Un Ejemplo de Clasificación de Movimiento

Jesús Alfonso López

jalopez@uao.edu.co

¿Quién es el Conferencista?

Jesús Alfonso López Sotelo

- Coordinador académico de la Especialización en Inteligencia Artificial y del Semillero en IA. Universidad Autónoma de Occidente Cali. Colombia. https://www.uao.edu.co/programa/especializacion-en-inteligencia-artificial/
- Investigador asociado (MinCiencias) vinculado al grupo de investigación en Energías GIEN
- Linkedin

https://www.linkedin.com/in/jesus-alfonso-l%C3%B3pez-sotelo-76100718/

Autor del Libro

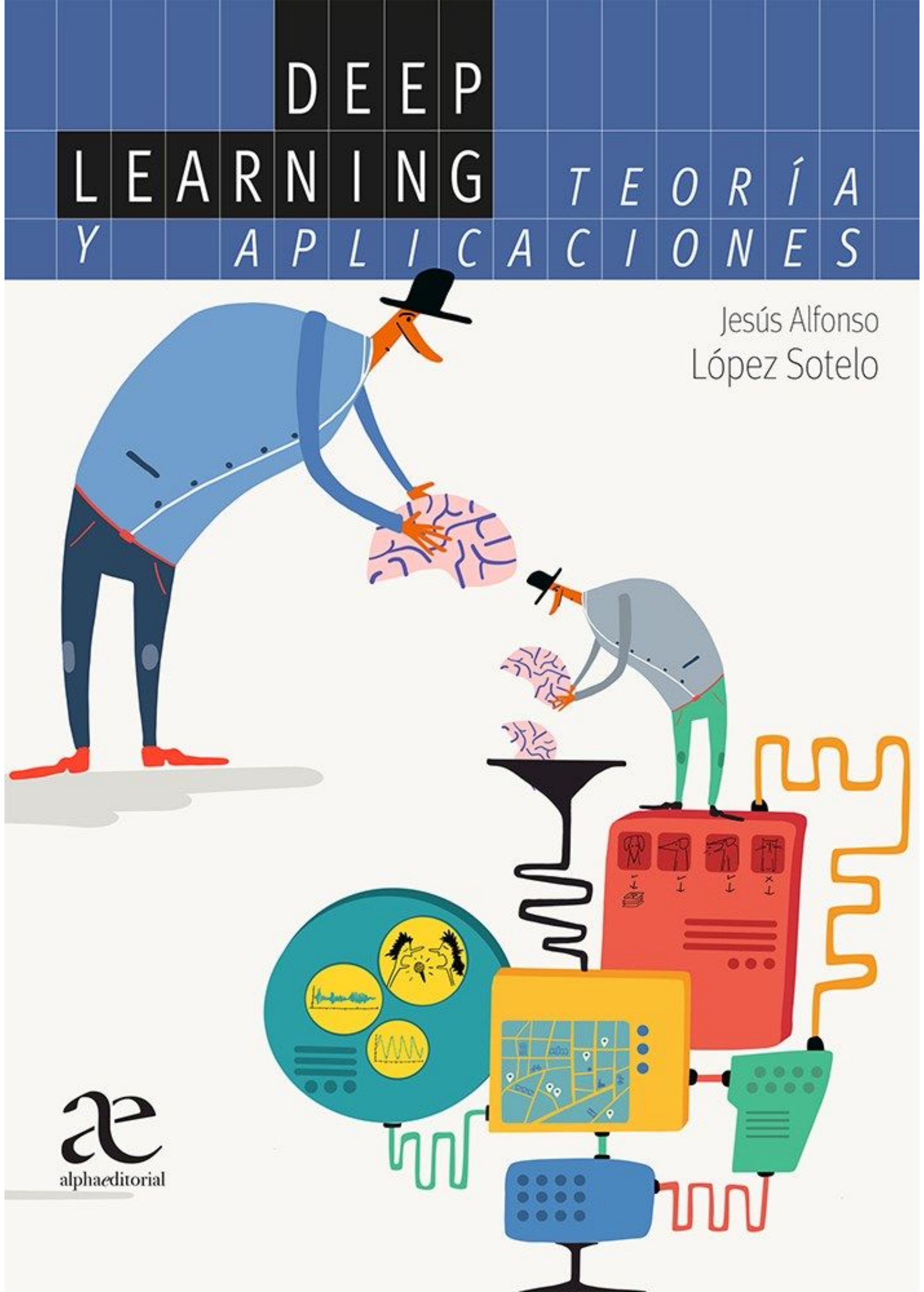
Deep Learning Teoría y Aplicaciones

Enlace a la Editorial

https://www.alpha-editorial.com/Papel/9789587786866/Deep+Learning

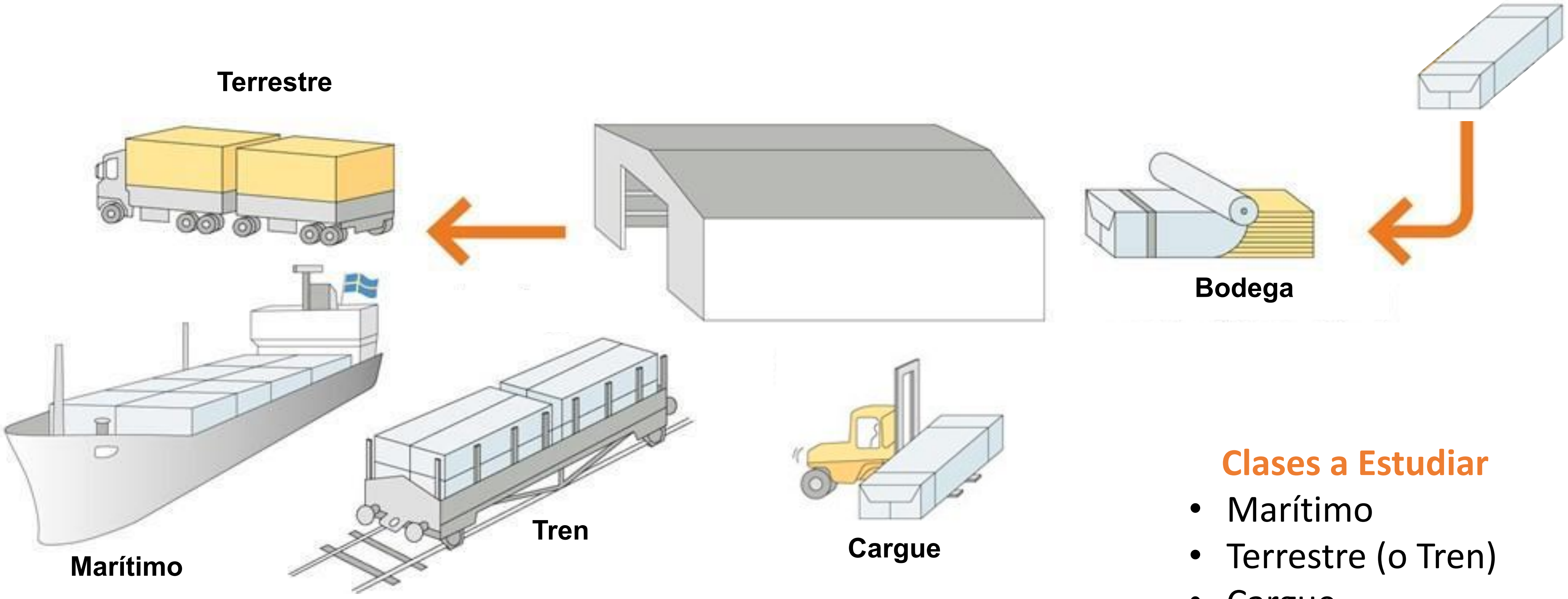
Github del Libro

https://github.com/JesusAlfonsoLopez/Libro_Deep_Learning_Teoria_Aplicaciones



Clasificación de Movimiento

Caso de estudio: Esfuerzos mecánicos en el transporte

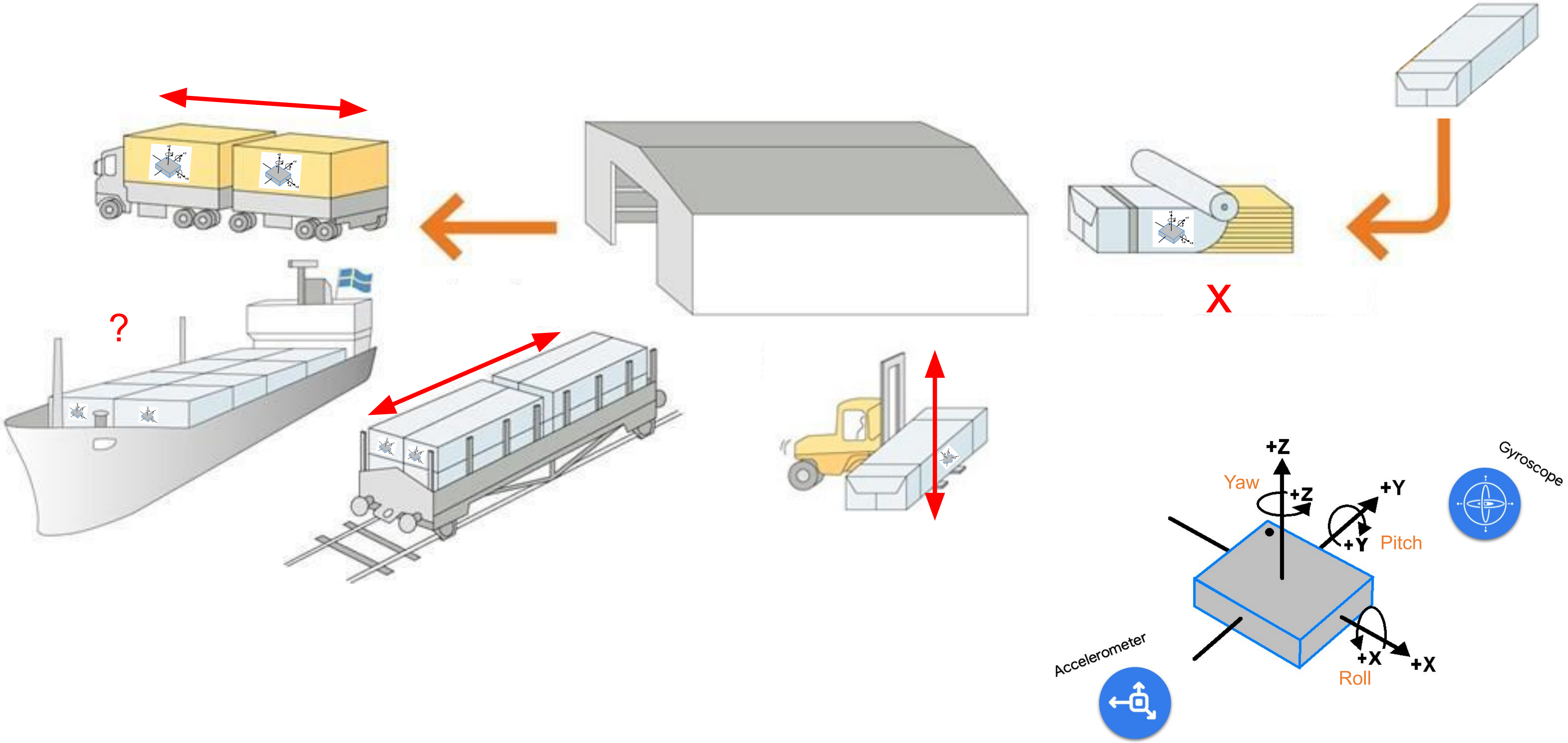


Clases a Estudiar

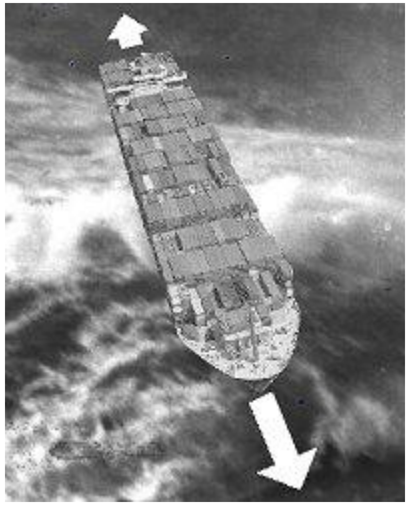
- Marítimo
- Terrestre (o Tren)
- Cargue
- Bodega

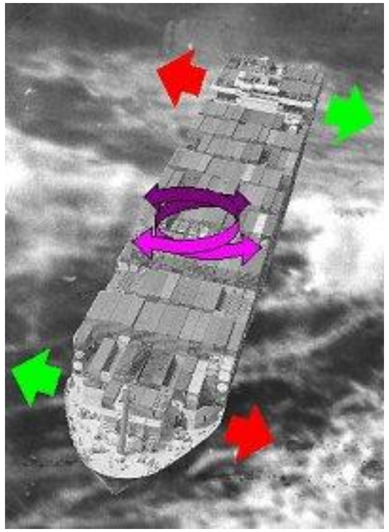
Flujo de trabajo en Aprendizaje Automático

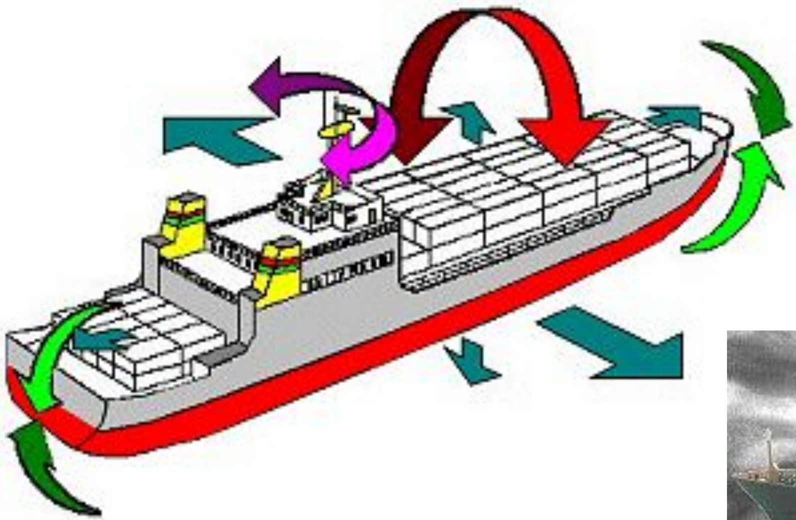
Recolección de Datos

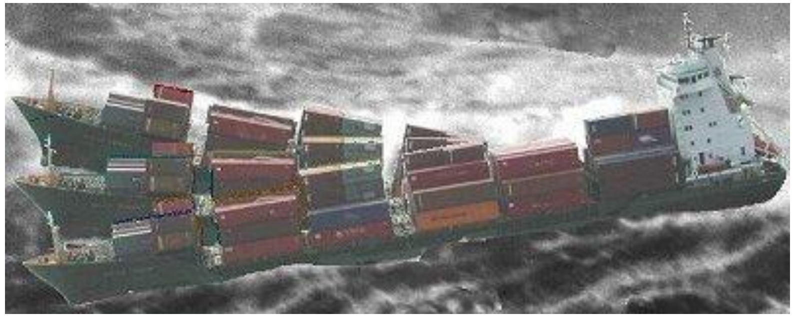


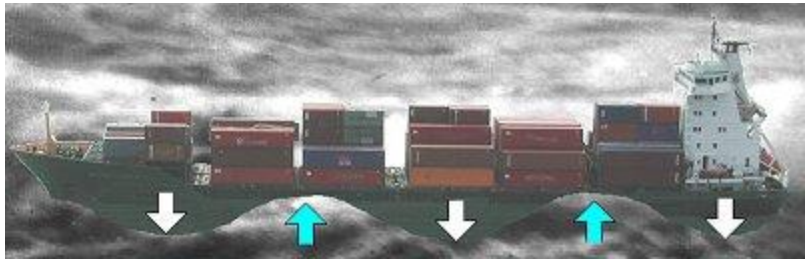
Esfuerzos mecánicos en el transporte Marítimo





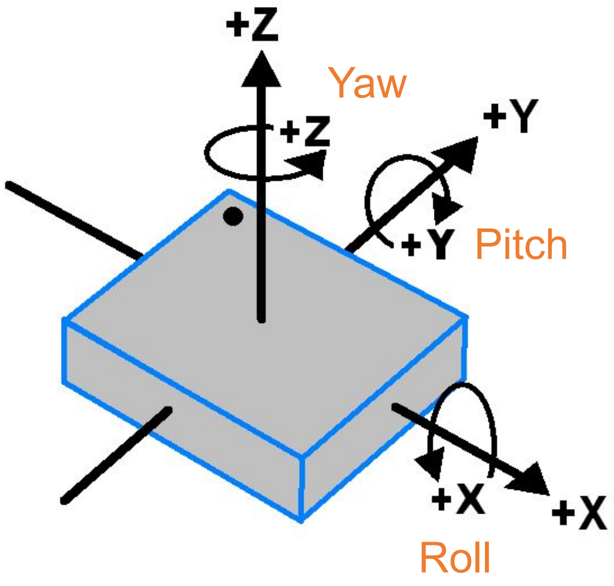


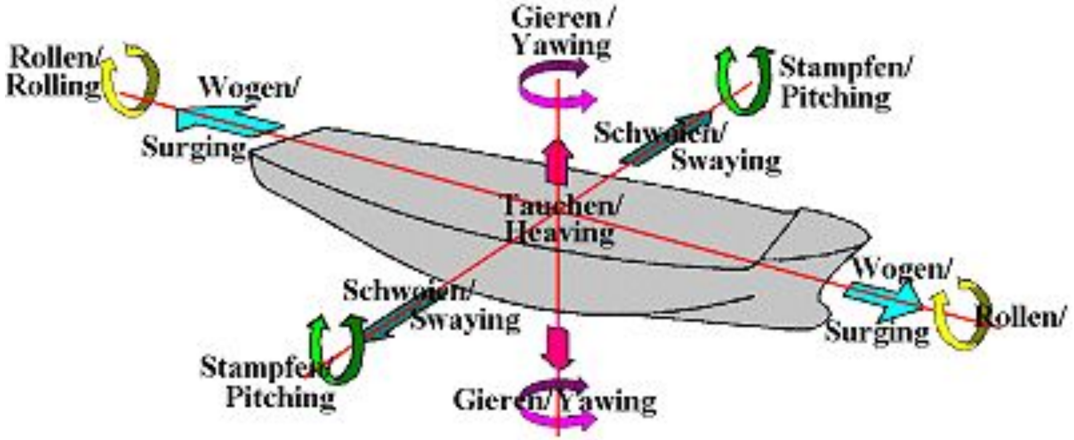




https://www.containerhandbuch.de/chb_e/stra/index.html?/chb_e/stra/stra_02_03_03.html

