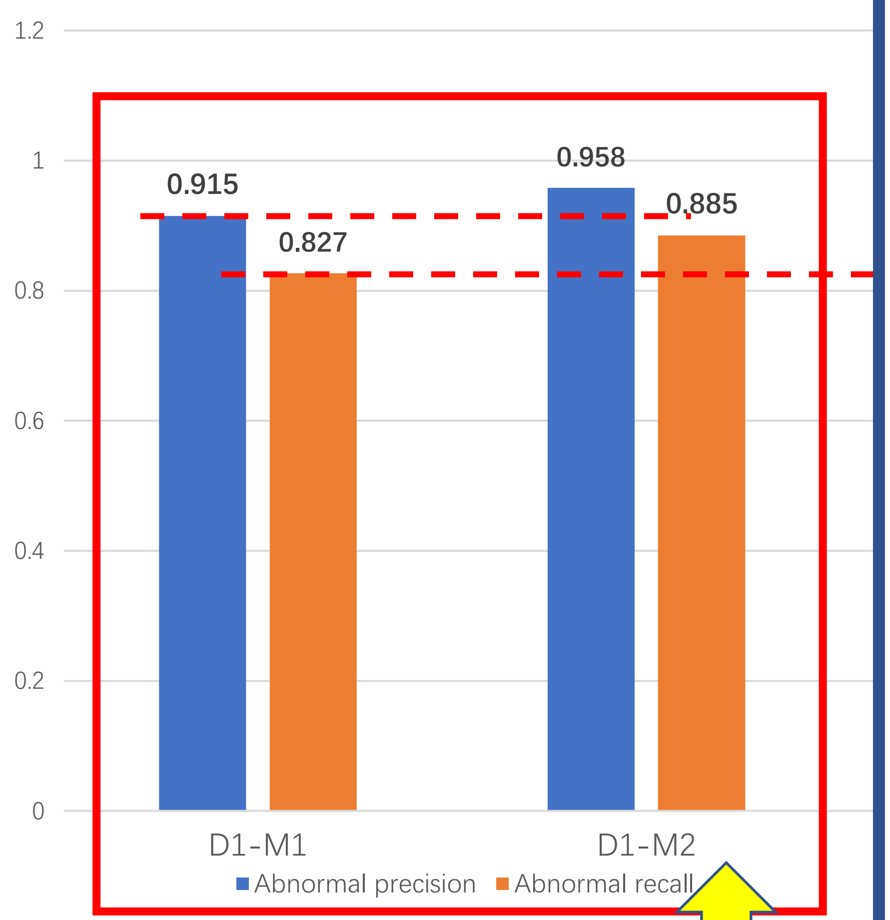
CNN-Model2

- use **3** features: Distance SOG COG

Dataset_1

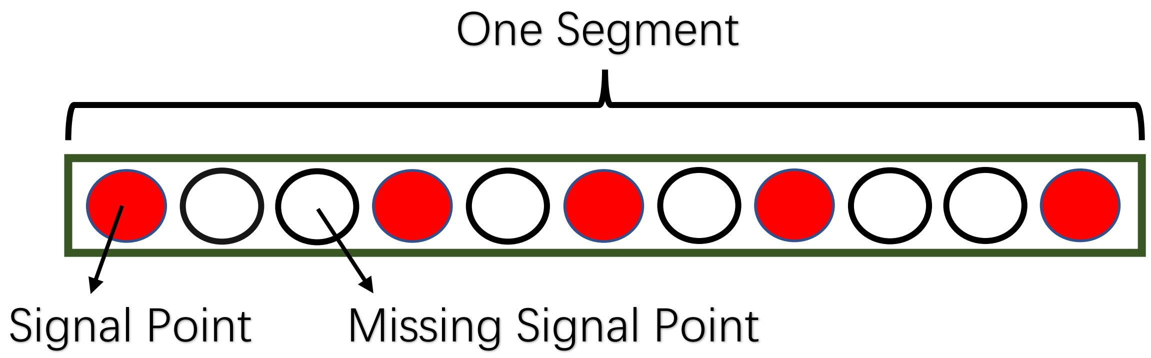
- If there are **missing signals** in each segment, **supplement** missing signals with 0.
- But **in generation data** there is **no missing signal**

Statistics View of Result_1 (D1-M1) and Result_2 (D1-M2)

