RBR

Welcome, the RBR Webinar will begin shortly…

RBR
rbr-global.com

Product Overview: RBR*solo*³ D

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Business Development Manager (France - Europe)

Loggers

OEM

Sensors

Systems

RBR


RBRcodaODO
RBRcoda³
RBRconcerto³
RBRmaestro³
RBRconcerto³
RBRbrevio³
RBRsolo³

RBR


RBRcervello
RBRsolo³
RBRduet³
RBRvirtuoso³
RBRfermata
RBRfermette³
RBRssm
RBRcoda T.ODO
Depth rating:
Serial number:
RBRquartz³
RBRcoda³
RBRconcerto³
RBRmaestro³
WIREWALKER
RBR

RBR*solo*³ D

Compact depth logger (self contained memory + battery)

Range: 0 to 20, 50, 100, 200, 500, 750, 1000 dbar (2000, 4000, 6000, 10 000 dbar in titanium)

±0.05% FS accuracy

<0.001% resolution

1Hz sampling = ~400 days / ~34 million readings on a single AA battery

2Hz sampling = >2 month / ~11 million readings on a single AA battery

5s sampling = 4.9 years / ~32 million readings on a single AA battery

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Compact depth logger versions

- RBR*solo*^{3} D – shallow (1,000m) with ≦2Hz sampling

- RBR*solo*^{3} D|fast8 (16Hz or 32Hz) – shallow with fast sampling
- RBR*solo*^{3} D|tide16 or |wave16 – with tide and/or wave averaging
- RBR*solo*^{3} D|deep – deep (10 000m) with above options

- RBR*duet*^{3} T.D – as above with addition of thermistor (standard / fast)

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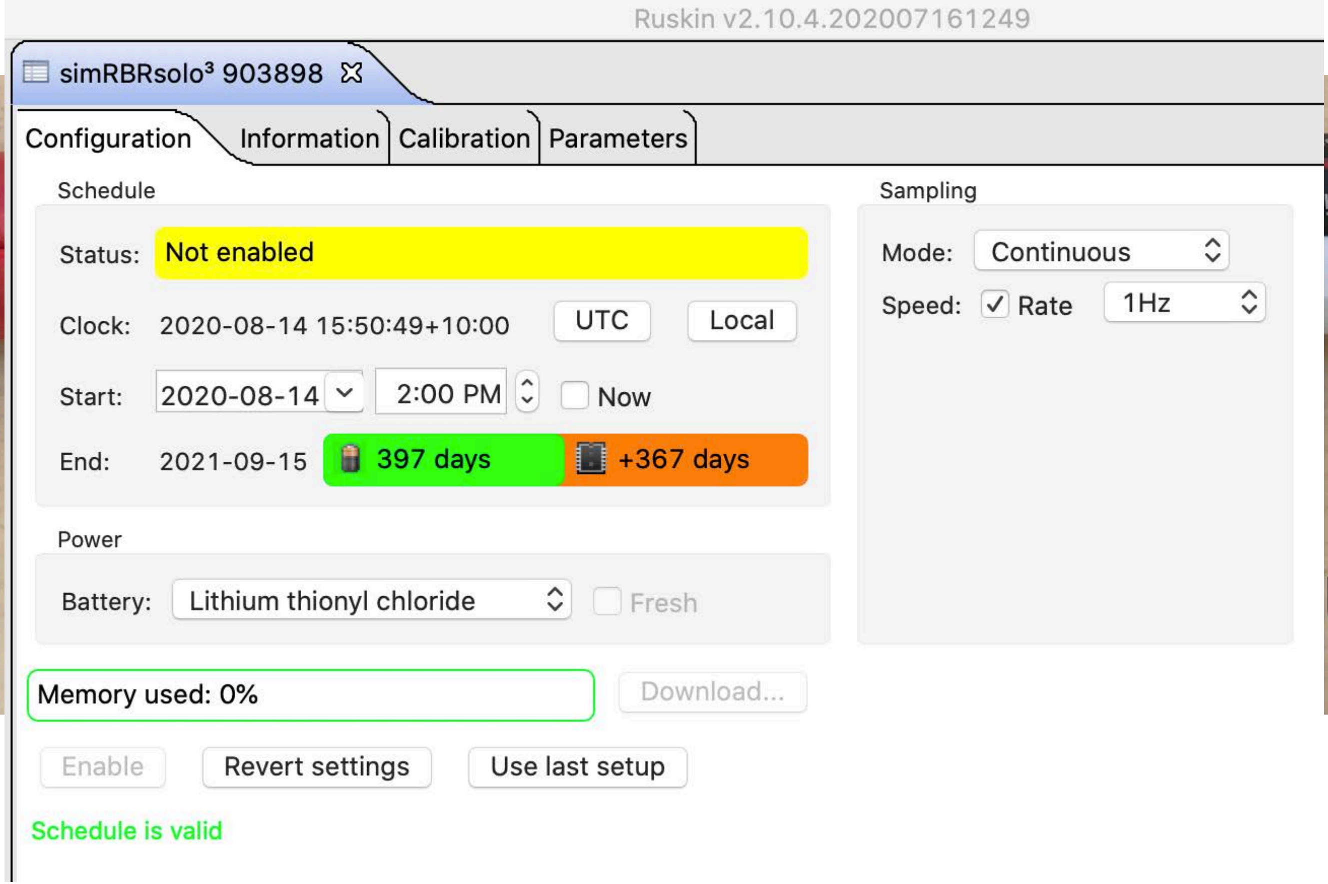
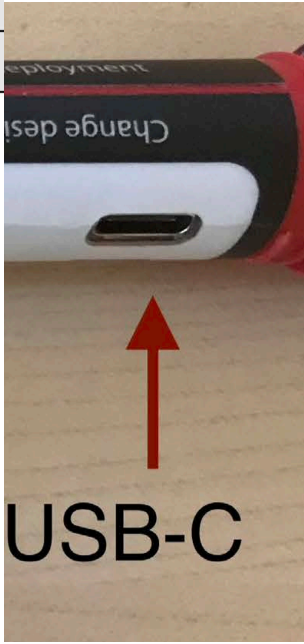
Inside the RBR*solo*³ D