Esfuerzos mecánicos en el transporte Marítimo





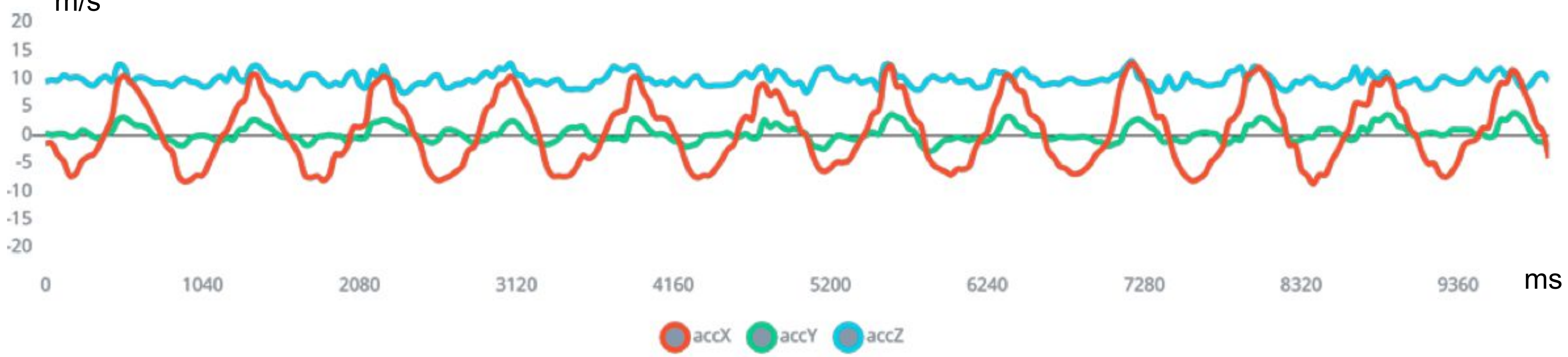
Accelerometer

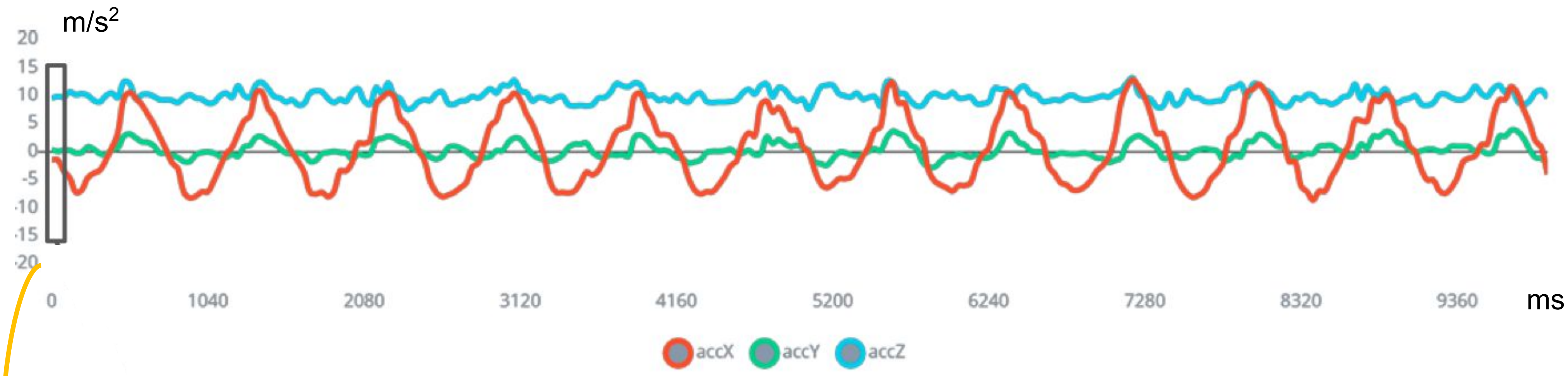
Gyroscope

	Linear motion	Rotational motion	
X	Surging is motion along the longitudinal axis.	Rolling is motion around the longitudinal axis.	Roll
Y	Swaying is motion along the transverse axis.	Pitching is motion around the transverse axis.	Pitch
Z	Heaving is motion along the vertical axis.	Yawing is motion around the vertical axis.	Yaw

Summary of ship movement

Ejemplo: 10 segundos de datos del acelerómetro, capturados a una frecuencia de muestreo de 100 Hz





Datos Crudos

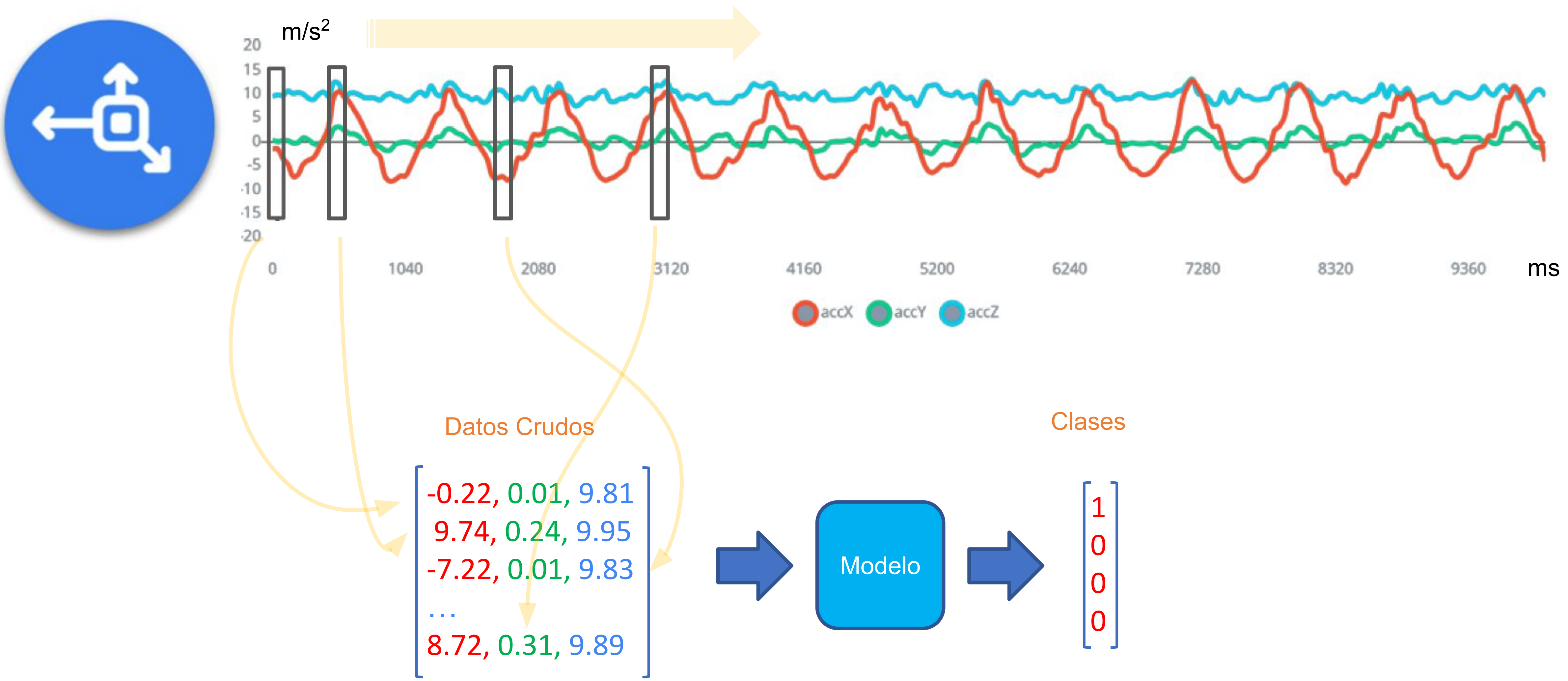
- accX
- accY
- accZ

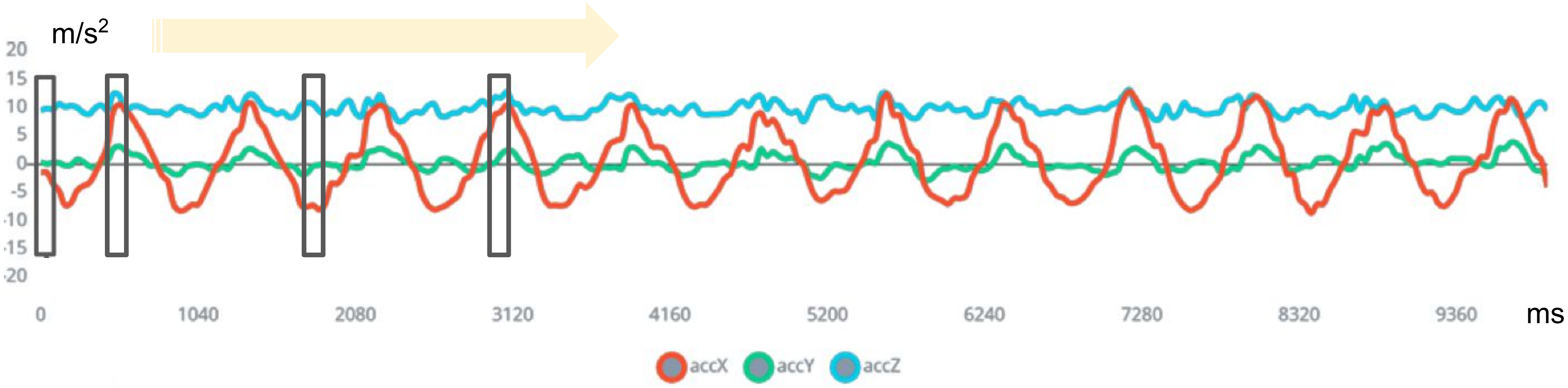
Modelo

Clases

- Marítimo
- Terrestre (o Tren)
- Cargue
- Bodega


m/s2
20
15
10
5
0
-5
-10
-15
-20
0
1040
2080
3120
4160
5200
6240
7280
8320
9360
ms
accX
accY
accZ
Datos Crudos
[-0.22, 0.01, 9.81]
Modelo
Clases
1
0
0
0


m/s2
20
15
10
5
0
-5
-10
-15
-20
0
1040
2080
3120
4160
5200
6240
7280
8320
9360
ms
accX
accY
accZ
Datos Crudos
-0.22, 0.01, 9.81
9.74, 0.24, 9.95
-7.22, 0.01, 9.83
...
8.72, 0.31, 9.89
Modelo
Clases
1
0
0
0



Datos Crudos

[-0.22, 0.01, 9.81
9.74, 0.24, 9.95
-7.22, 0.01, 9.83
…
8.72, 0.31, 9.89]

Modelo

Clases

[?
?
?
?]

Problema!

✔ Serie de tiempo


Ventana
20
15
10
5
0
-5
-10
-15
-20
0
1040
2080
3120
4160
5200
6240
7280
8320
9360
ms
accX
accY
accZ

Ventana de 2 Segundos

Datos crudos en una ventana

- 200** muestras por cada eje (100Hz x 2s)
- 600 datos en total (200 x 3 ejes)

* 2 segundos son necesarios para capturar 1 o 2 ciclos del movimiento
** 2 segundos a una taza de muestreo de 100 Hz -> 200 muestras

Ventana de 2 Segundos

Datos crudos en una ventana

- 200** muestras por cada eje (100Hz x 2s)
- 600 datos en total (200 x 3 ejes)

Extracción Automática de características usando Deep Learning

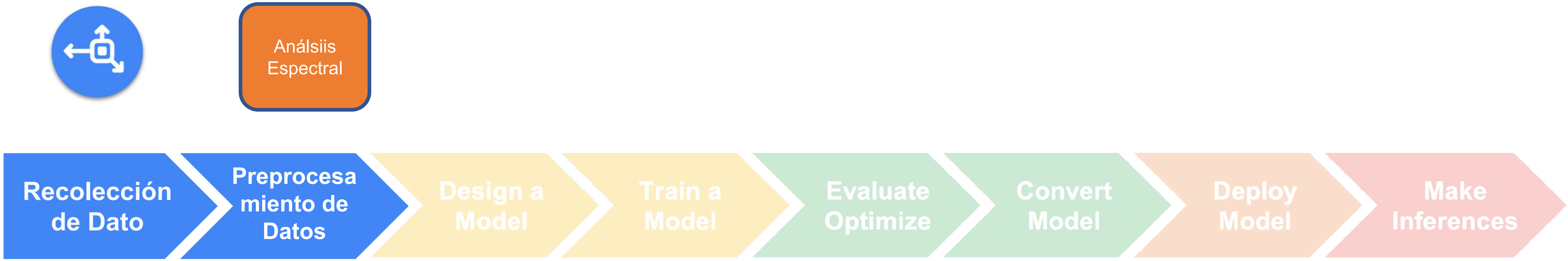
- Complejidad Computacional
- Gran cantidad de datos de entrenamiento

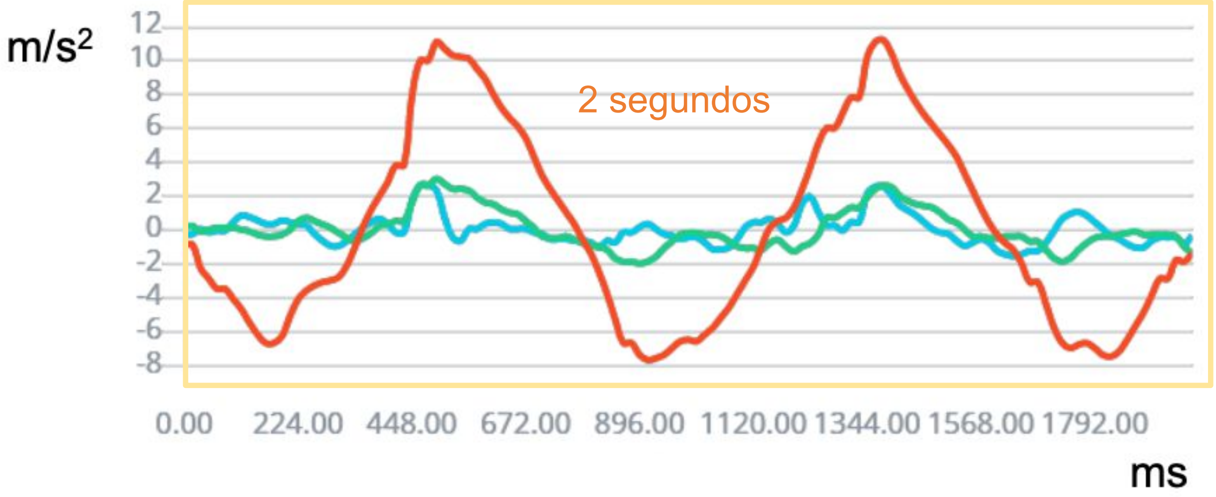
Problema!

✔ Se necesita más memoria

* 2 segundos son necesarios para capturar 1 o 2 ciclos del movimiento
** 2 segundos a una taza de muestreo de 100 Hz -> 200 muestras

Pre-Procesamiento de los Datos



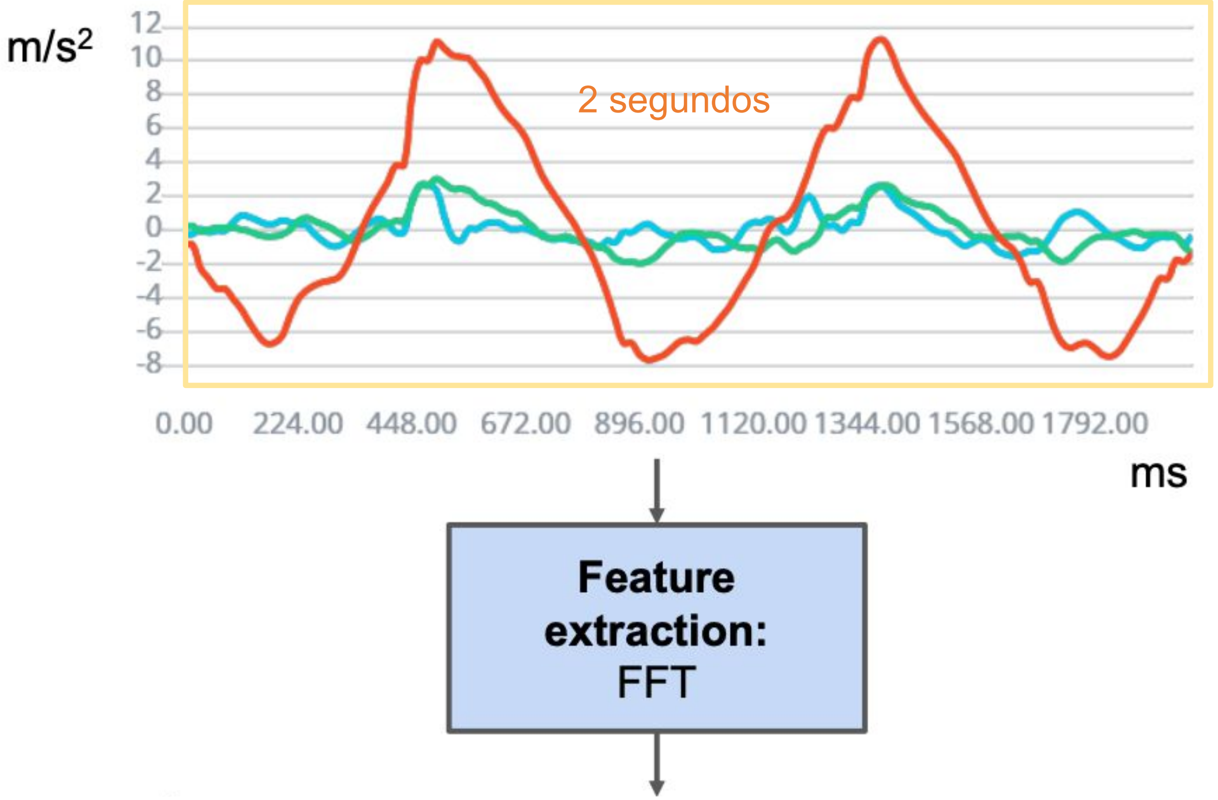


Extracción de Características

3 Valores RMS (Root Mean Square), uno por cada eje (x, y, z)

$$x_{\mathrm{RMS}} = \sqrt{\frac{1}{n}\left(x_1^2 + x_2^2 + \cdots + x_n^2\right)}.$$

n=200

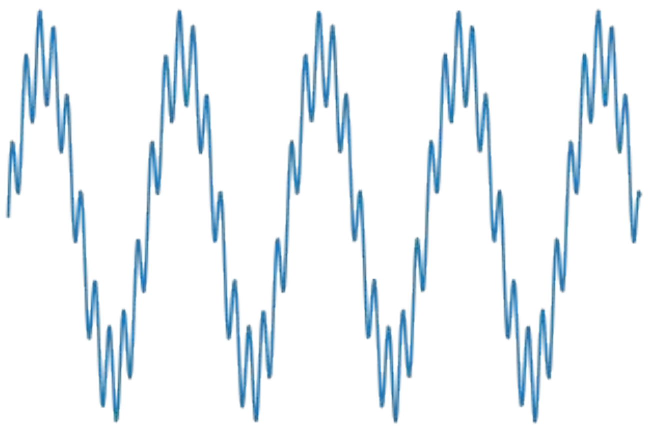


Extracción de Características

3 RMS

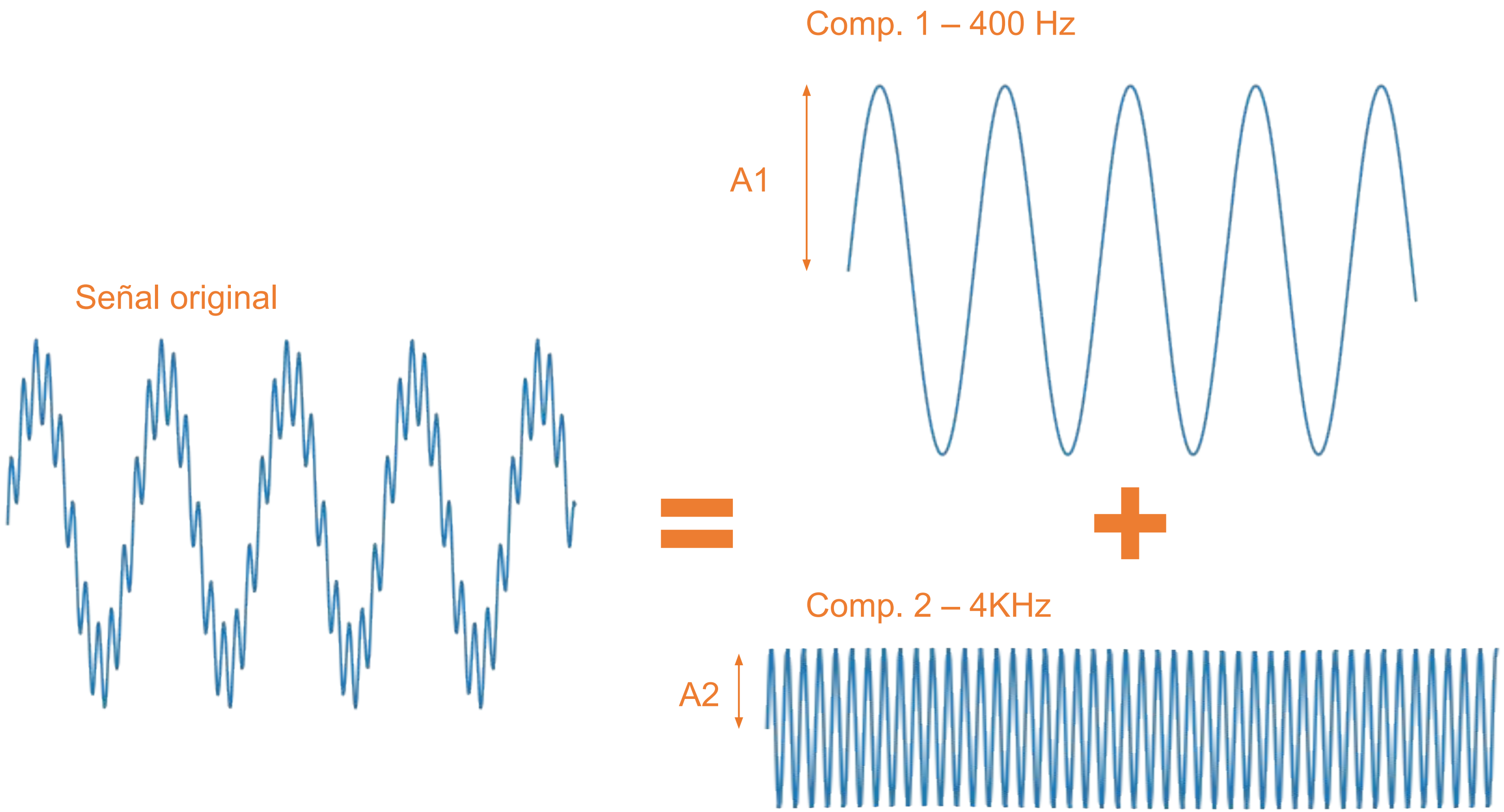
Transformada Rápida de Fourier (FFT)