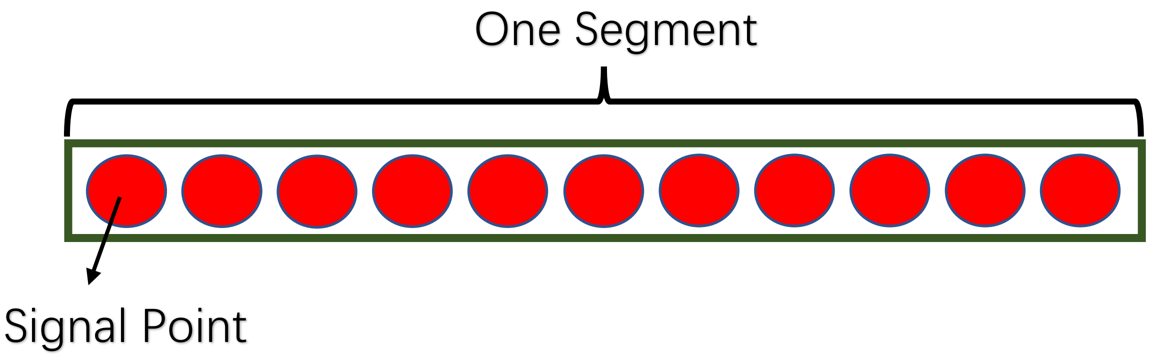


	Dataset_1
CNN-Model_1	D1-M1
CNN-Model_2	D1-M2

Segments in real data:



Segments in generation data:



This is the differences we don‘t want the model to take into account.

Result_3 (D2-M1) and Result_4 (D2-M2)

	Dataset_1	Dataset_2
CNN-Model_1	D1-M1	D2-M1
CNN-Model_2	D1-M2	D2-M2

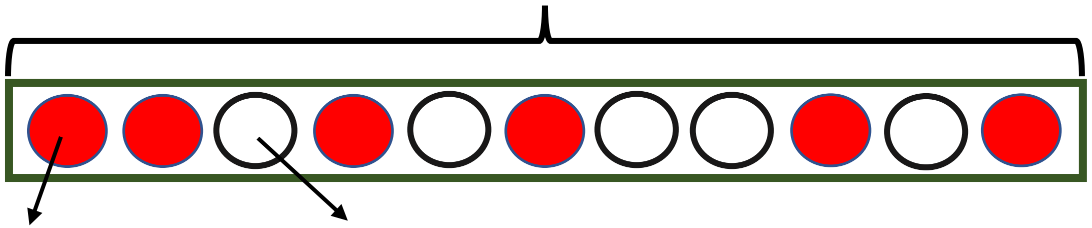
Dataset_1

- If there are **missing signals** in each segment, **supplement** missing signals with 0.
- But **in generation data** there is **no missing signals**

Dataset_2

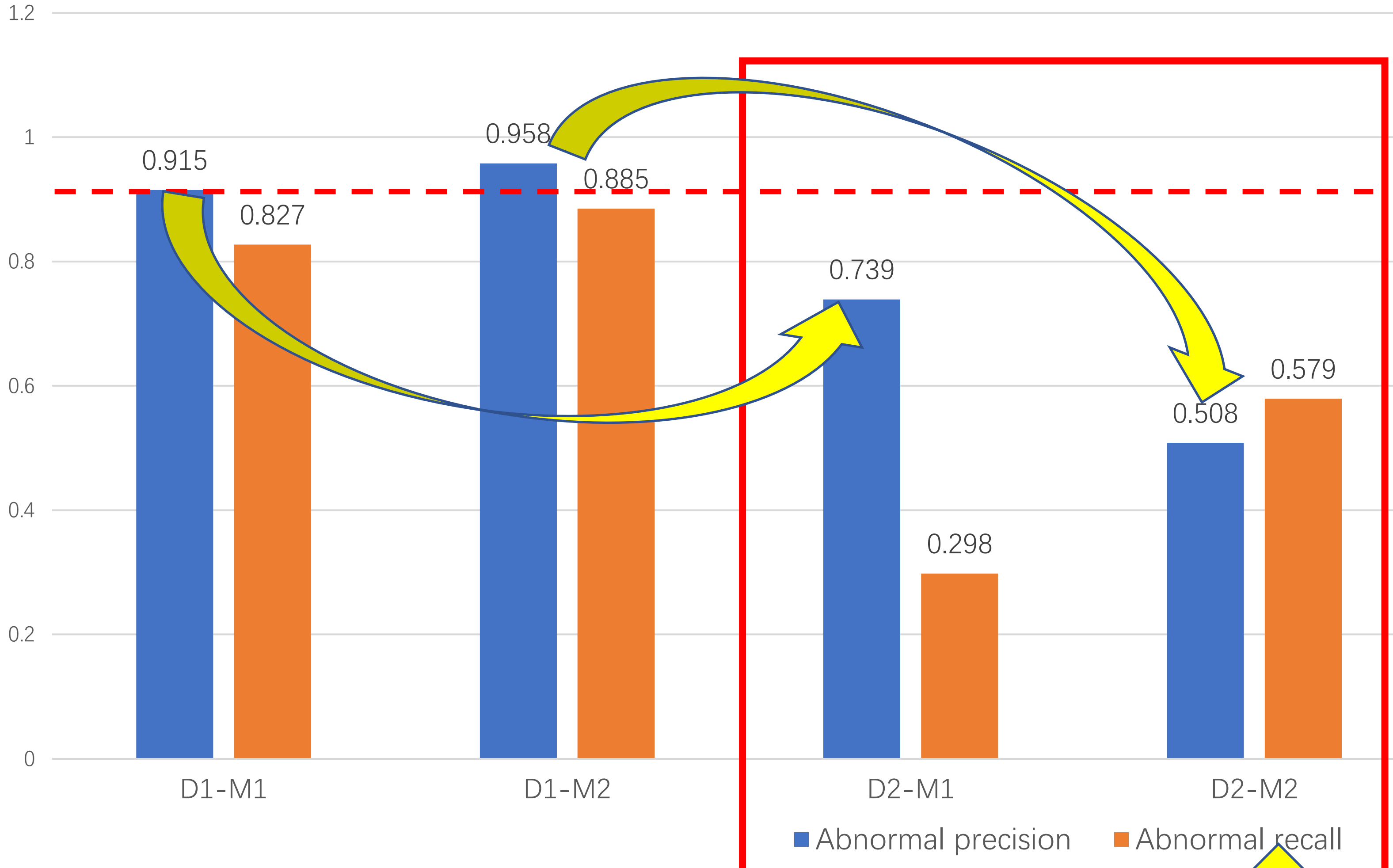
- If there are **less than 3 signals** in one segment, **drop it**. otherwise supplement missing signals with 0
- And **in generation dataset** there is **random missing** signals and supplement with 0