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Compact and Standard Depth Loggers

Compact	Standard
Ideal when instrument size is critical Lowest running costs	Ideal for very long deployments
RBR*solo*^{3} D RBR*solo*^{3} D|tide16 RBR*solo*^{3} D|wave16 RBR*solo*^{3} D|fast8 RBR*solo*^{3} D|fast16 RBR*solo*^{3} D|fast32	RBR*virtuoso*^{3} D RBR*virtuoso*^{3} D|tide16 RBR*virtuoso*^{3} D|wave16 RBR*virtuoso*^{3} D|fast8 RBR*virtuoso*^{3} D|fast16 RBR*virtuoso*^{3} D|fast32
RBR*duet*^{3} T.D RBR*duet*^{3} T.D|tide16 RBR*duet*^{3} T.D|wave16 RBR*duet*^{3} D|fast8 RBR*duet*^{3} D|fast16 RBR*duet*^{3} D|fast32	RBR*duo*^{3} T.D RBR*duo*^{3} T.D|tide16 RBR*duo*^{3} T.D|wave16 RBR*duo*^{3} T.D|fast8 RBR*duo*^{3} T.D|fast16 RBR*duo*^{3} T.D|fast32

Options : Titanium (1,000 to 10,000m range) T: <u>standard</u> (~1s) or <u>fast</u> (~0.1s) thermistor

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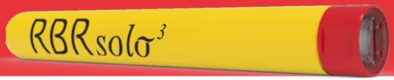
Compact and Standard Depth Loggers : Specs



Compact	Standard
1 x AA Battery	8 x AA Battery
~60M Readings	~240M Readings
0 to 20 / 50 / 100 / 200 / 500 / 1000m 0 to 1,000 / 2,000 / 4,000 / 6,000 / 10,000m	
-	Twist Activation
-	External Connectivity Available
-	Wi-Fi Available
±0.05% Accuracy / ±0.001% FS	
Example 1: Continuous @ 1Hz = > 1 year	
Example 2: Continuous @ 16Hz = ~44 days (b)	Continuous @ 16Hz = ~95 days (m)
Ex. 3: Burst (4096 burst @ 16Hz / 15mins) = N/A	Ex. 3: Burst (4096 burst @ 16Hz / 15mins) = ~ 11 months (m)