Señal original



Dominio del
tiempo

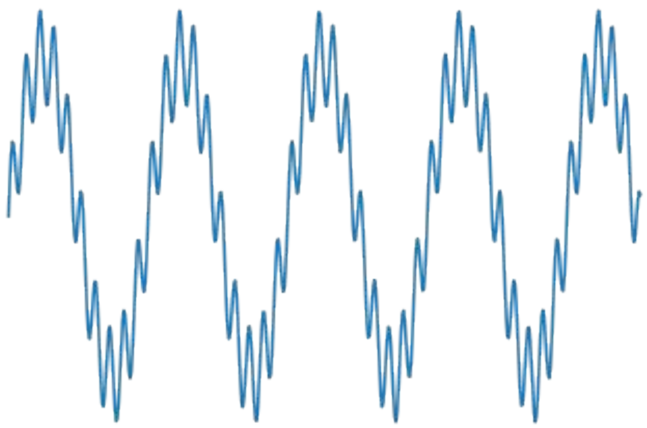
Transformada Rápida de Fourier (FFT)



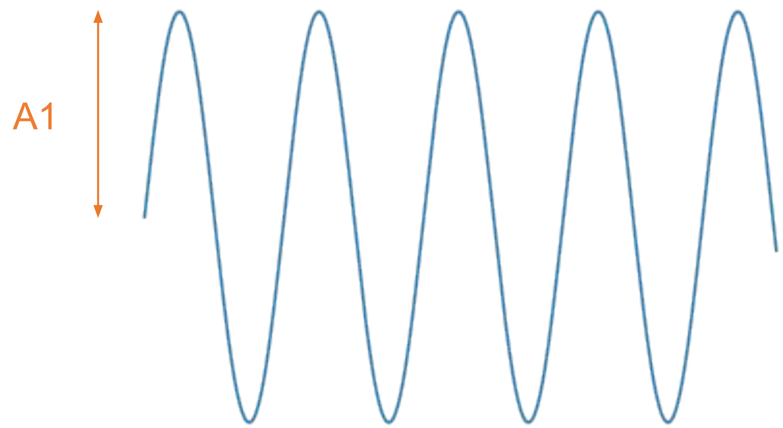
Dominio del Tiempo

Transformada Rápida de Fourier (FFT)

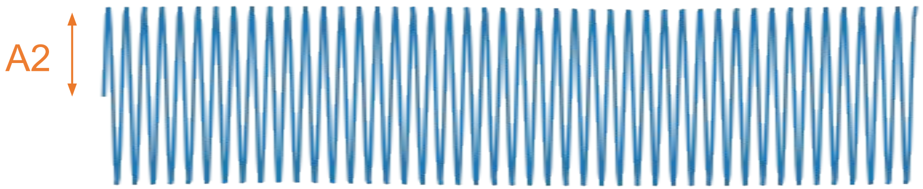
Señal original



Comp. 1 – 400 Hz

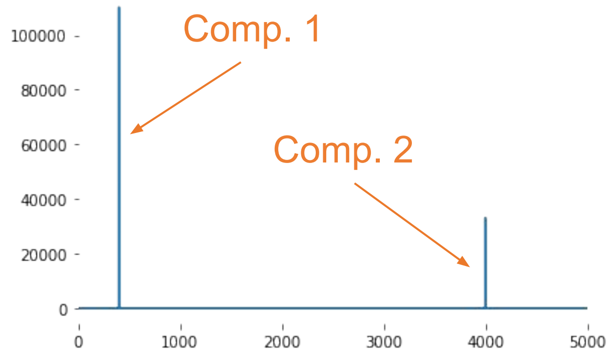


Comp. 2 – 4 KHz

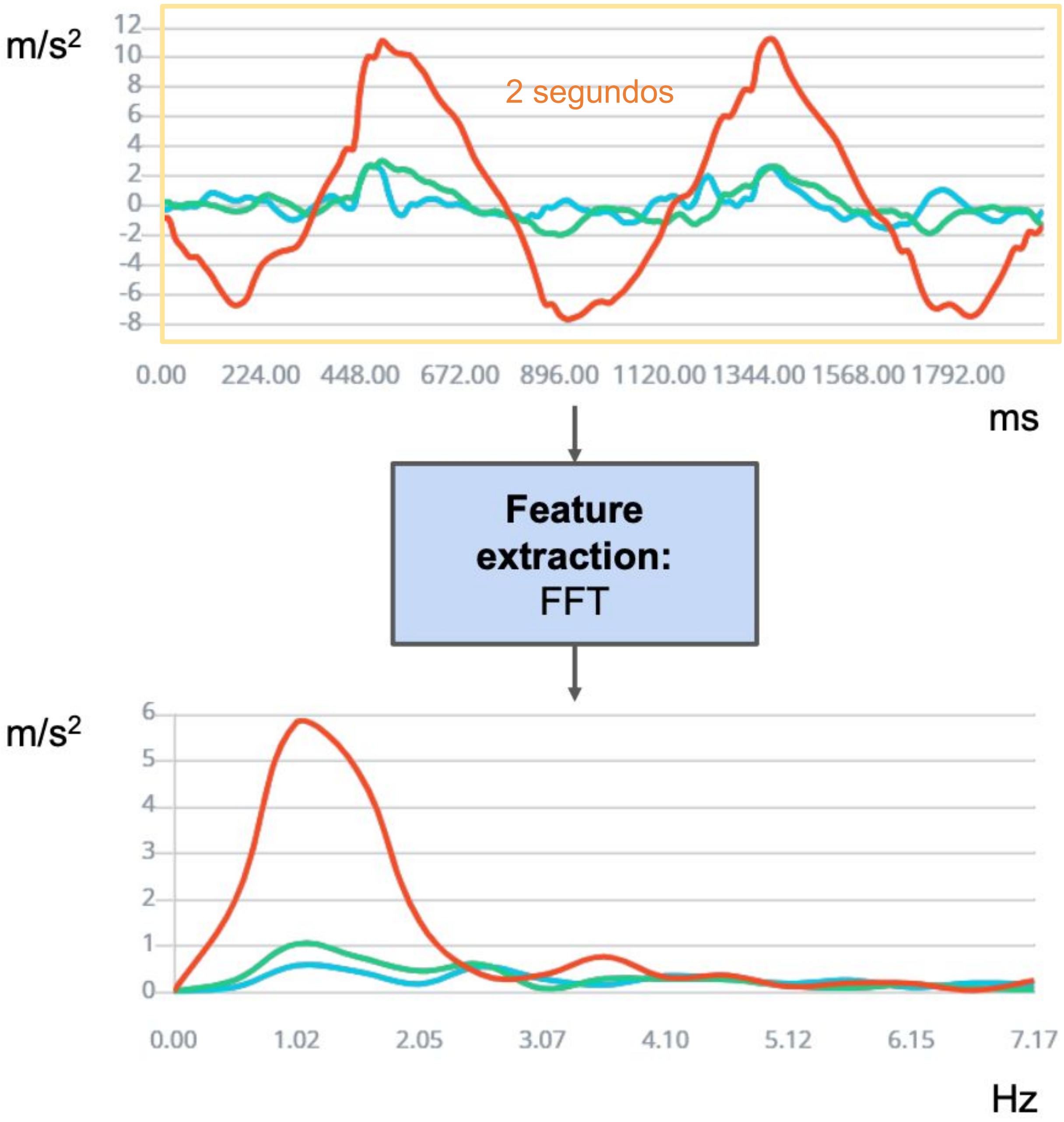


Dominio del Tiempo

```
from scipy.fft import fft
yf = fft(raw signal)
plt.plot(xf, np.abs(yf));
```



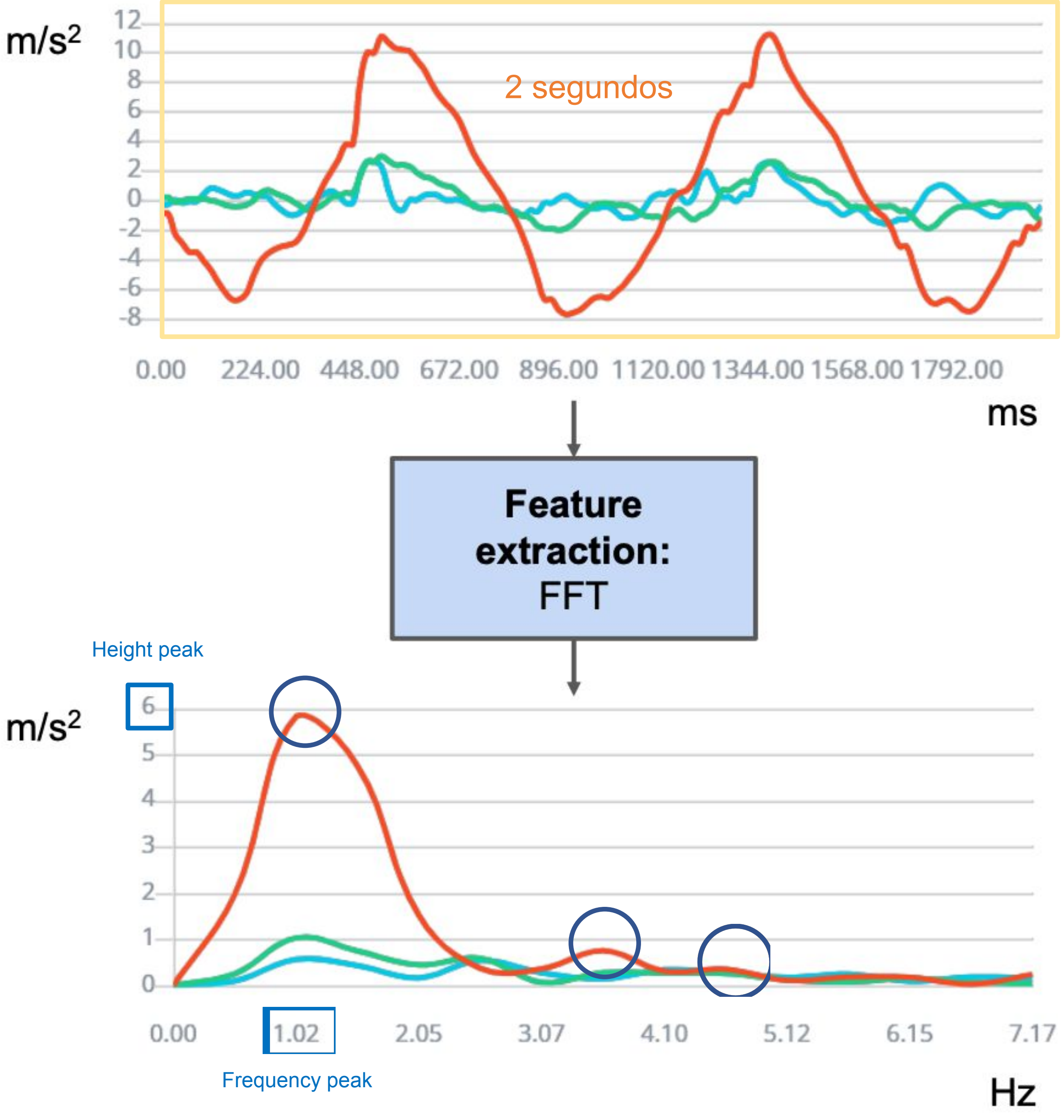
Dominio de la Frecuencia



Extracción de Características

3 RMS

Extracción de Características

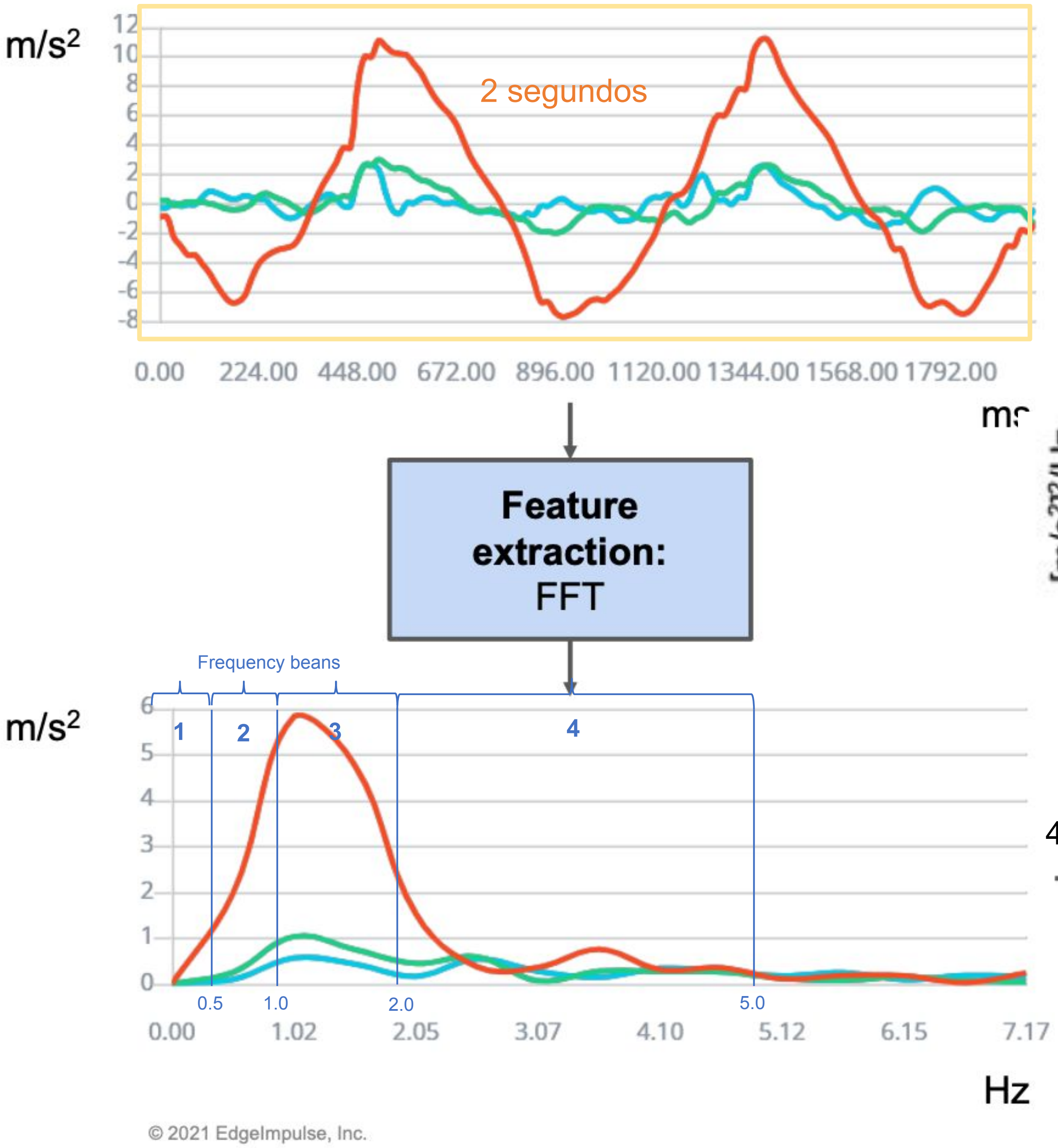


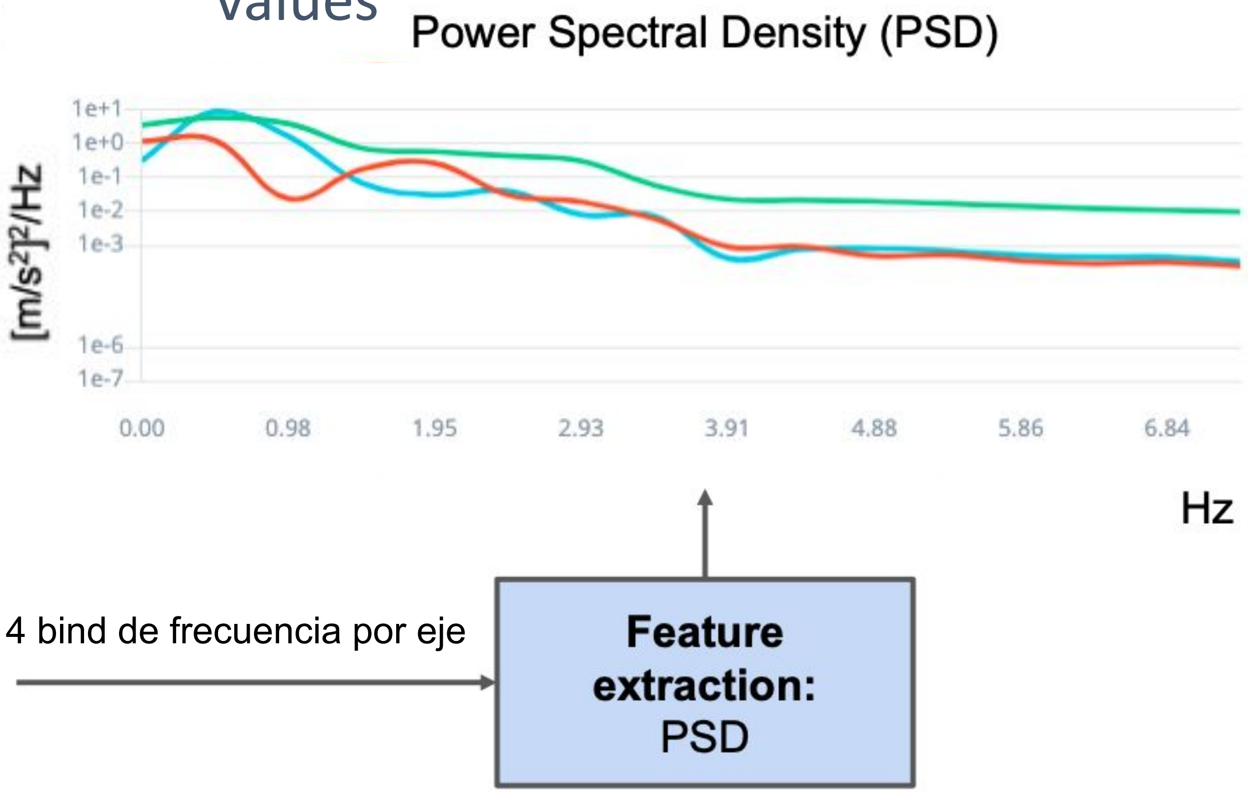
3 RMS

9 Amplitudes + 9 Pico de Freq.

Extracción de Características

3 RMS + 9 Amp + 9 FP + 12 PSD values





https://blog.endaq.com/why-the-power-spectral-density-psd-is-the-gold-standard-of-vibration-analysis

Ventana deslizante: 80 ms

Ventana de 2 Segundos

600 Características crudas

- Datos crudos del sensor

Extracción Manual de Características

Análisis Espectral

11 Características

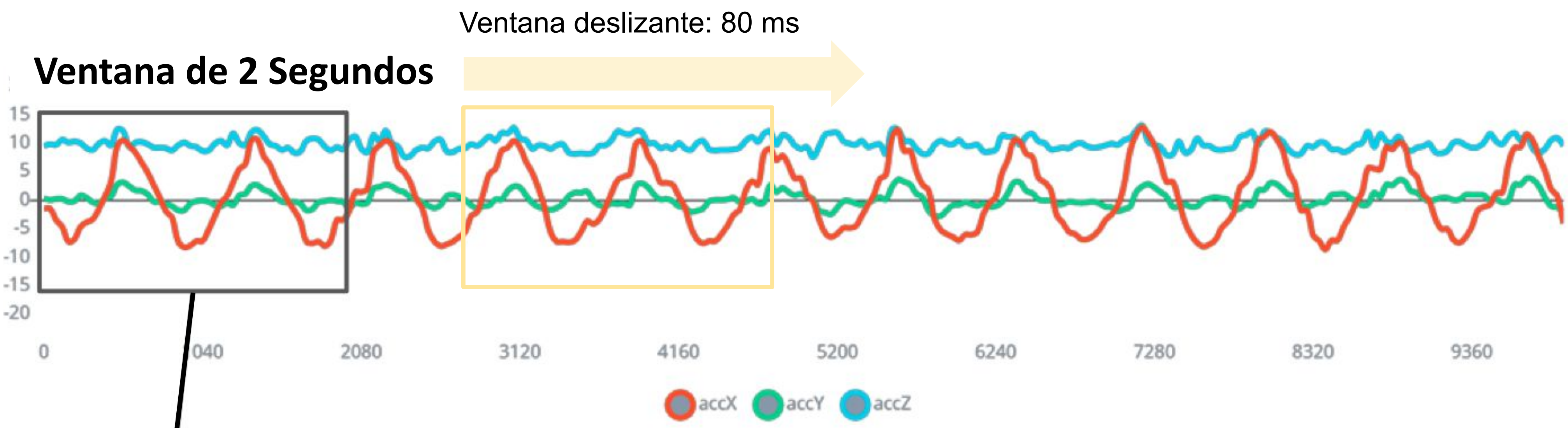
accX RMS
accX Peak
accX Peak
accX Peak
accX Peak
accX Peak
accX Peak
accX Spec
accX Spec
accX Spec
accX Spec