One Segment in generation data



Signal Point Randomly add missing signal points

Statistics View of Result_3 (D2-M1) and Result_4 (D2-M2)



	Dataset_1	Dataset_2
CNN-Model_1	D1-M1	D2-M1
CNN-Model_2	D1-M2	D2-M2

The model **cannot** simply distinguish between real and generated data **by the number of missing signals in the segment**

But there is **too little Information** in each segment.

Result_5 (D3-M1) and Result_6 (D3-M2)

	Dataset_1	Dataset_2	Dataset_3
CNN-Model_1	D1-M1	D2-M1	D3-M1
CNN-Model_2	D1-M2	D2-M2	D3-M2

Dataset_1

- If there are **missing signals** in each segment, **supplement** missing signals with 0.
- But **in generation data** there is **no missing signals**

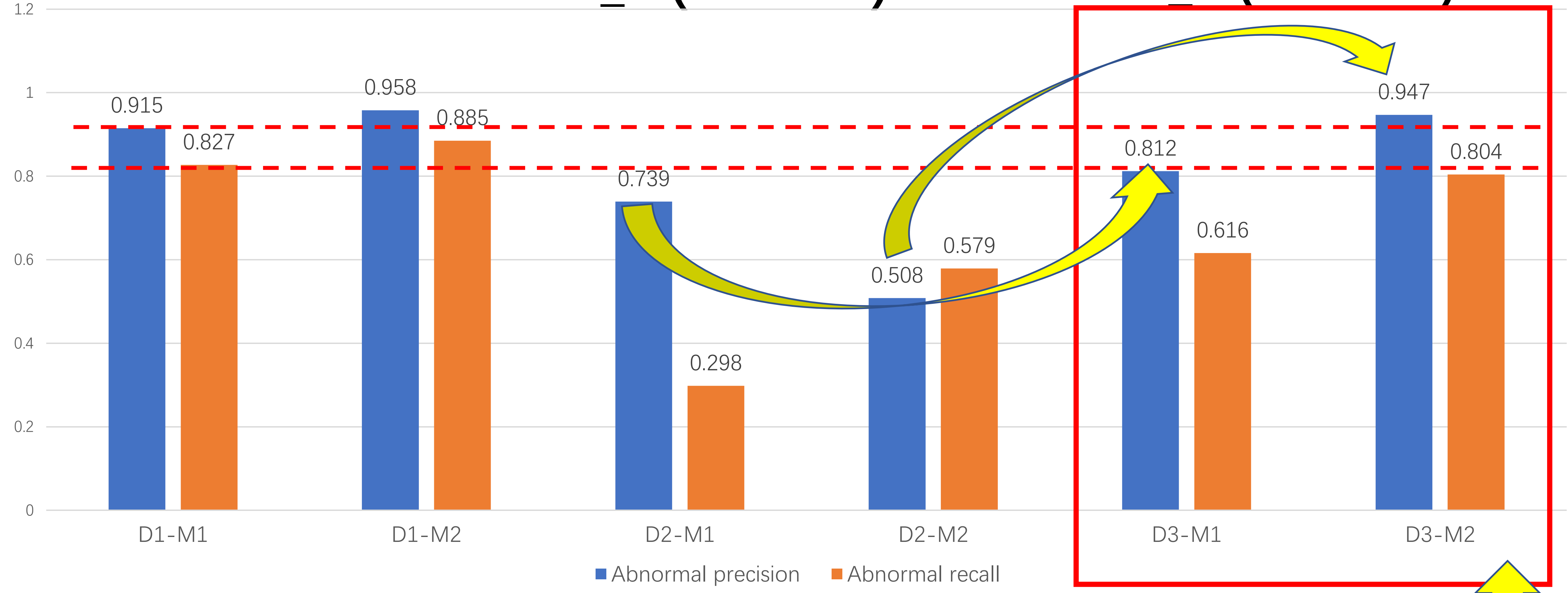
Dataset_2

- If there are **less than 3 signals** in one segment, **drop it**. otherwise supplement missing signals with 0
- And **in generation dataset** there is **random missing** signals and supplement with 0

Dataset_3

- If there are **less than 5 signals** in one segment, **drop it**. otherwise supplement missing signals with 0
- And **in generation dataset** there is **random missing** signals and supplement with 0

Statistics View of Result_5 (D3-M1) and Result_6 (D3-M2)

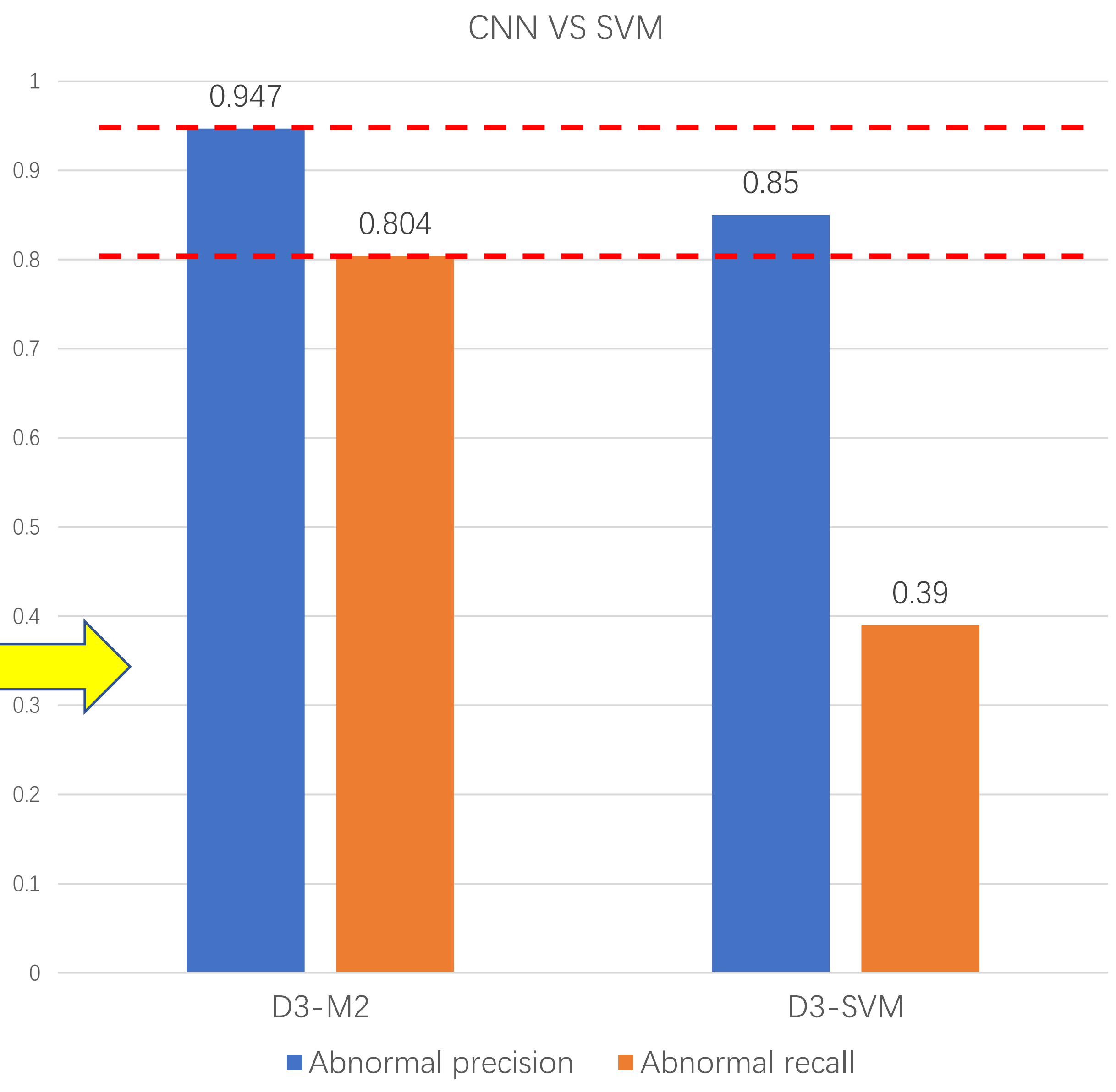


	Dataset_1	Dataset_2	Dataset_3
CNN-Model_1	D1-M1	D2-M1	D3-M1
CNN-Model_2	D1-M2	D2-M2	D3-M2