11 Características

accY RMS
accY Peak
accY Peak
accY Peak
accY Peak
accY Peak
accY Peak
accY Spec
accY Spec
accY Spec
accY Spec

11 Características

accZ RMS
accZ Peak 1 Freq
accZ Peak 1 Height
accZ Peak 2 Freq
accZ Peak 2 Height
accZ Peak 3 Freq
accZ Peak 3 Height
accZ Spectral Power 0.1 - 0.5
accZ Spectral Power 0.5 - 1.0
accZ Spectral Power 1.0 - 2.0
accZ Spectral Power 2.0 - 5.0



600 Características crudas

- Datos crudos del sensor

Extracción Manual de Características

Análisis Espectra

33 Características

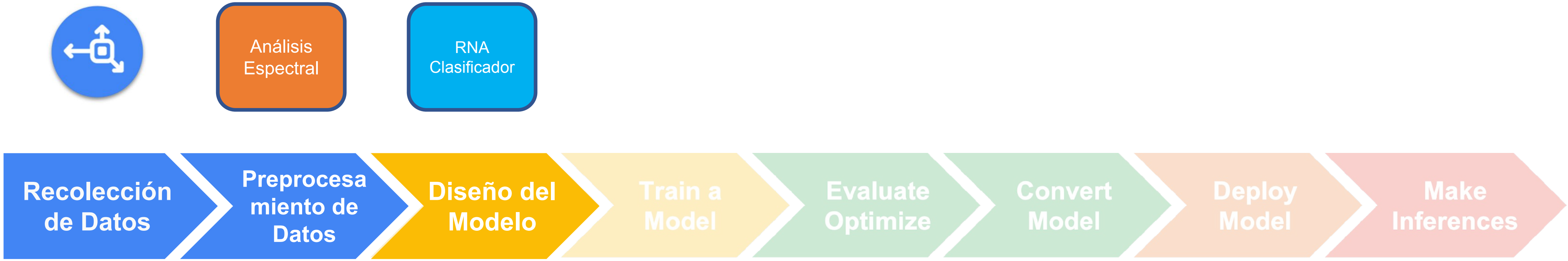
- RMS
- FFT
- PSD

RNA Clasificador

Clases

- Marítimo
- Terrestre (o Tren)
- Cargue
- Bodega

Diseño del Modelo (Clasificador basado en RNA)



Diseño del Modelo (Clasificador basado en RNA)

33 Características

- RMS
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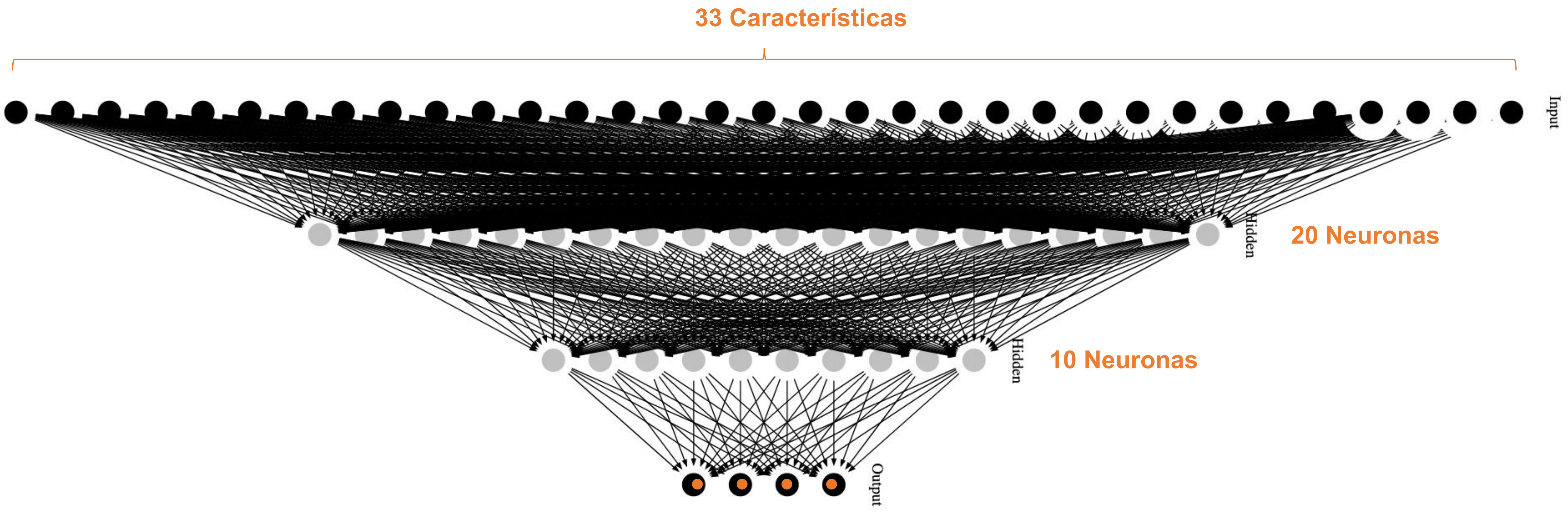

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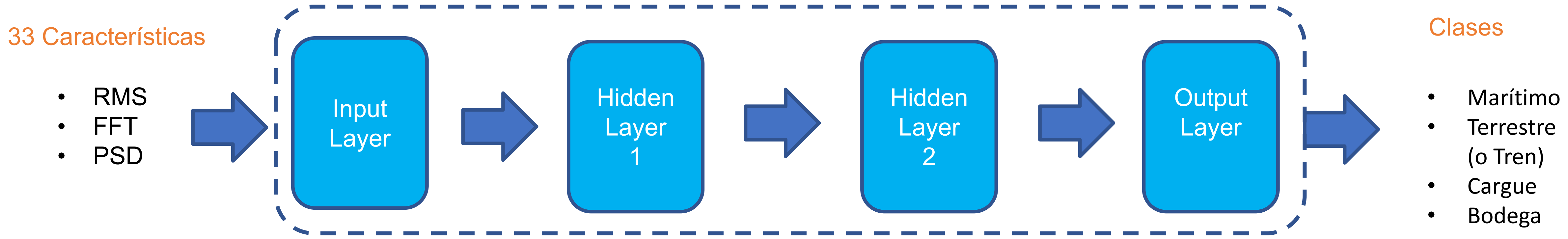
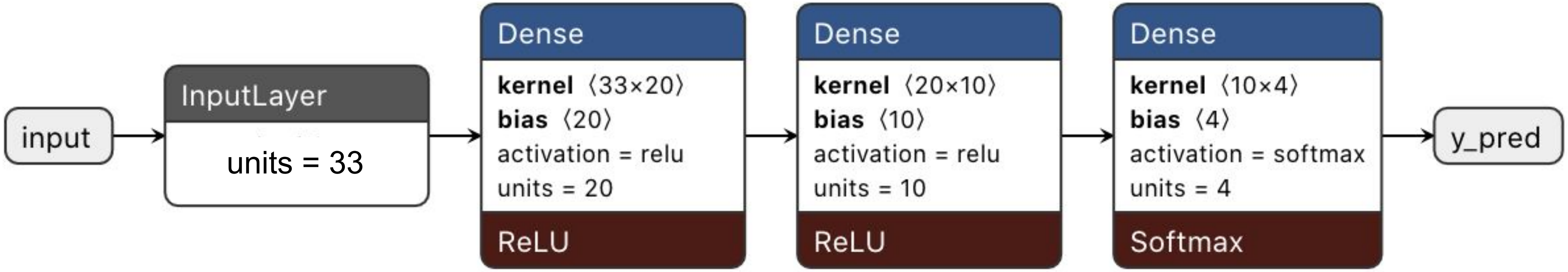
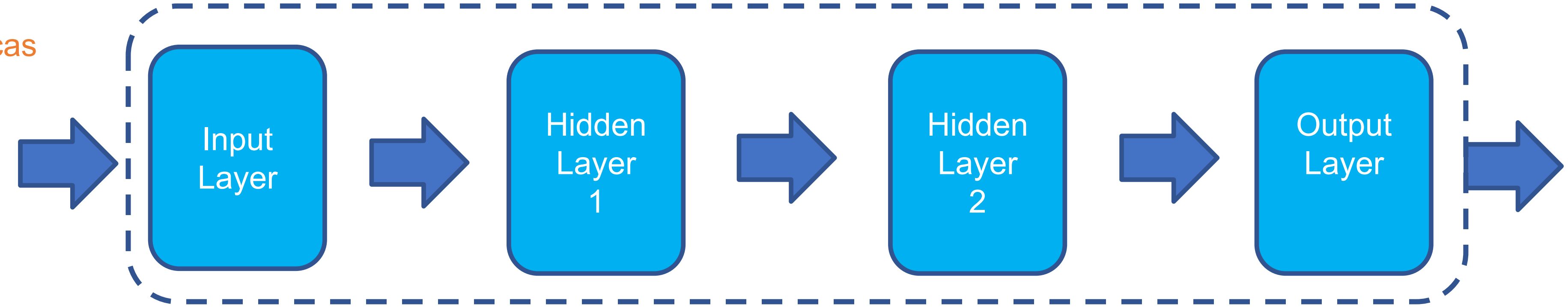


Diseño del Modelo (Clasificador basado en RNA)



33 Características

- RMS
- FFT
- PSD



Clases

- Marítimo
- Terrestre (o Tren)
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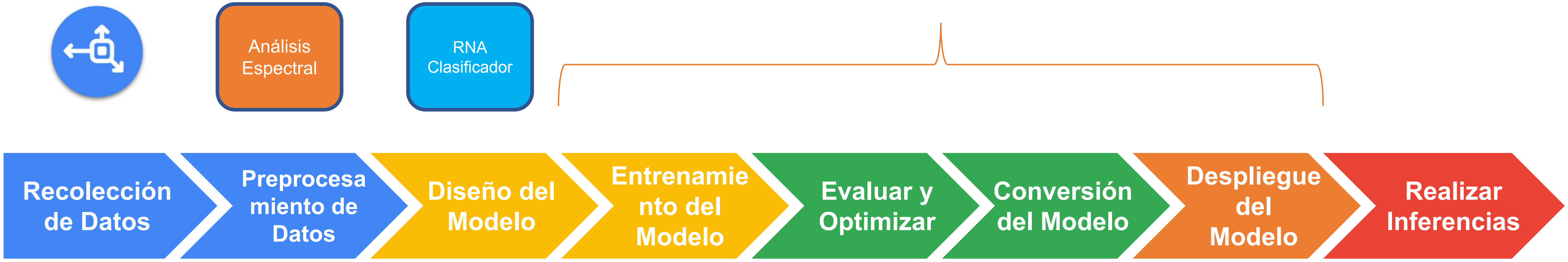
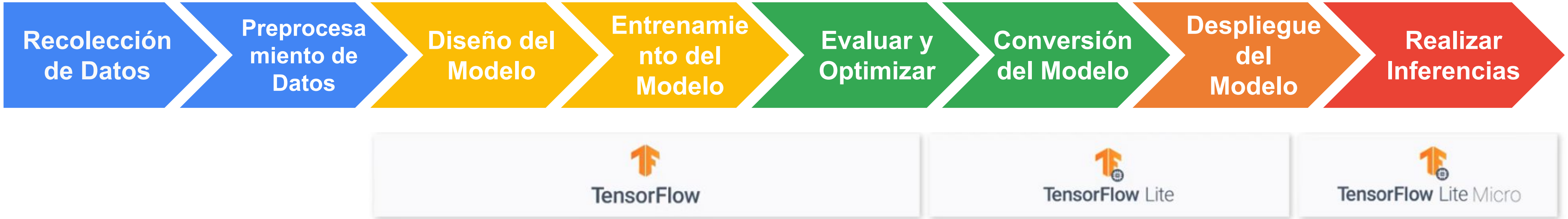
Entrenar, Evaluar, Convertir y Desplegar el Modelo



Entrenar, Evaluar, Convertir y Desplegar el Modelo

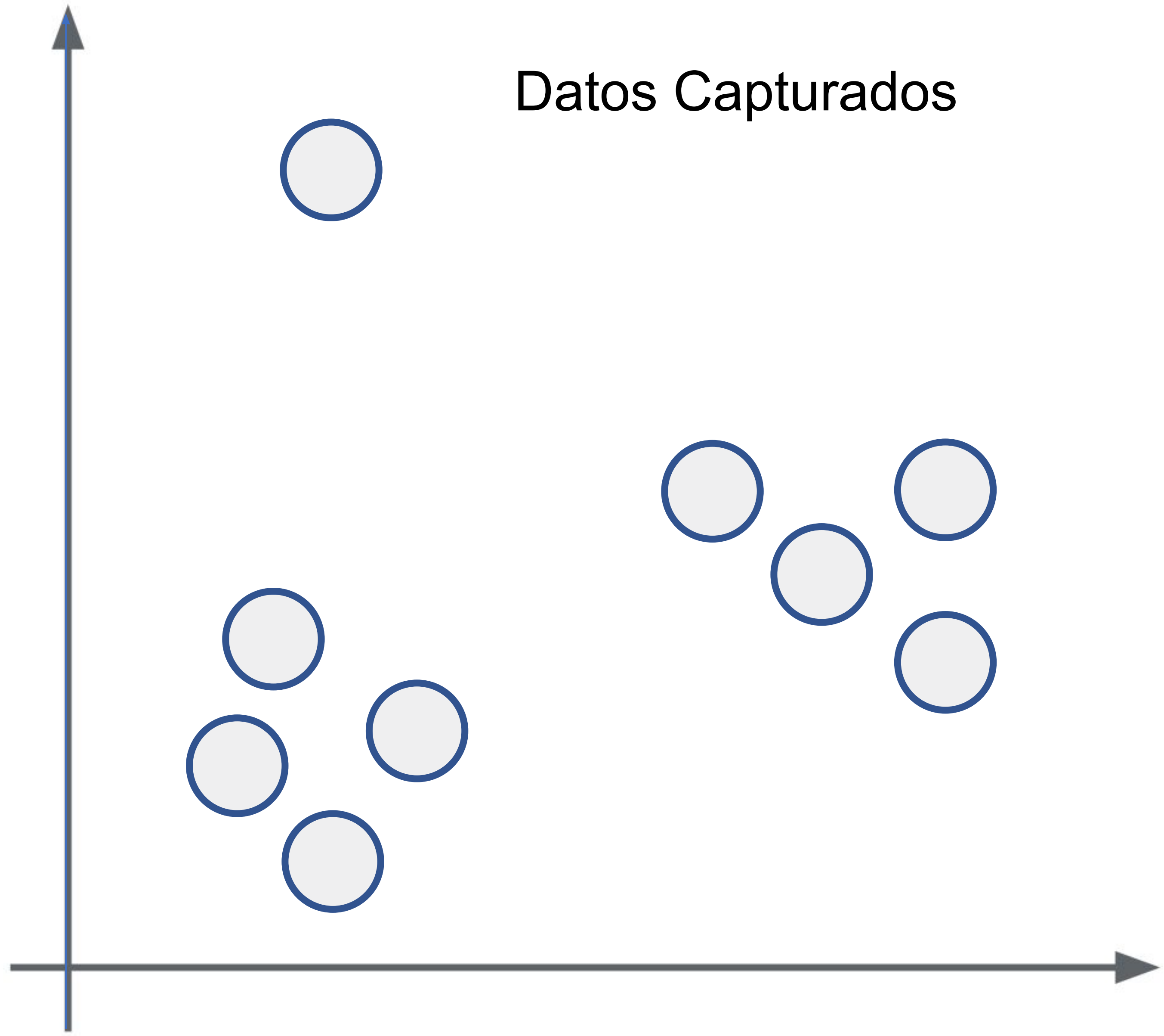


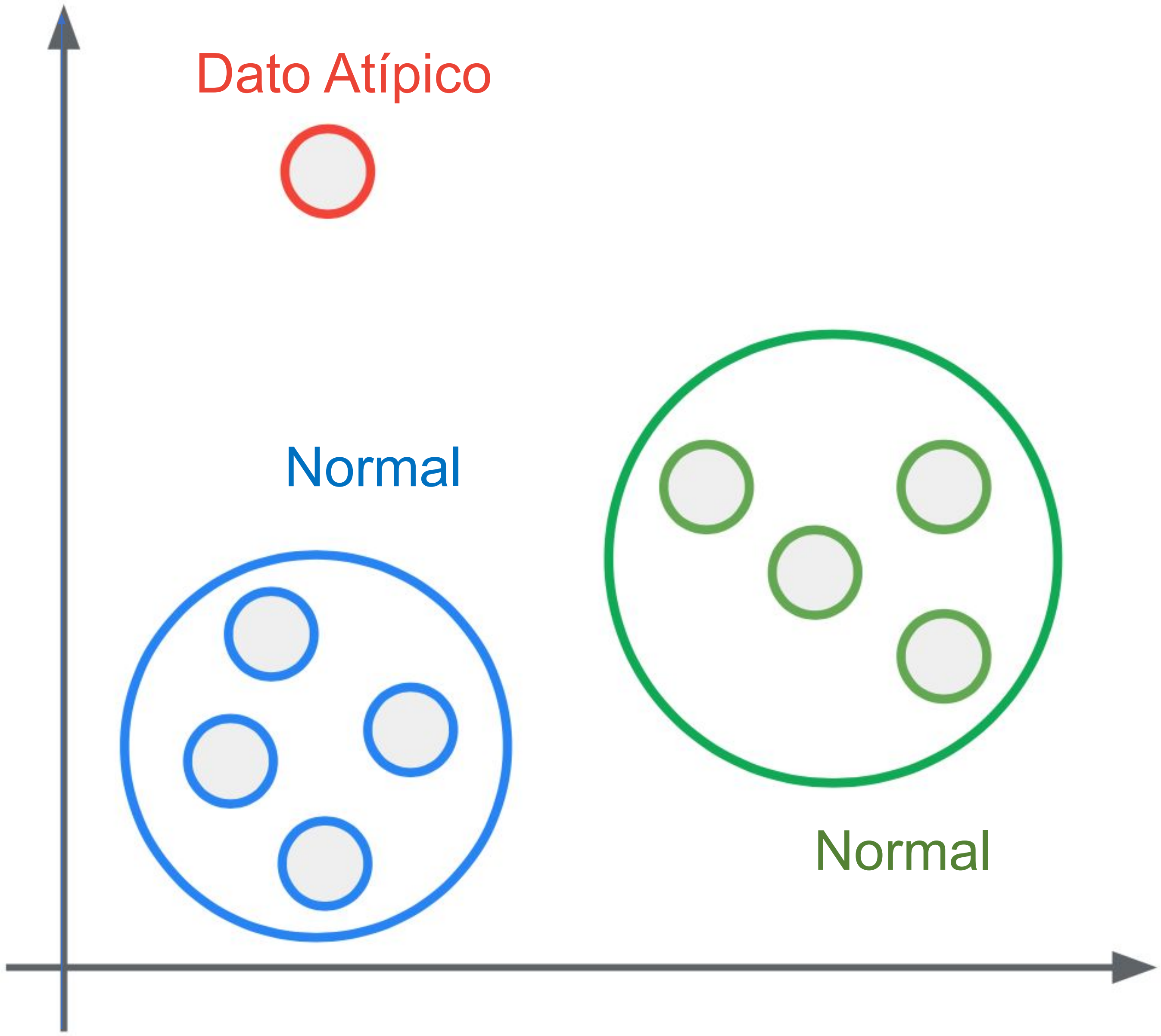
Flujo de trabajo en Aprendizaje Automático

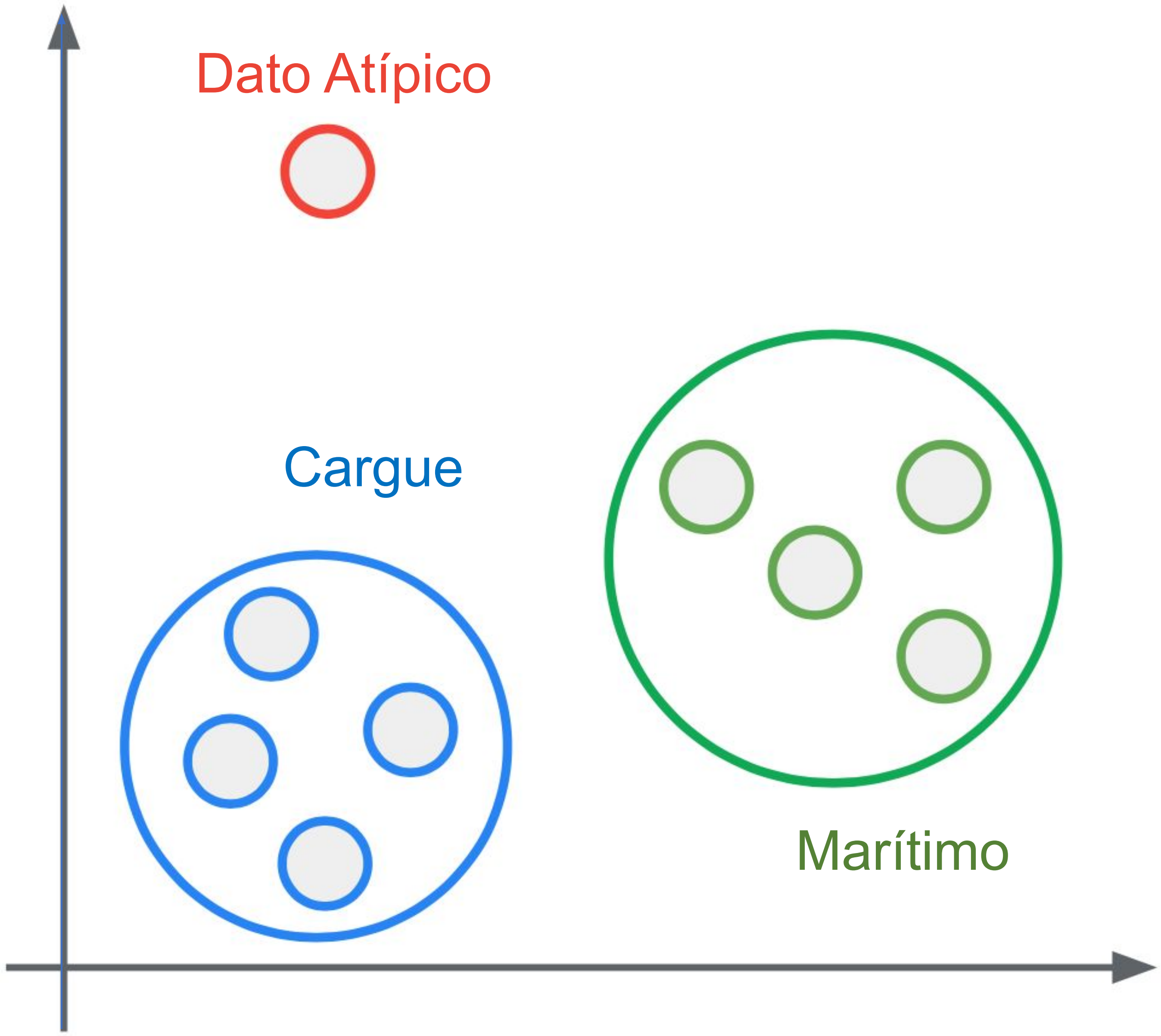
Detección de Anomalías

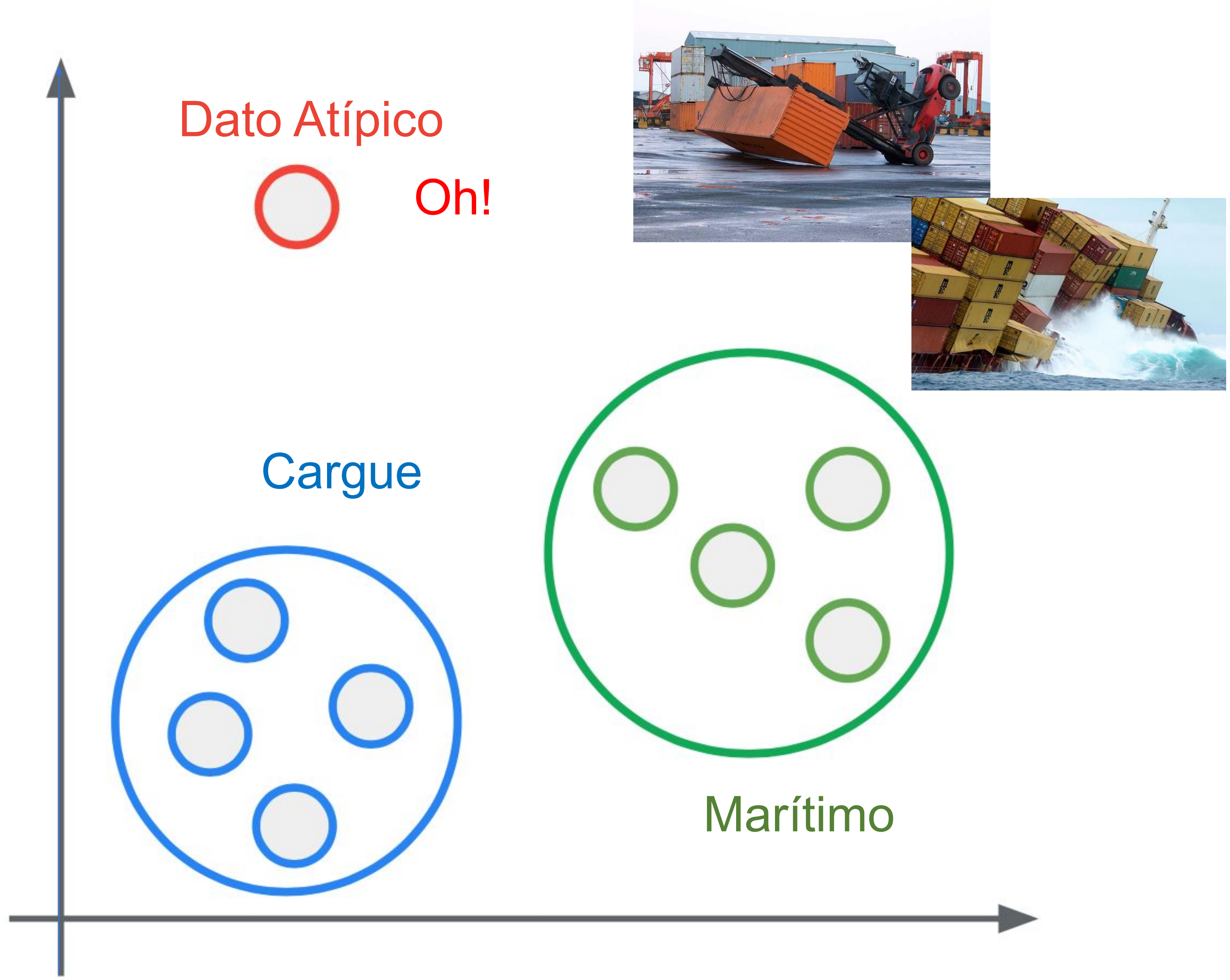
¿Qué es Detección de Anomalías?

En el análisis de datos, la detección de anomalías es la identificación de elementos, eventos u observaciones “raros” o “extraños” que generan sospechas porque difieren significativamente de la **mayoría de los datos.**

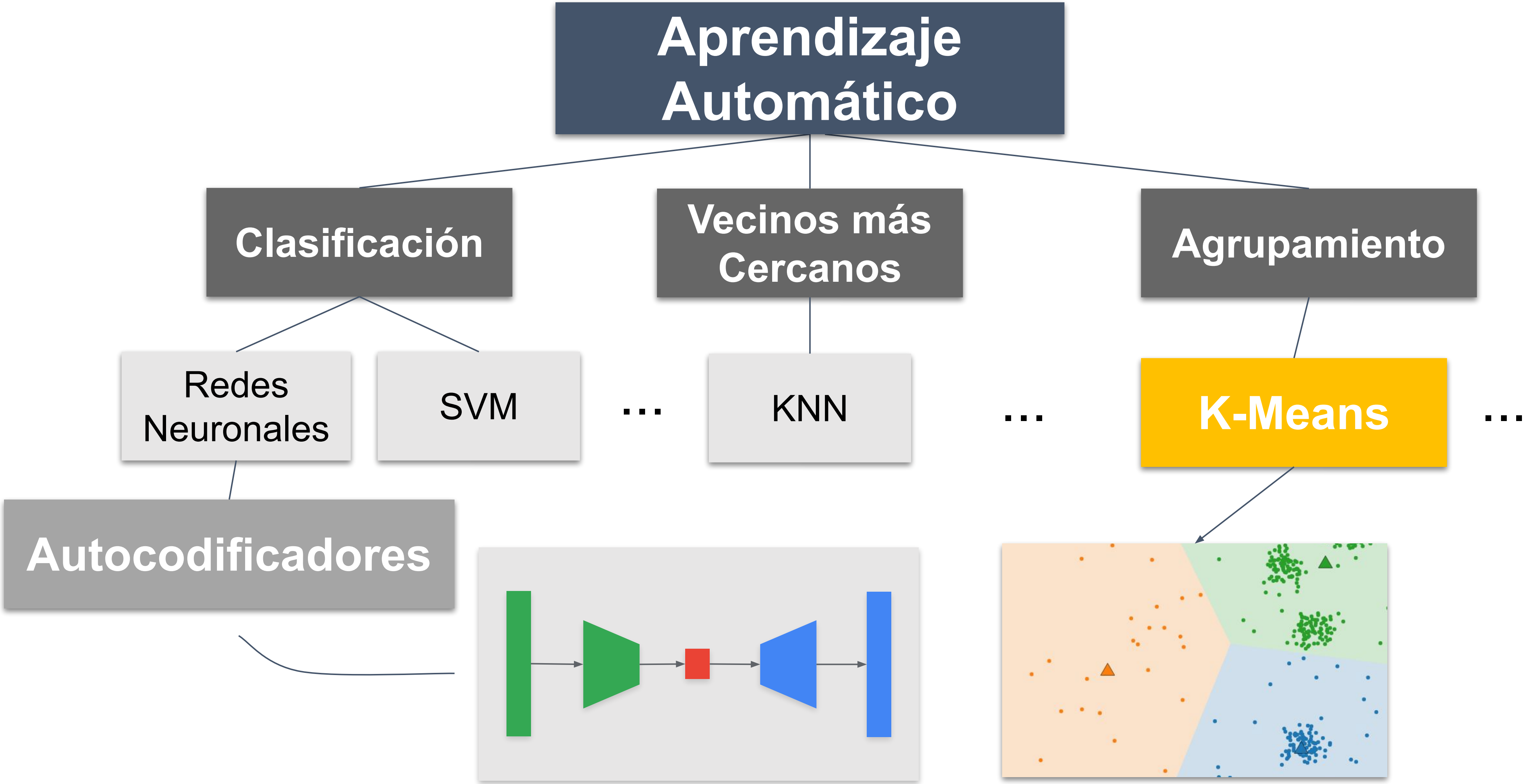

Datos Capturados

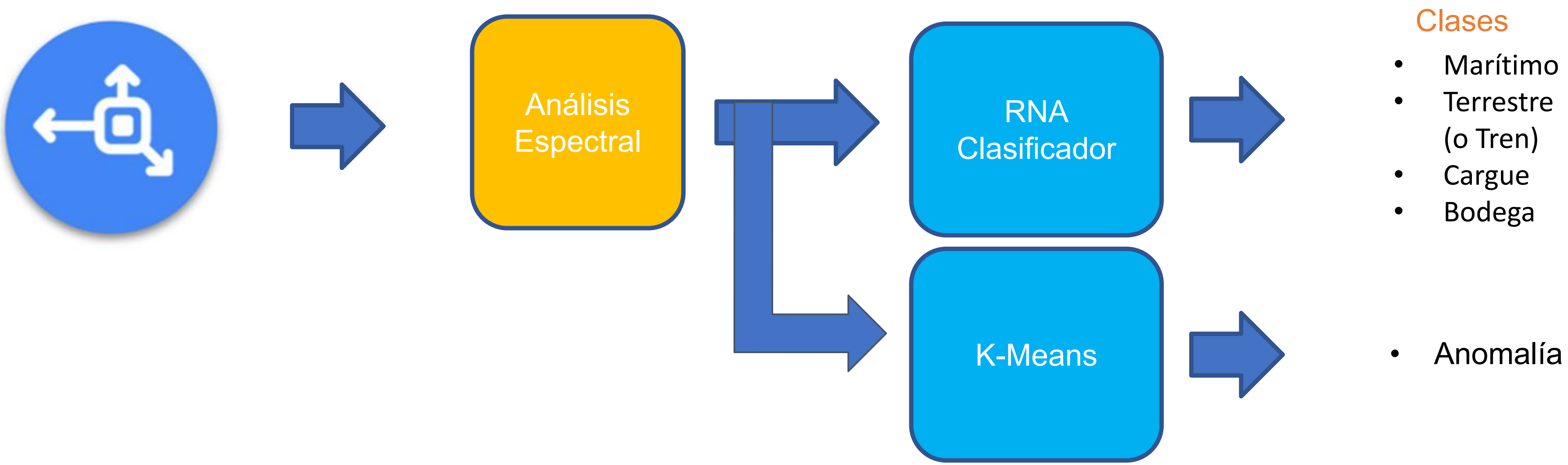

Dato Atípico
Normal
Normal

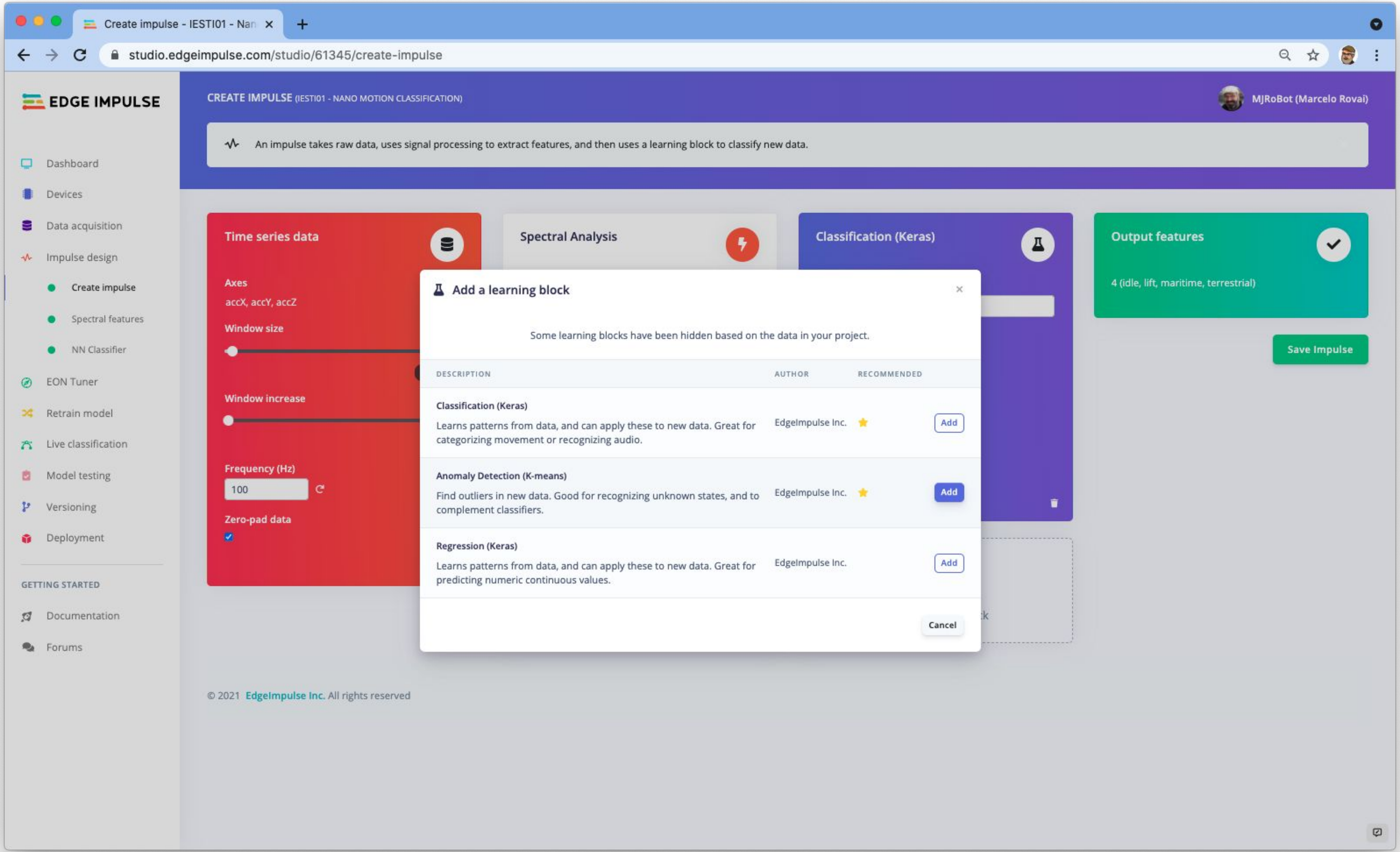

Dato Atípico
Cargue
Marítimo

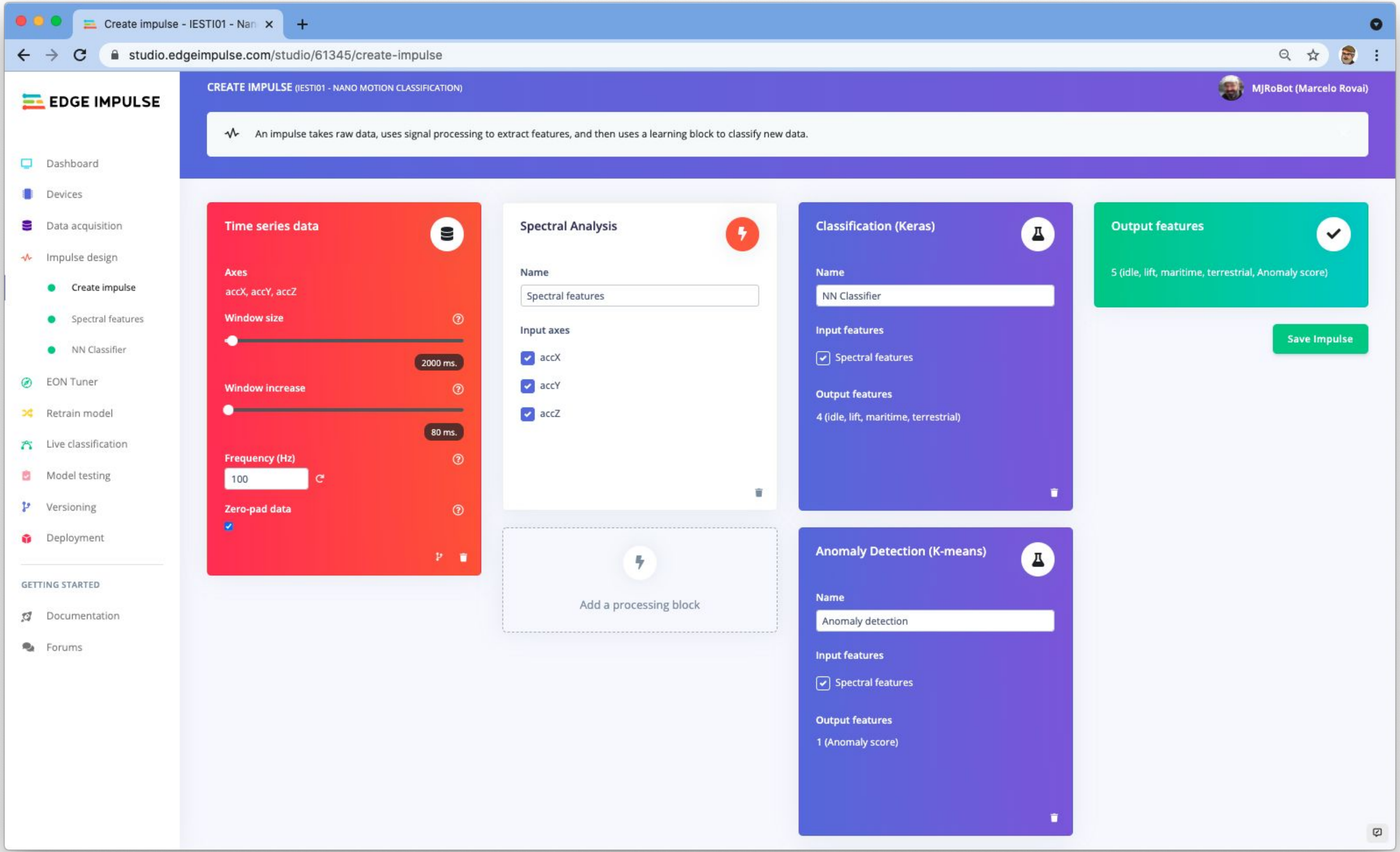

Dato Atípico
Oh!
Cargue
Marítimo

¡No todo es deep learning!