Statistics View of Result_6 (D3-M2) and Result_7 (D3-SVM)

Performance of CNN-Model is better than SVM-Model

	Dataset_3
CNN-Model_1	D3-M1
CNN-Model_2	D3-M2
SVM-Model	D3-SVM

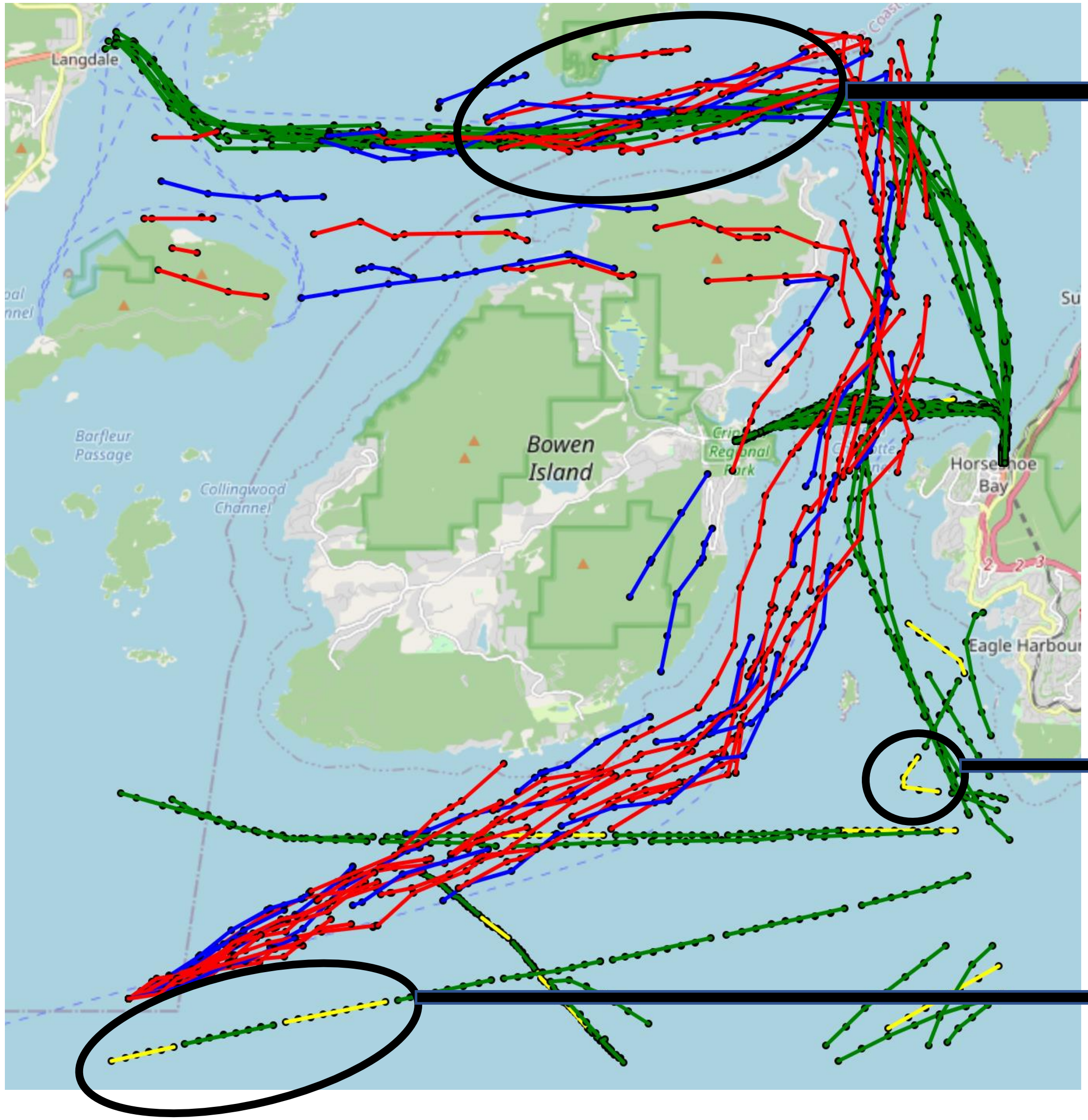


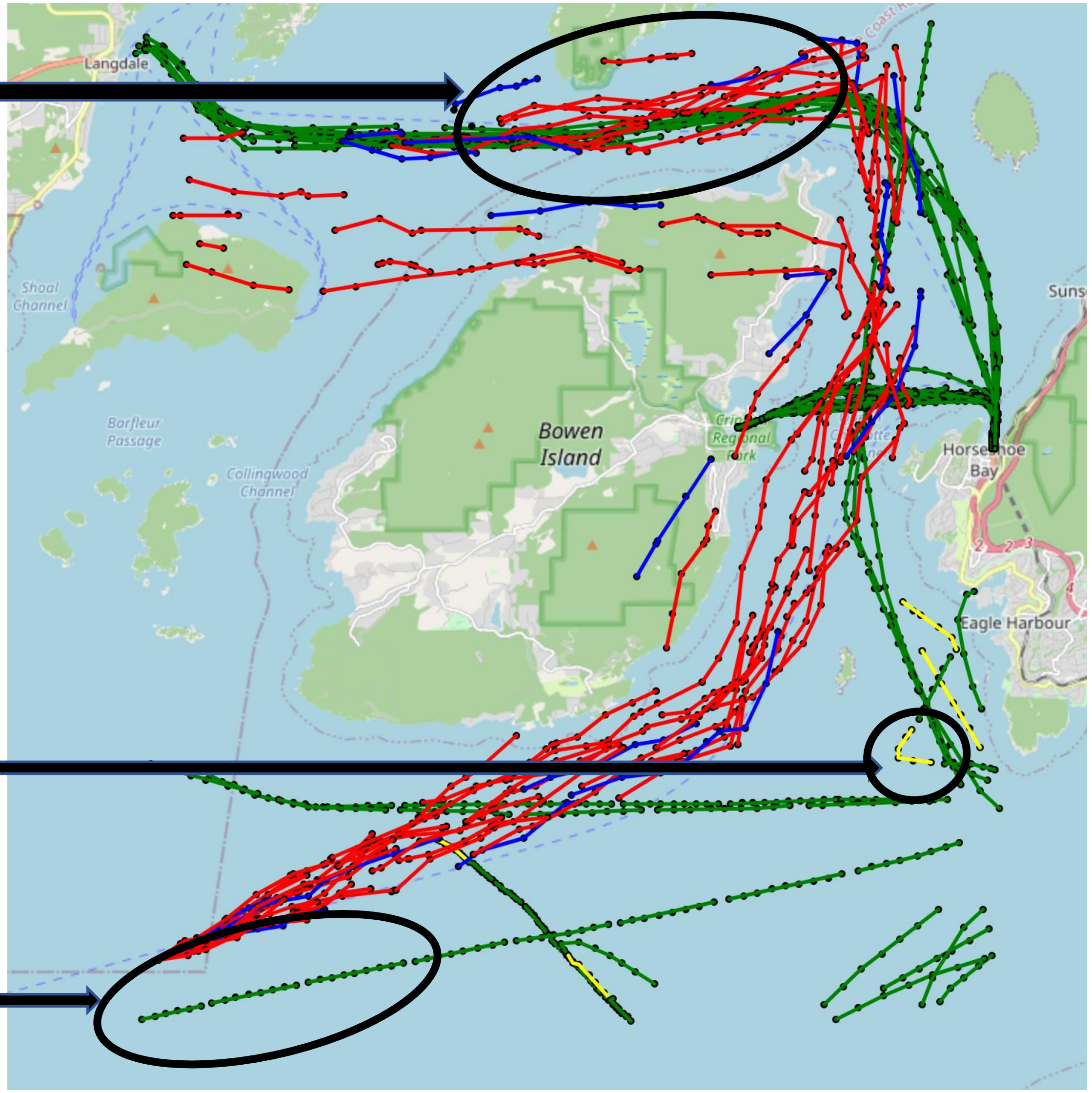