Análisis Espectral
RNA Clasificador
K-Means
Clases
Marítimo
Terrestre (o Tren)
Cargue
Bodega
Anomalía


Create impulse - IESTI01 - Nan
studio.edgeimpulse.com/studio/61345/create-impulse
EDGE IMPULSE
CREATE IMPULSE (IESTI01 - NANO MOTION CLASSIFICATION)
MJRoBot (Marcelo Rovai)
An impulse takes raw data, uses signal processing to extract features, and then uses a learning block to classify new data.
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Spectral features
NN Classifier
EON Tuner
Retrain model
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
Time series data
Axes
accX, accY, accZ
Window size
Window increase
Frequency (Hz)
100
Zero-pad data
Spectral Analysis
Classification (Keras)
Output features
4 (idle, lift, maritime, terrestrial)
Save Impulse
Add a learning block
Some learning blocks have been hidden based on the data in your project.
DESCRIPTION
AUTHOR
RECOMMENDED
Classification (Keras)
Learns patterns from data, and can apply these to new data. Great for categorizing movement or recognizing audio.
EdgeImpulse Inc.
Add
Anomaly Detection (K-means)
Find outliers in new data. Good for recognizing unknown states, and to complement classifiers.
EdgeImpulse Inc.
Add
Regression (Keras)
Learns patterns from data, and can apply these to new data. Great for predicting numeric continuous values.
EdgeImpulse Inc.
Add
Cancel
© 2021 EdgeImpulse Inc. All rights reserved


Create impulse - IESTI01 - Nan
studio.edgeimpulse.com/studio/61345/create-impulse
EDGE IMPULSE
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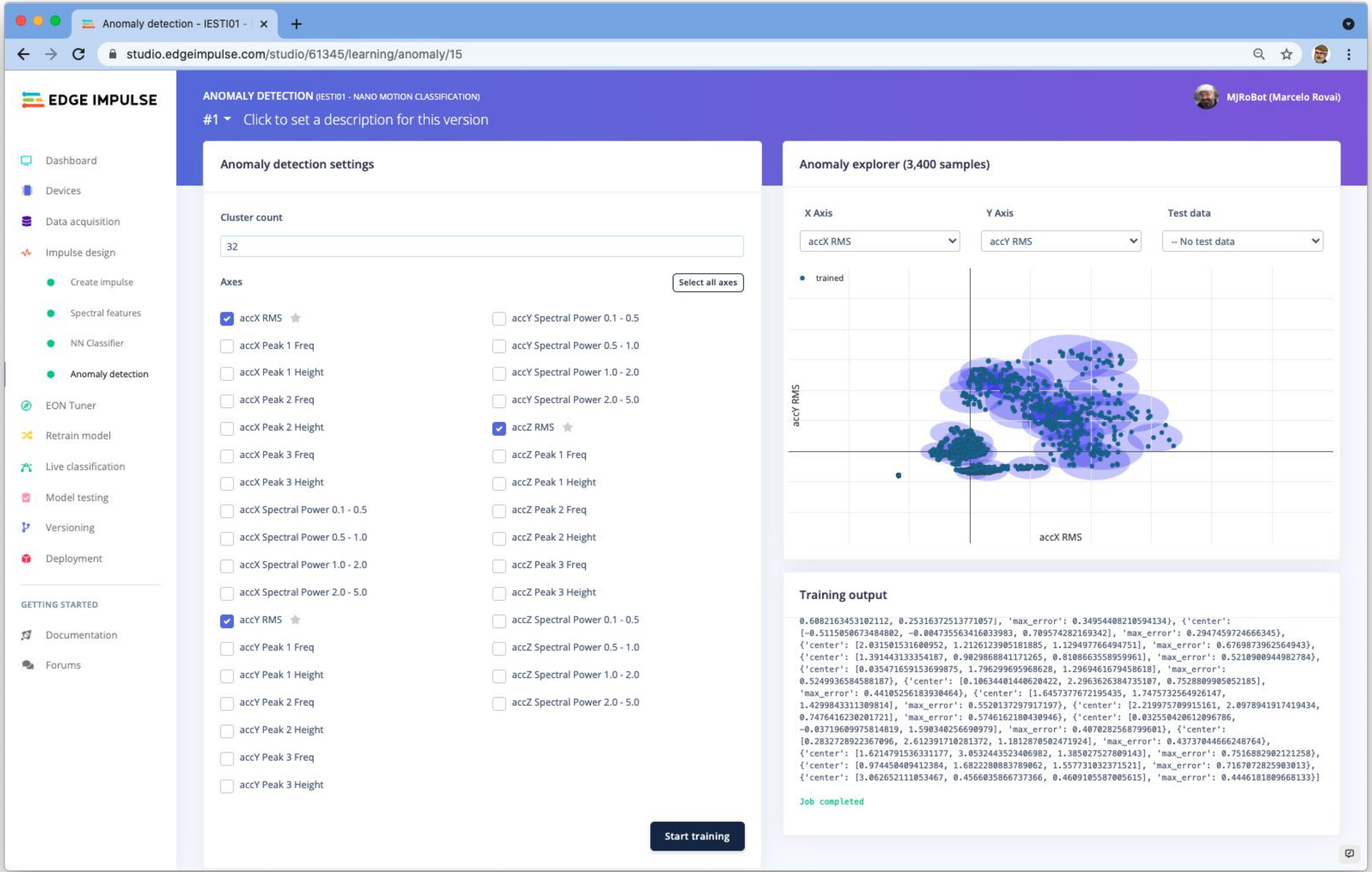
GETTING STARTED
Documentation
Forums
Time series data
Axes
accX, accY, accZ
Window size
2000 ms.
Window increase
80 ms.
Frequency (Hz)
100
Zero-pad data
Spectral Analysis
Name
Spectral features
Input axes
accX
accY
accZ
Add a processing block
Classification (Keras)
Name
NN Classifier
Input features
Spectral features
Output features
4 (idle, lift, maritime, terrestrial)
Anomaly Detection (K-means)
Name
Anomaly detection
Input features
Spectral features
Output features
1 (Anomaly score)
Output features
5 (idle, lift, maritime, terrestrial, Anomaly score)
Save Impulse


Anomaly detection - IESTI01 -
studio.edgeimpulse.com/studio/61345/learning/anomaly/15
EDGE IMPULSE
ANOMALY DETECTION (IESTI01 - NANO MOTION CLASSIFICATION)
#1 Click to set a description for this version
MJRoBot (Marcelo Rovai)
Dashboard
Devices
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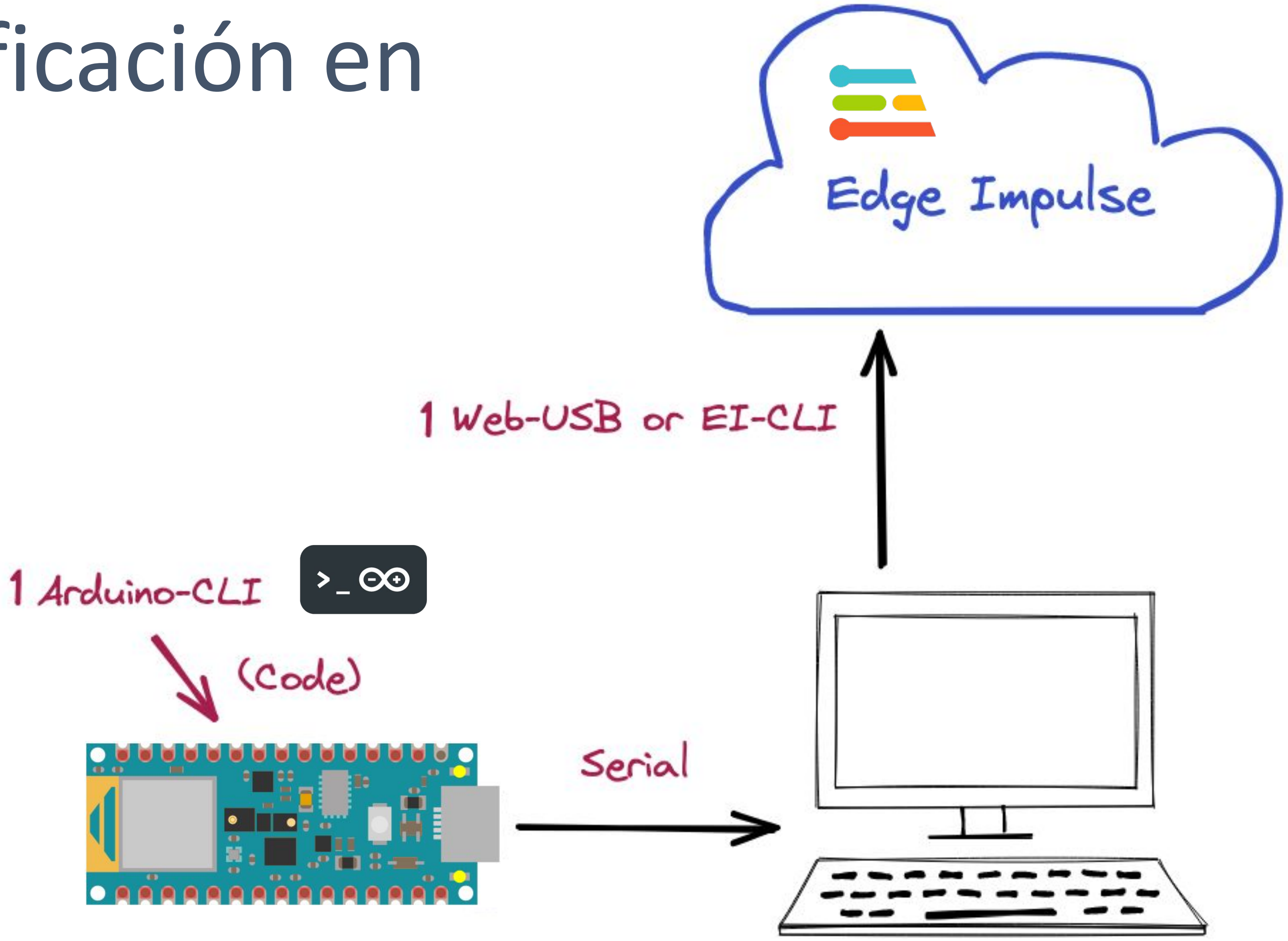
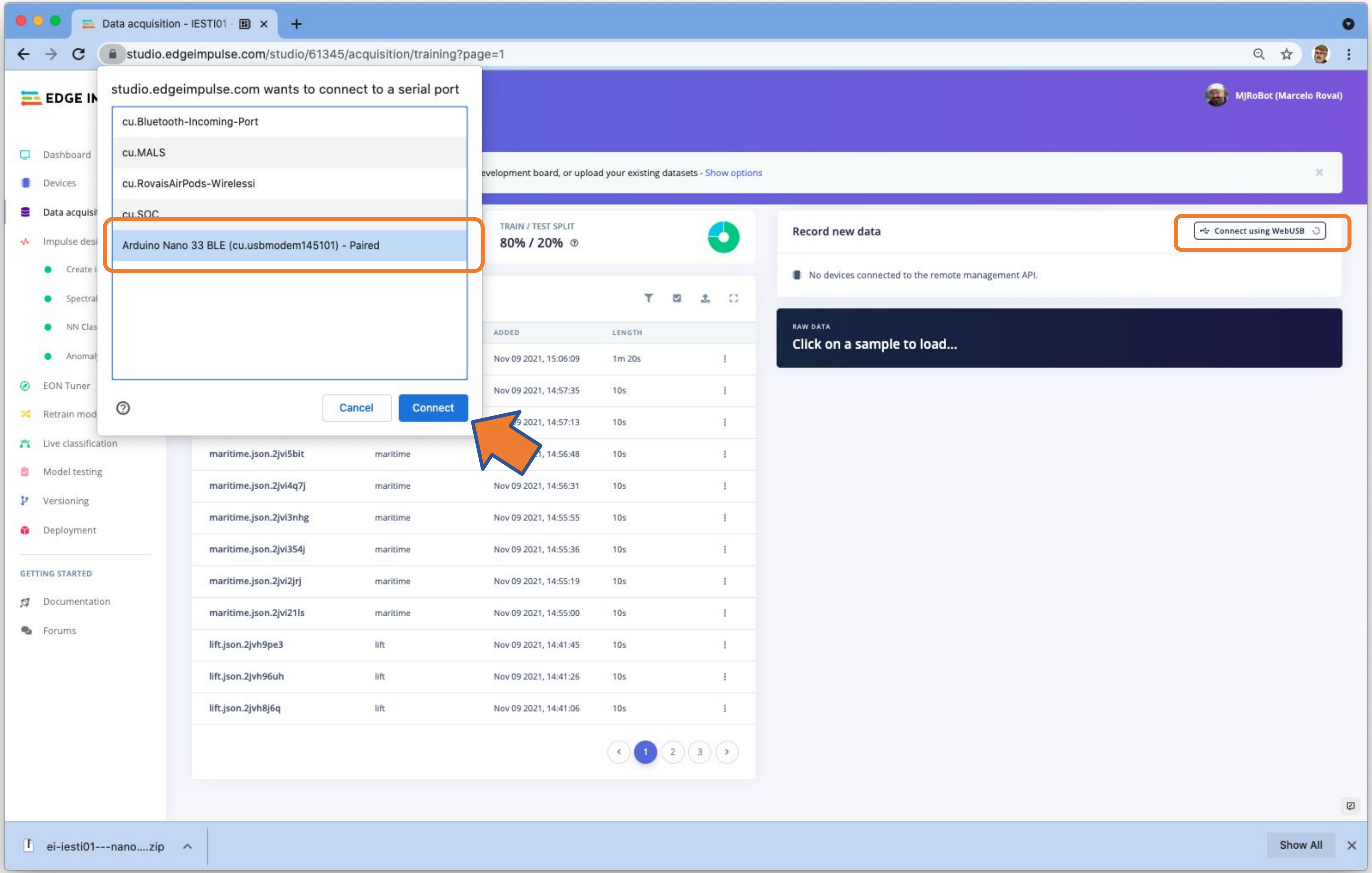
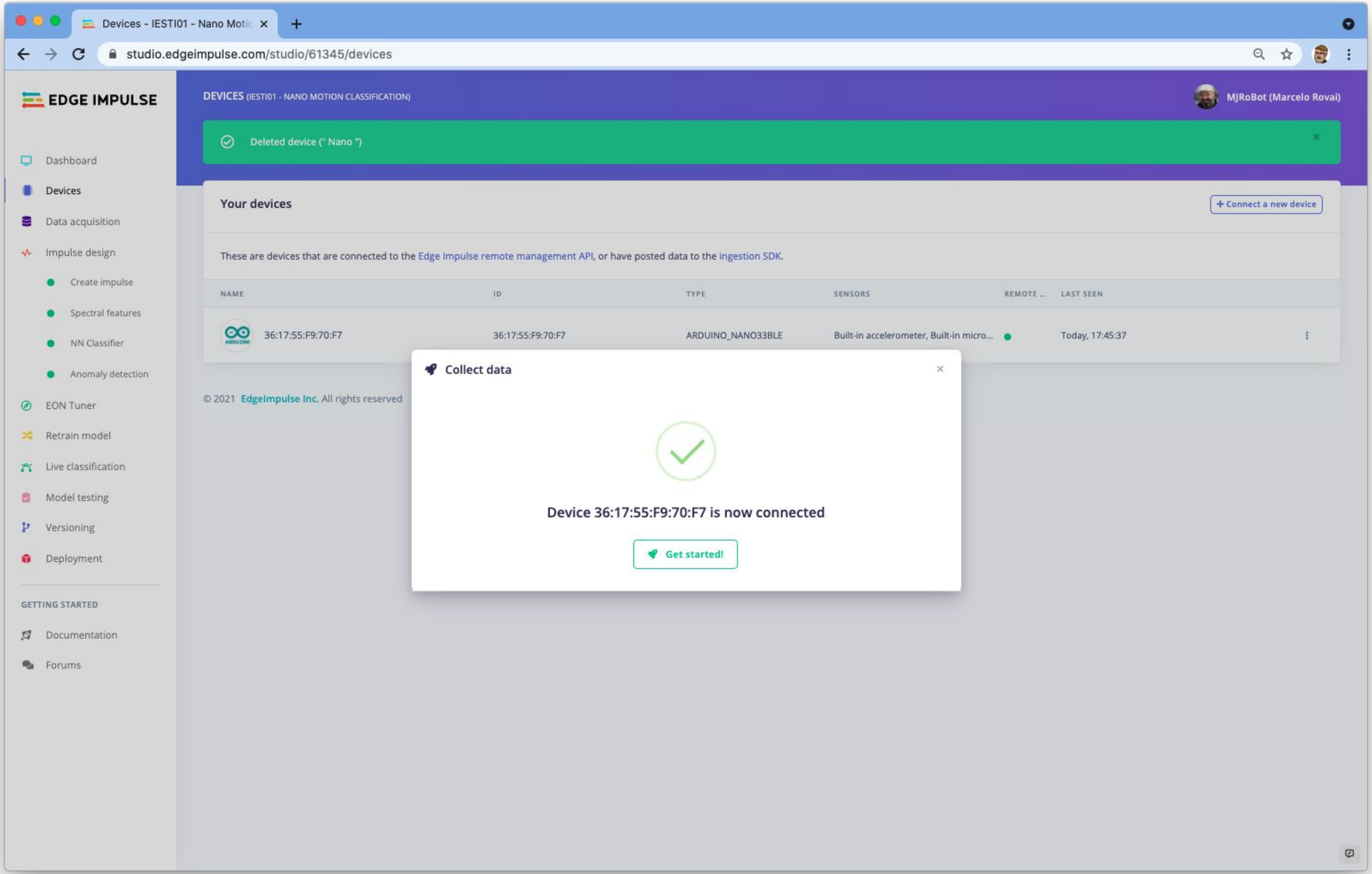
Deployment
GETTING STARTED
Documentation
Forums
Anomaly detection settings
Cluster count
32
Axes
Select all axes
accX RMS
accX Peak 1 Freq
accX Peak 1 Height
accX Peak 2 Freq
accX Peak 2 Height
accX Peak 3 Freq
accX Peak 3 Height
accX Spectral Power 0.1 - 0.5
accX Spectral Power 0.5 - 1.0
accX Spectral Power 1.0 - 2.0
accX Spectral Power 2.0 - 5.0
accY RMS
accY Peak 1 Freq
accY Peak 1 Height
accY Peak 2 Freq
accY Peak 2 Height
accY Peak 3 Freq
accY Peak 3 Height
accY Spectral Power 0.1 - 0.5
accY Spectral Power 0.5 - 1.0
accY Spectral Power 1.0 - 2.0
accY Spectral Power 2.0 - 5.0
accZ RMS
accZ Peak 1 Freq
accZ Peak 1 Height
accZ Peak 2 Freq
accZ Peak 2 Height
accZ Peak 3 Freq
accZ Peak 3 Height
accZ Spectral Power 0.1 - 0.5
accZ Spectral Power 0.5 - 1.0
accZ Spectral Power 1.0 - 2.0
accZ Spectral Power 2.0 - 5.0
Start training
Anomaly explorer (3,400 samples)
X Axis
Y Axis
Test data
accX RMS
accY RMS
-- No test data
trained
accY RMS
accX RMS
Training output
0.6082163453102112, 0.2531637251377105 7], 'max_error': 0.34954408210594134}, {'center':
[-0.5115050673484802, -0.004735563416033983, 0.709574282169342], 'max_error': 0.2947459724666345},
{'center': [2.031501531600952, 1.2126123905181885, 1.129497766494751], 'max_error': 0.6769873962564943},
{'center': [1.391443133354187, 0.9029868841171265, 0.8108663558959961], 'max_error': 0.5210900944982784},
{'center': [0.035471659153699875, 1.796299695968628, 1.2969461679458618], 'max_error':
0.5249936584588187}, {'center': [0.10634401440620422, 2.2963626384735107, 0.7528809905052185],
'max_error': 0.44105256183930464}, {'center': [1.6457377672195435, 1.7475732564926147,
1.4299843311309814], 'max_error': 0.5520137297917197}, {'center': [2.219975709915161, 2.0978941917419434,
0.7476416230201721], 'max_error': 0.5746162180430946}, {'center': [0.032550420612096786,
-0.03719609975814819, 1.590340256690979], 'max_error': 0.4070282568799601}, {'center':
[0.2832728922367096, 2.612391710281372, 1.1812870502471924], 'max_error': 0.43737044666248764},
{'center': [1.6214791536331177, 3.0532443523406982, 1.385027527809143], 'max_error': 0.751688290212125 8},
{'center': [0.974450409412384, 1.6822280883789062, 1.557731032371521], 'max_error': 0.7167072825903013},
{'center': [3.062652111053467, 0.4566035866737366, 0.4609105587005615], 'max_error': 0.4446181809668133}]
Job completed

Clasificación en Vivo





Data acquisition - IESTI01
studio.edgeimpulse.com/studio/61345/acquisition/training?page=1
EDGE IM
studio.edgeimpulse.com wants to connect to a serial port
cu.Bluetooth-Incoming-Port
cu.MALS
cu.RovaisAirPods-Wirelessi
cu.SOC
Arduino Nano 33 BLE (cu.usbmodem145101) - Paired
Cancel
Connect
MJRoBot (Marcelo Rovai)
evelopment board, or upload your existing datasets - Show options
Dashboard
Devices
Data acquisi
Impulse desi
Create i
Spectral
NN Clas
Anomal
EON Tuner
Retrain mod
Live classification
Model testing
Versioning
Deployment
GETTING STARTED
Documentation
Forums
TRAIN / TEST SPLIT
80% / 20%
Record new data
Connect using WebUSB
No devices connected to the remote management API.
RAW DATA
Click on a sample to load...
ADDED
LENGTH
Nov 09 2021, 15:06:09
1m 20s
Nov 09 2021, 14:57:35
10s
9 2021, 14:57:13
10s
maritime.json.2jvi5bit
maritime
1, 14:56:48
10s
maritime.json.2jvi4q7j
maritime
Nov 09 2021, 14:56:31
10s
maritime.json.2jvi3nhg
maritime
Nov 09 2021, 14:55:55
10s
maritime.json.2jvi354j
maritime
Nov 09 2021, 14:55:36
10s
maritime.json.2jvi2jrj
maritime
Nov 09 2021, 14:55:19
10s
maritime.json.2jvi21ls
maritime
Nov 09 2021, 14:55:00
10s
lift.json.2jvh9pe3
lift
Nov 09 2021, 14:41:45
10s
lift.json.2jvh96uh
lift
Nov 09 2021, 14:41:26
10s
lift.json.2jvh8j6q
lift
Nov 09 2021, 14:41:06
10s
1
2
3
ei-iesti01---nano....zip
Show All


Devices - IESTI01 - Nano Motic
studio.edgeimpulse.com/studio/61345/devices
EDGE IMPULSE
DEVICES (IESTI01 - NANO MOTION CLASSIFICATION)
MJRoBot (Marcelo Rovai)
Deleted device (" Nano ")
Dashboard
Devices
Data acquisition
Impulse design
Create impulse
Spectral features
NN Classifier
Anomaly detection
EON Tuner
Retrain model
Live classification
Model testing
Versioning
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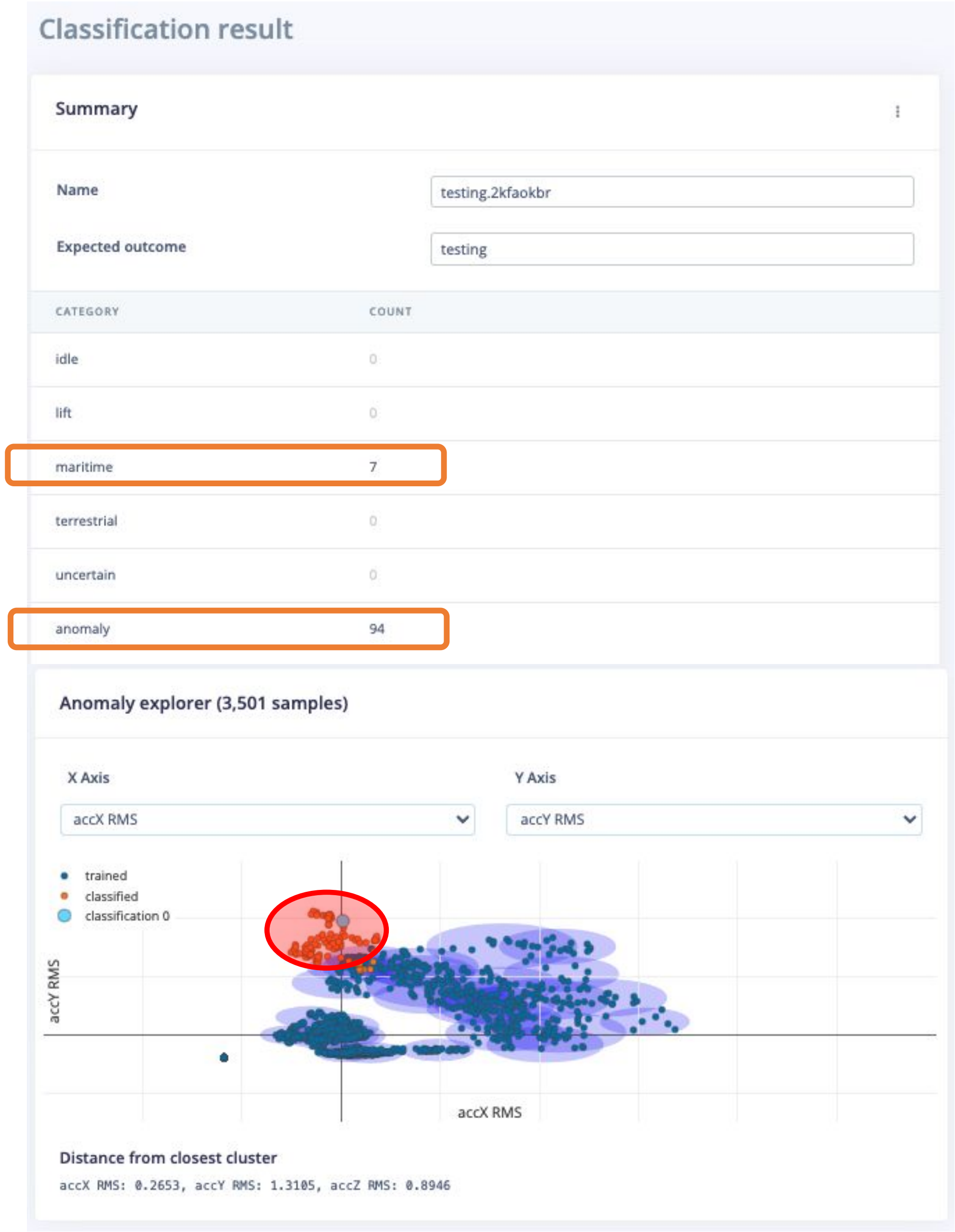
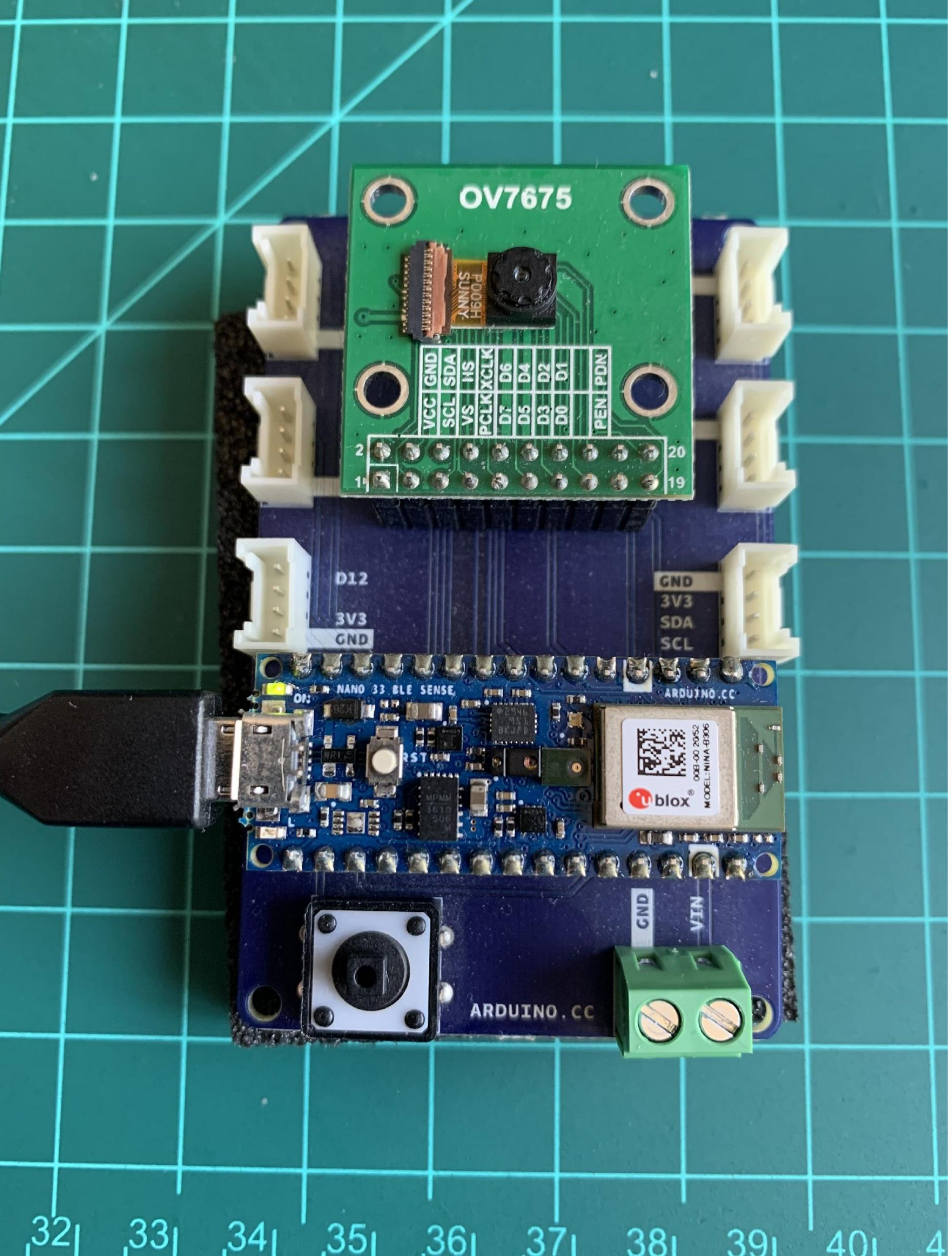
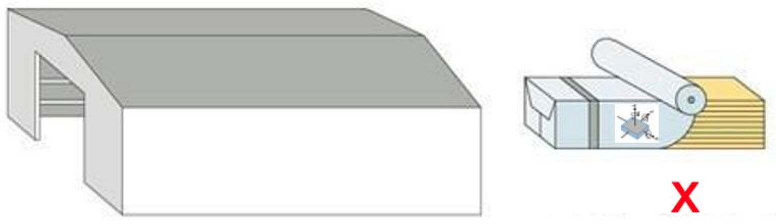
GETTING STARTED
Documentation
Forums
Your devices
+ Connect a new device
These are devices that are connected to the Edge Impulse remote management API, or have posted data to the ingestion SDK.
NAME
ID
TYPE
SENSORS
REMOTE ...
LAST SEEN
36:17:55:F9:70:F7
36:17:55:F9:70:F7
ARDUINO_NANO33BLE
Built-in accelerometer, Built-in micro...
Today, 17:45:37
© 2021 EdgeImpulse Inc. All rights reserved
Collect data
Device 36:17:55:F9:70:F7 is now connected
Get started!