Map View of Results

	Predicted Negative	Predicted Positive
Actual Negative	Red (TN)	Blue (FP)
Actual Positive	Yellow (FN)	Green (TP)

M1-D3(use 2 features)

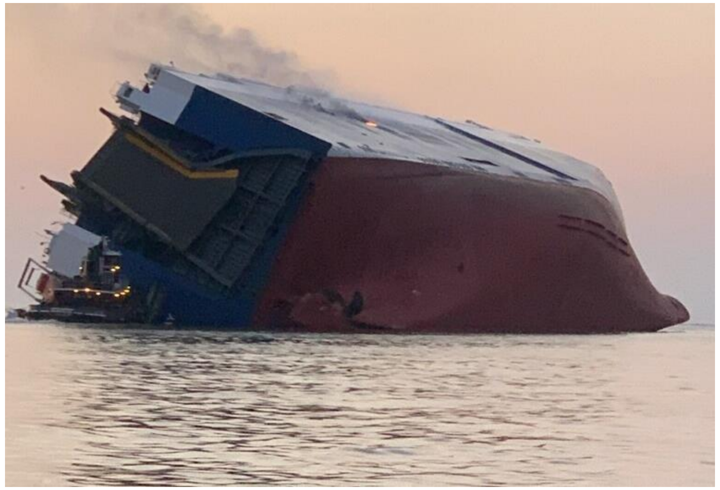
M2-D3(use 3 features)