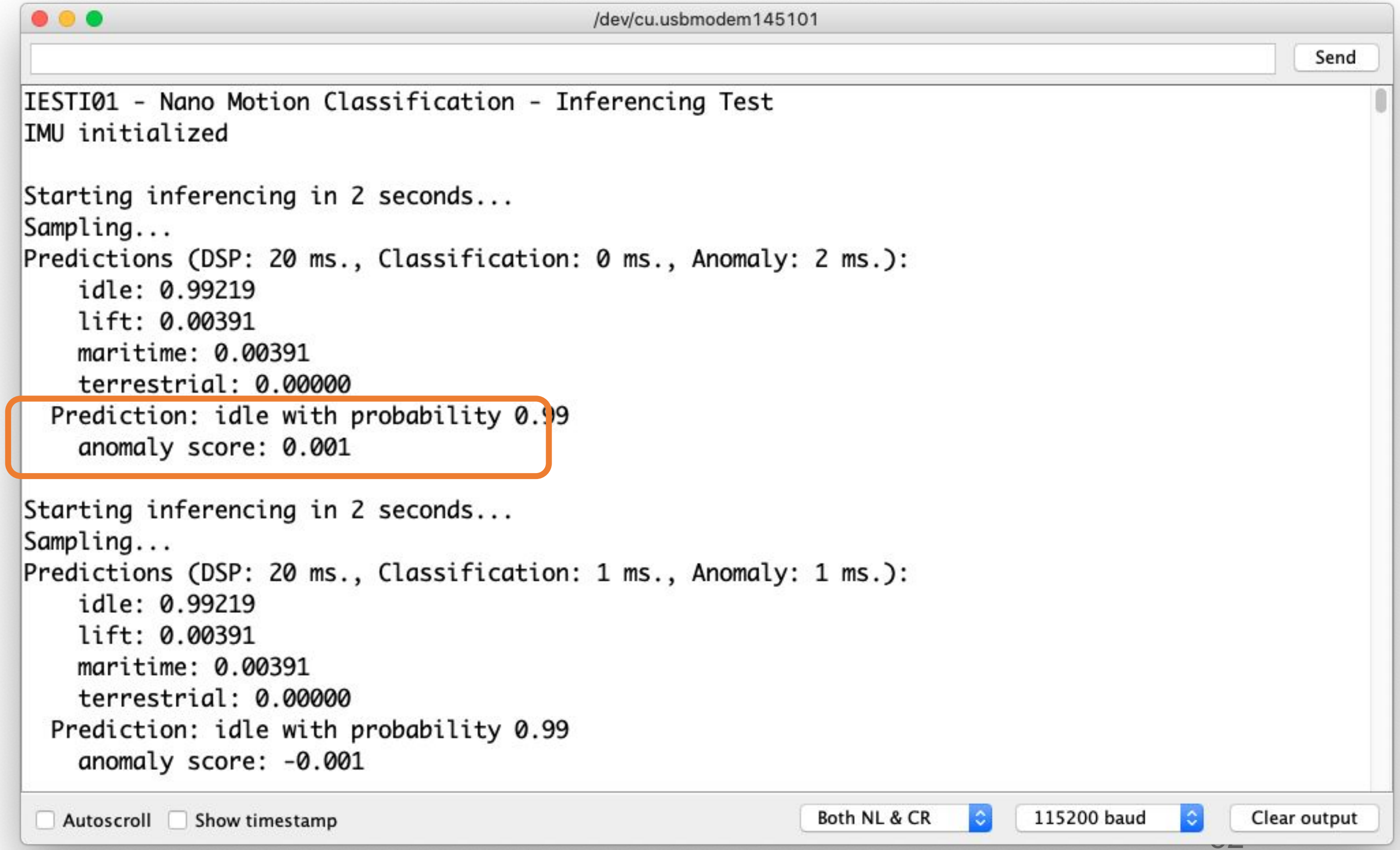
Prueba: Anomalía



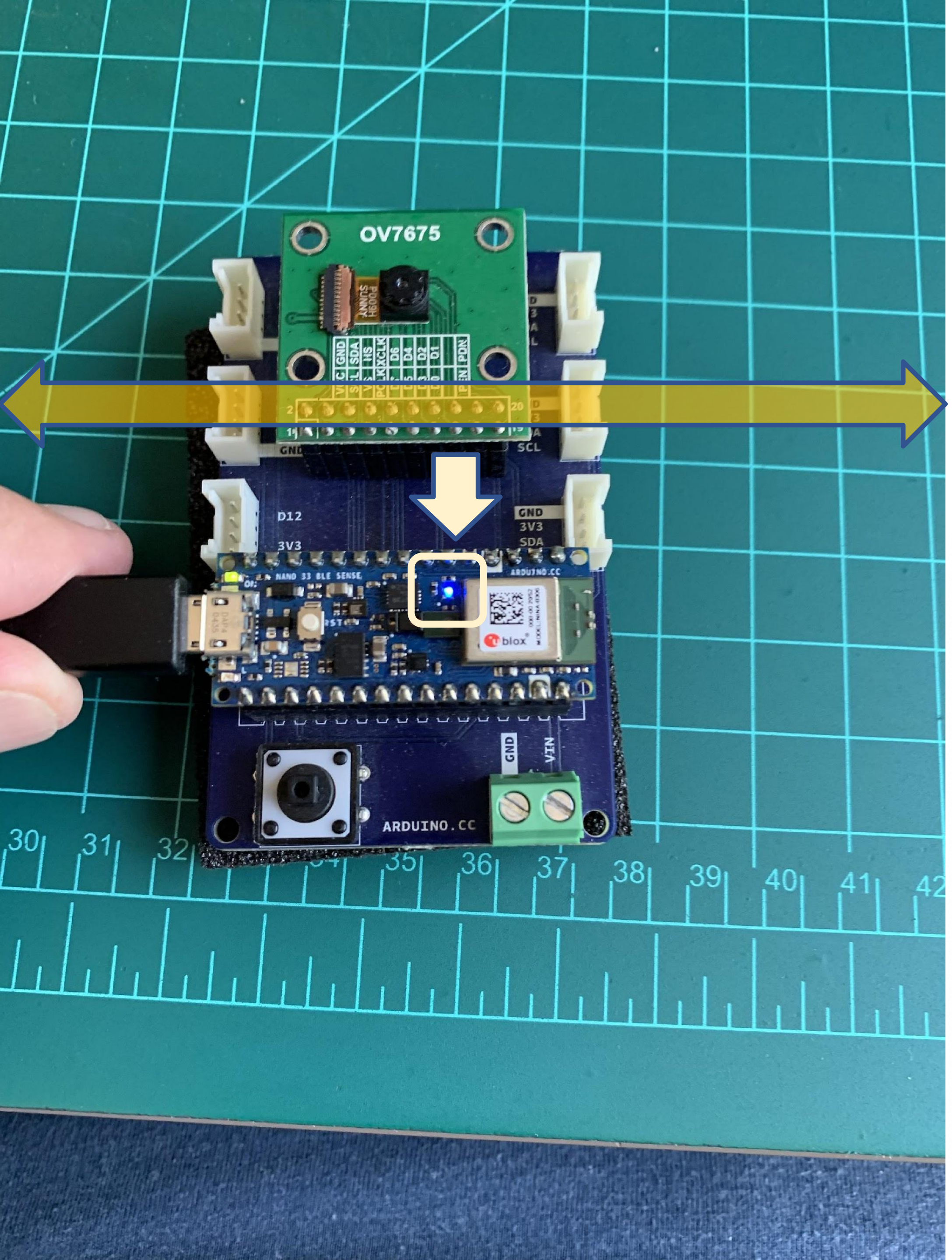


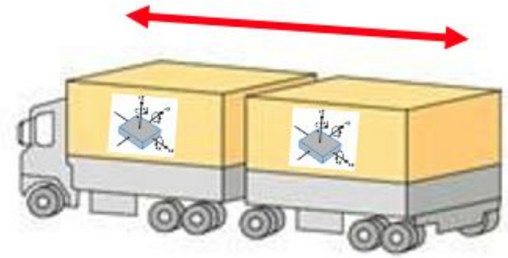
Etiqueta: Bodega

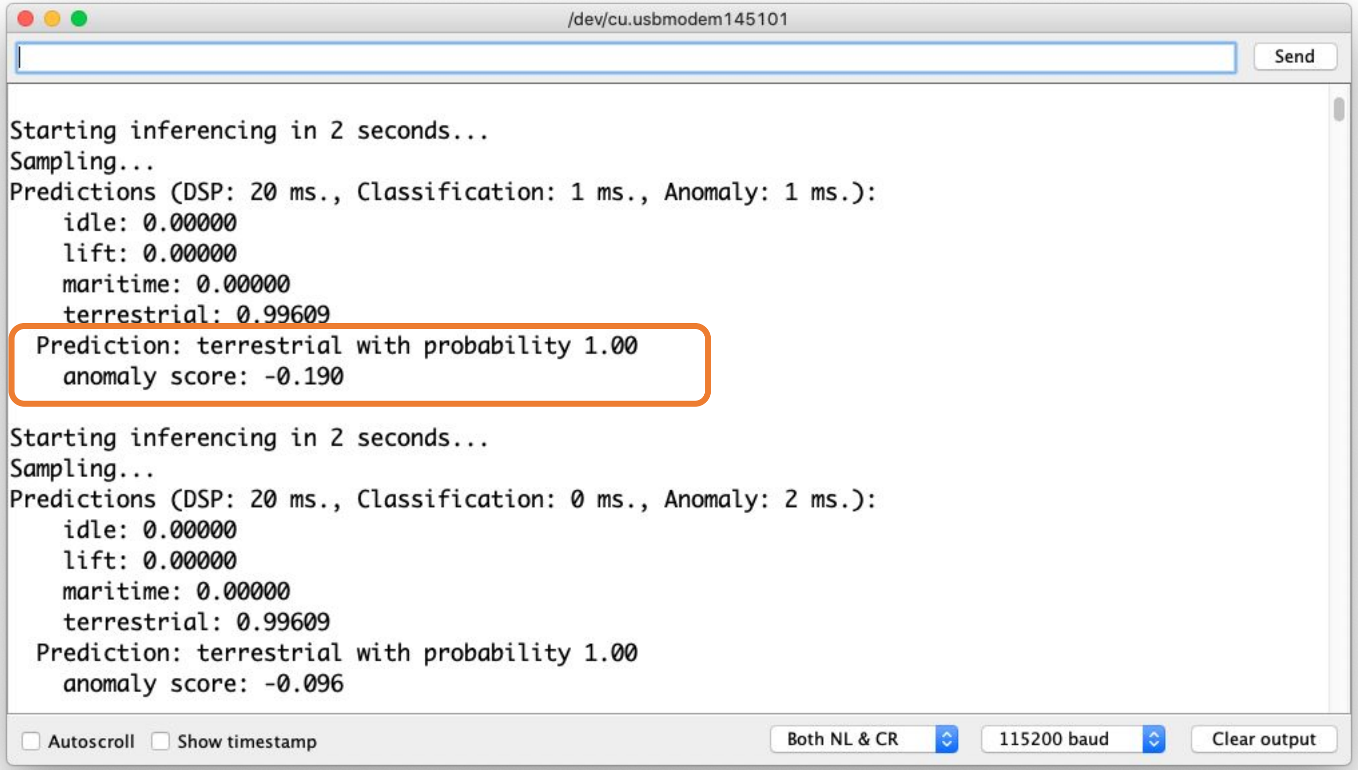


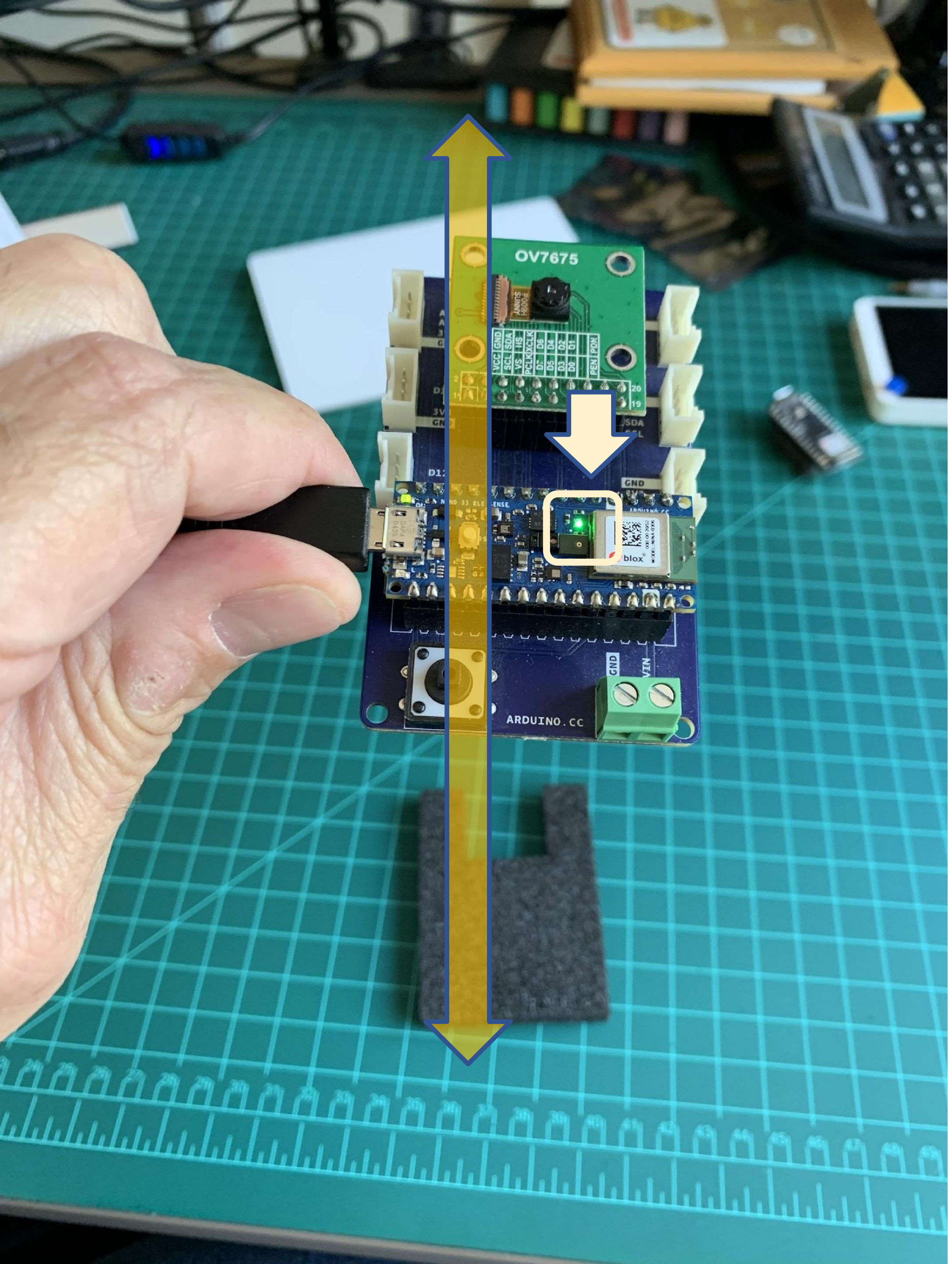


Etiqueta: Terrestre

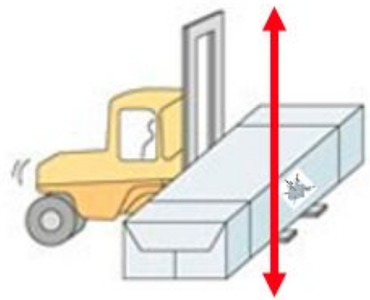




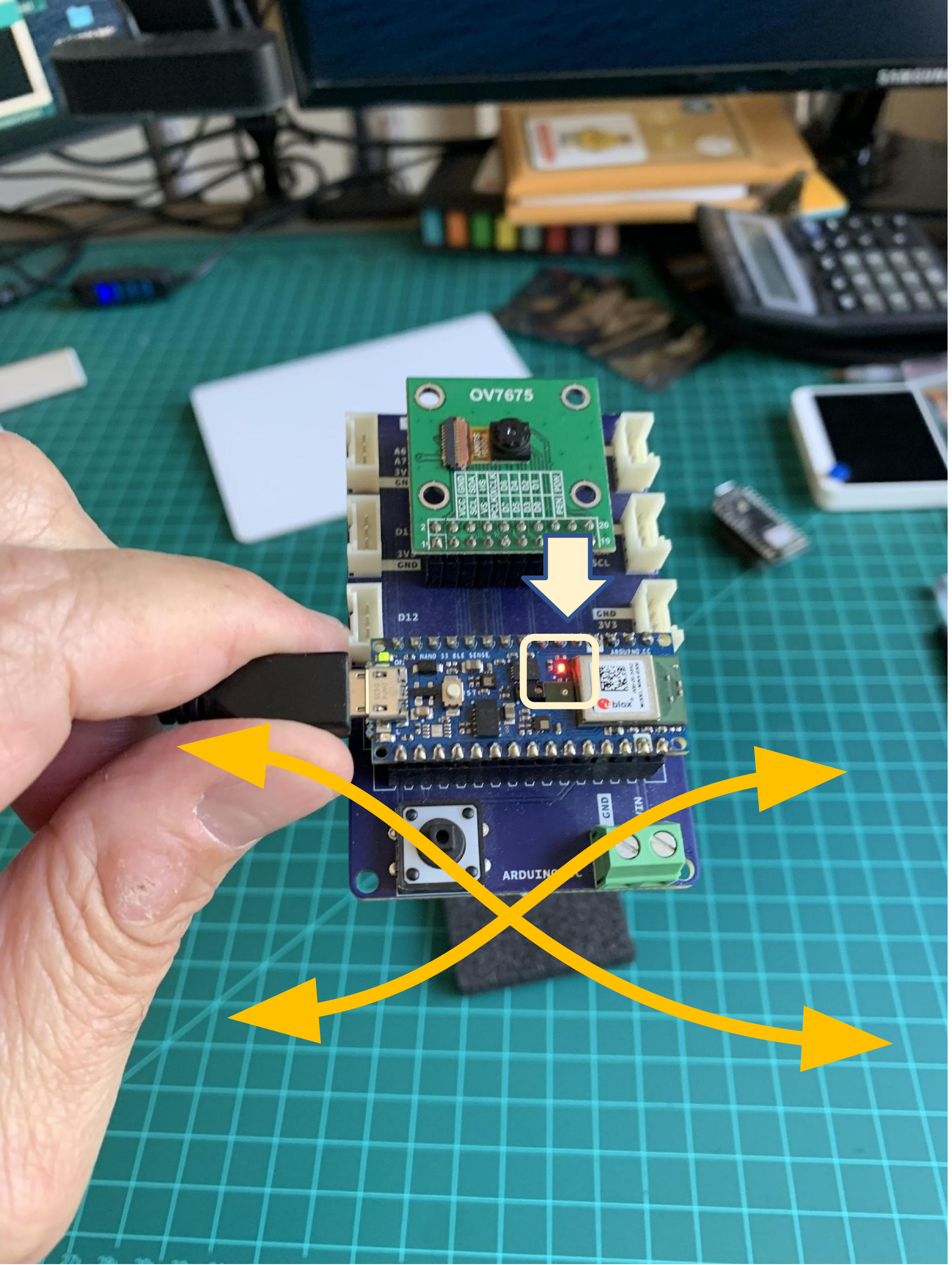




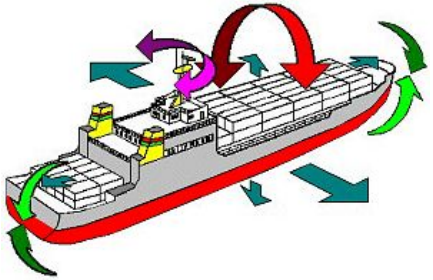
Etiqueta: Cargue



```
/dev/cu.usbmodem145101                                        Send

Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 20 ms., Classification: 0 ms., Anomaly: 2 ms.):
    idle: 0.00000
    lift: 0.99609
    maritime: 0.00000
    terrestrial: 0.00000
  Prediction: lift with probability 1.00
    anomaly score: 0.047

Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 20 ms., Classification: 1 ms., Anomaly: 1 ms.):
    idle: 0.76172
    lift: 0.12500
    maritime: 0.10547
    terrestrial: 0.00781
  Prediction: idle with probability 0.76
    anomaly score: 0.874

Autoscroll   Show timestamp        Both NL & CR   115200 baud   Clear output
```



Etiqueta: Marítimo

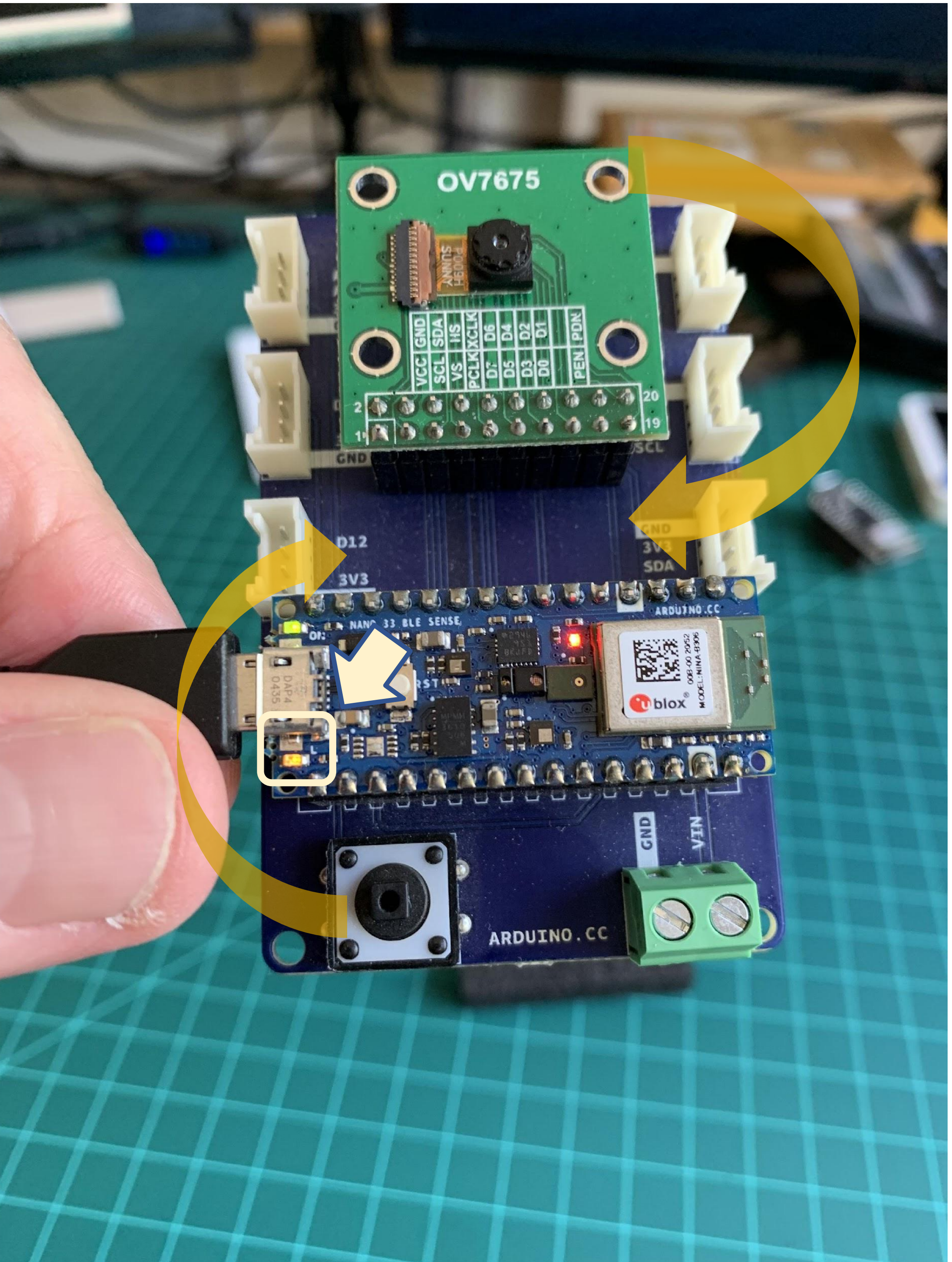


/dev/cu.usbmodem145101

```
Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 20 ms., Classification: 0 ms., Anomaly: 2 ms.):
    idle: 0.00391
    lift: 0.29297
    maritime: 0.40625
    terrestrial: 0.29297
  Prediction: maritime with probability 0.41
    anomaly score: 0.431

Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 20 ms., Classification: 0 ms., Anomaly: 1 ms.):
    idle: 0.95312
    lift: 0.03516
    maritime: 0.00781
    terrestrial: 0.00391
  Prediction: idle with probability 0.95
    anomaly score: 0.247
```

Send

Autoscroll Show timestamp Both NL & CR 115200 baud Clear output



Etiqueta: Anomalía

/dev/cu.usbmodem145101

```
Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 20 ms., Classification: 1 ms., Anomaly: 1 ms.):
    idle: 0.00781
    lift: 0.12109
    maritime: 0.87109
    terrestrial: 0.00000
  Prediction: maritime with probability 0.87
    anomaly score: 0.902

Starting inferencing in 2 seconds...
Sampling...
Predictions (DSP: 20 ms., Classification: 1 ms., Anomaly: 1 ms.):
    idle: 0.89453
    lift: 0.08984
    maritime: 0.01172
    terrestrial: 0.00781
  Prediction: idle with probability 0.89
    anomaly score: 0.248
```

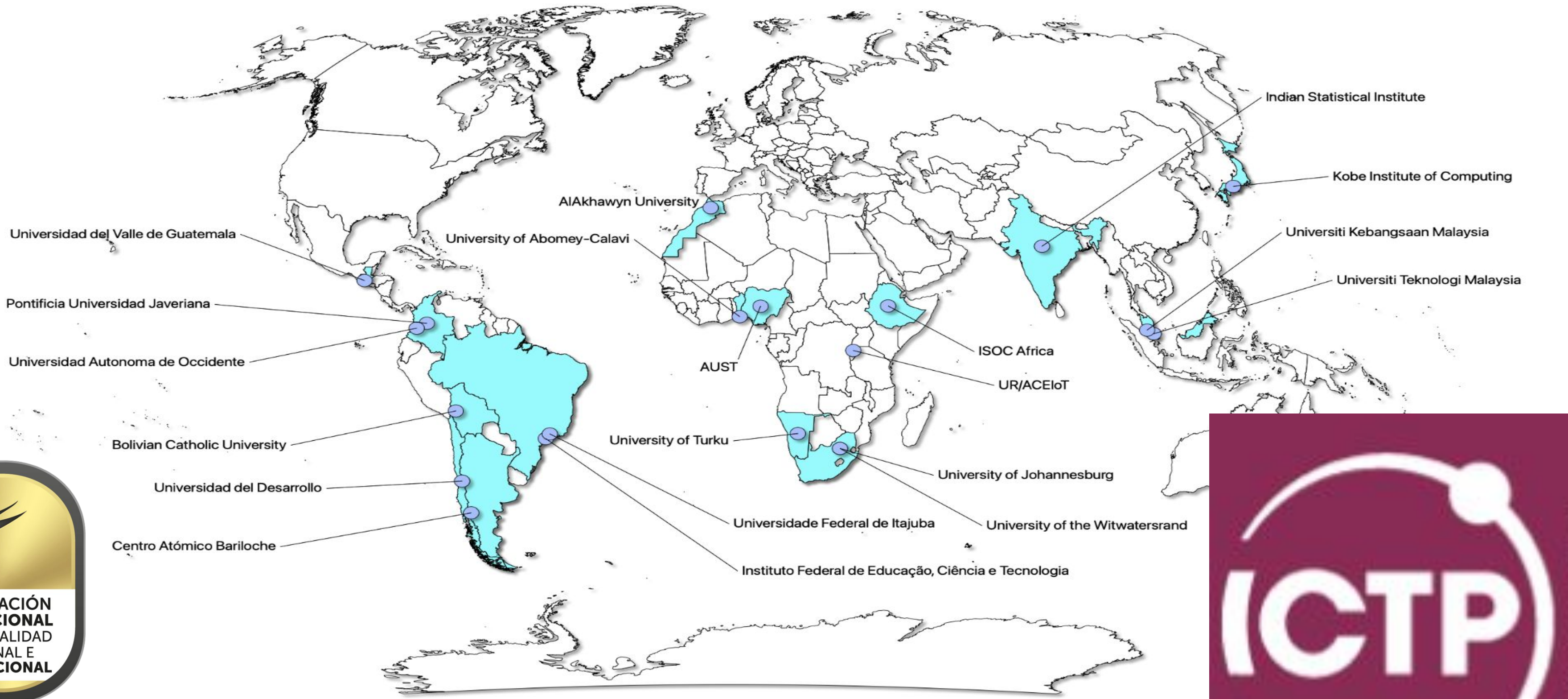
Send

Autoscroll   Show timestamp   Both NL & CR   115200 baud   Clear output

Tiny ML Red Internacional Académica

Este seminario hace parte de las actividades del grupo de trabajo TinyML4D: TinyML for Developing Countries perteneciente a la red Tiny Machine Learning Open Education Initiative (TinyMLedu)

https://tinyml.seas.harvard.edu/4D/



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ICTP TINY ML

Recursos Adicionales

- Harvard School of Engineering and Applied Sciences - CS249r: Tiny Machine Learning
- Professional Certificate in Tiny Machine Learning (TinyML) – edX/Harvard
- Introduction to Embedded Machine Learning (Coursera)
- Text Book: "TinyML" by Pete Warden, Daniel Situnayake
- https://github.com/Mjrovai/UNIFEI-IESTI01-TinyML-2021.2

Deseo agradecer al profesor de Harvard professor Vijay Janapa Reddi, y a Brian Plancher y al profesor Marcelo Rovay por preparar el material sobre TinyML que es la base para esta charla