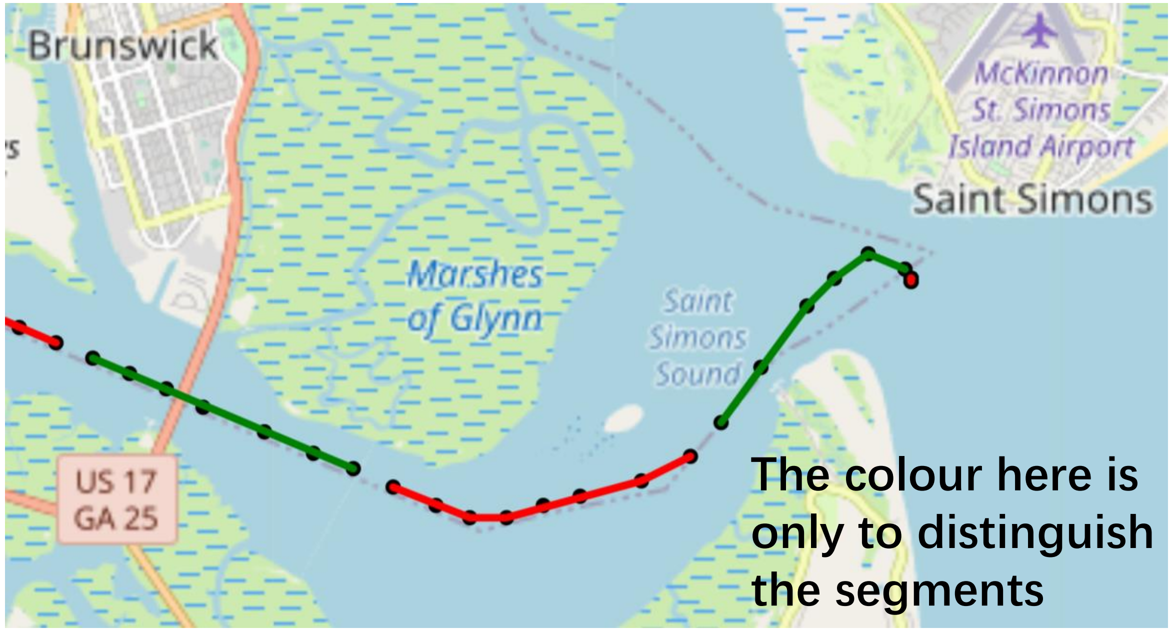
Real accident test

Real accident description： The MV Golden Ray was a 200-metre long (660 ft) roll-on/roll-off cargo ship， On 8 September 2019 at approximately 0137 EDT, the Golden Ray capsized within the Port of Brunswick's harbor, shortly after unberthing and proceeding towards the Port of Baltimore.



Wikipedia's reliable information on the location of the incident:

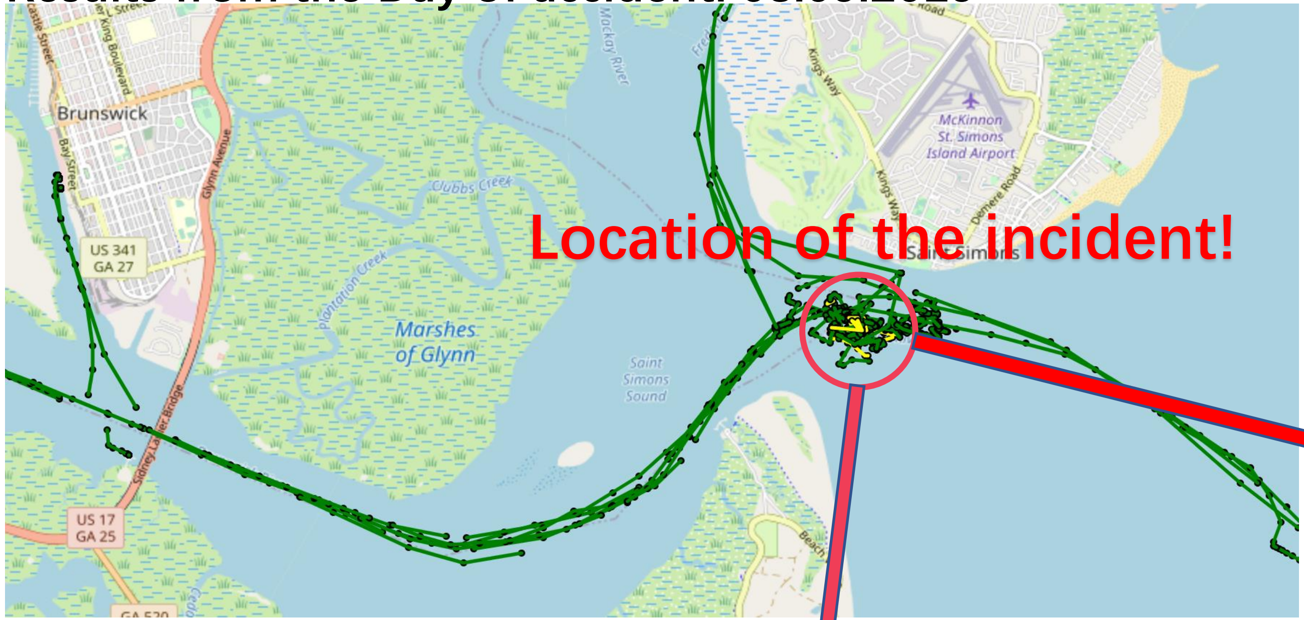
AIS data of the ship at the time of the incident that we found in the dataset:



The colour here is only to distinguish the segments

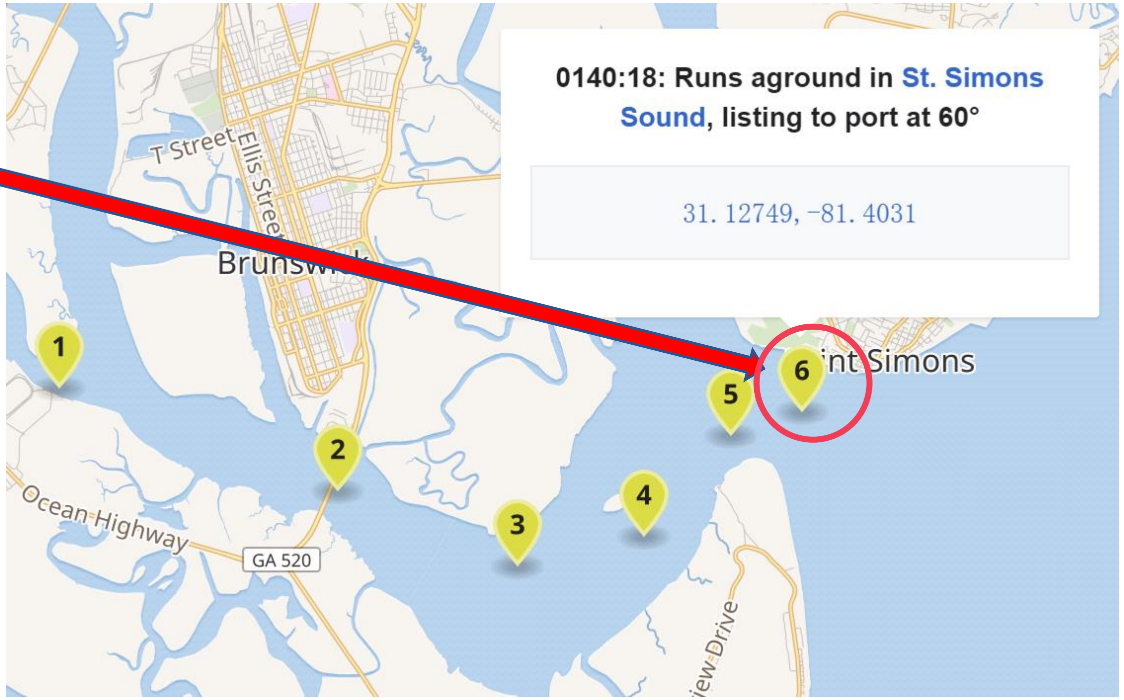
Performance of the Model Predict for real accident

Results from the Day of accident: 08.09.2019



Result from the Day before accident: 07.09.2019

Wikipedia's reliable information on the location of the incident:



	Abnormal	Normal
Predict	Yellow	Green

What problems did we solve?

Our model can detect anomalous speed changes or directional changes of a vessel during a certain time period.

So if a accident is because of anomalous speed changes or directional changes,

After the accident, we can detect the accident by analyzing the AIS data.

But the model cannot predict accidents that do not occur.

What is still lacking?

- Due to the limitations of the data generation method, only anomalous changes in speed and direction can be identified

Solution: Find more realistic anomalous events or artificially set up more anomalous scenarios and simulate anomalous data based on them.

- If the accident occurs between two segments, this accident is ignored by the model

Solution: Cut segments in different ways for the same trajectory so that different segment data can be generated for data enhancement.

- For a more diverse set of anomalies, three features are not enough

Solution: Leverage features in AIS data and combine them with geographic information


Q&A