(b) – battery limiting
(m) – memory limiting

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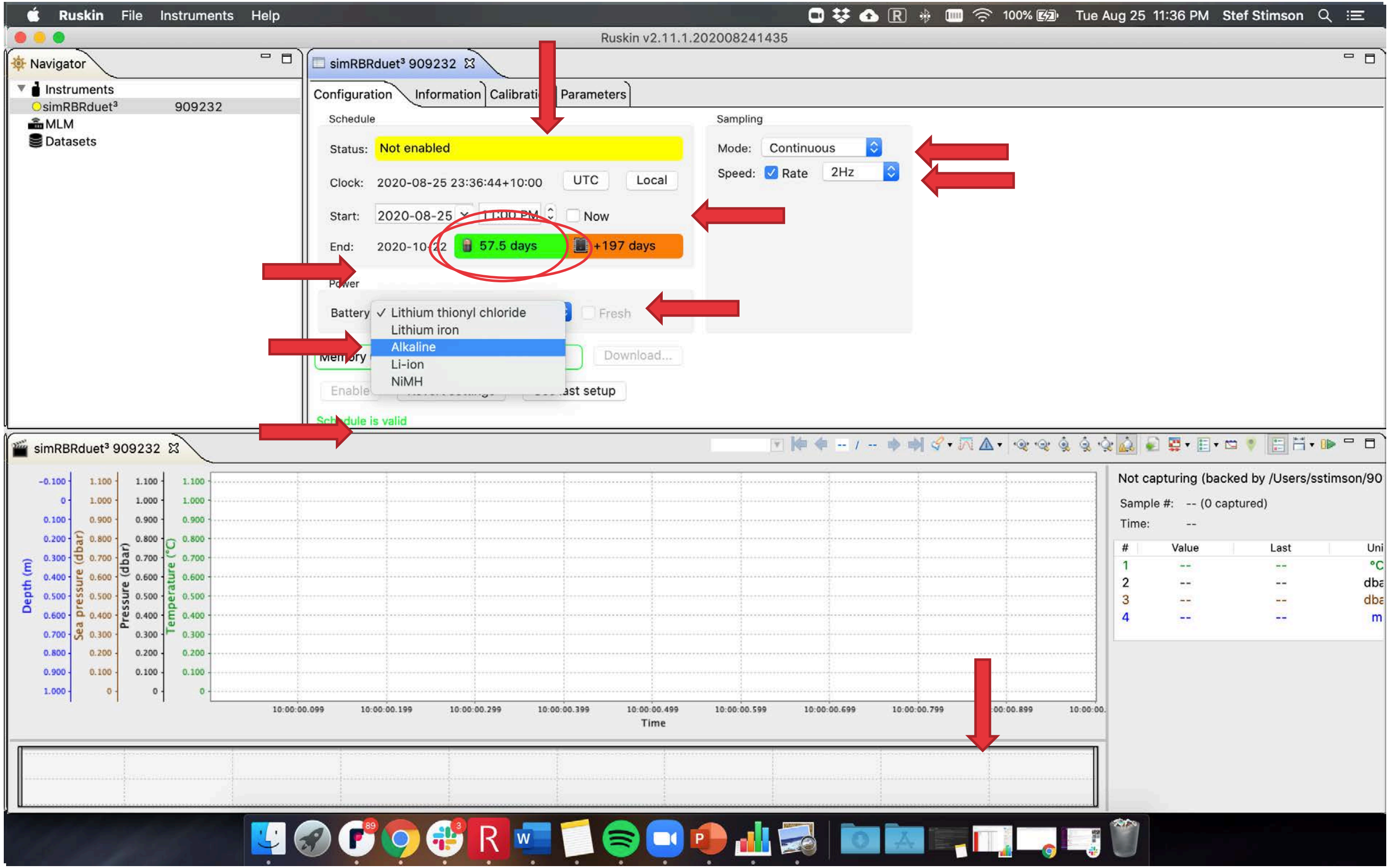
Top Tip#2 : Using Ruskin As A Planning Tool



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Upcoming Webinars

Future Webinars

Ping the President – Getting the most out of your RBR instrumentation
Greg Johnson (President of RBR)
September 24, 2020 at 11AM AEST (GMT+10)

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Thank You

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Pressure sensors in the age of artificial intelligence

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HANNAH POWER, PHD

THE UNIVERSITY OF NEWCASTLE AUSTRALIA

Outline

- **This will be a talk about applying Artificial Intelligence (AI) and Machine Learning (ML) methods to Pressure Sensor data**

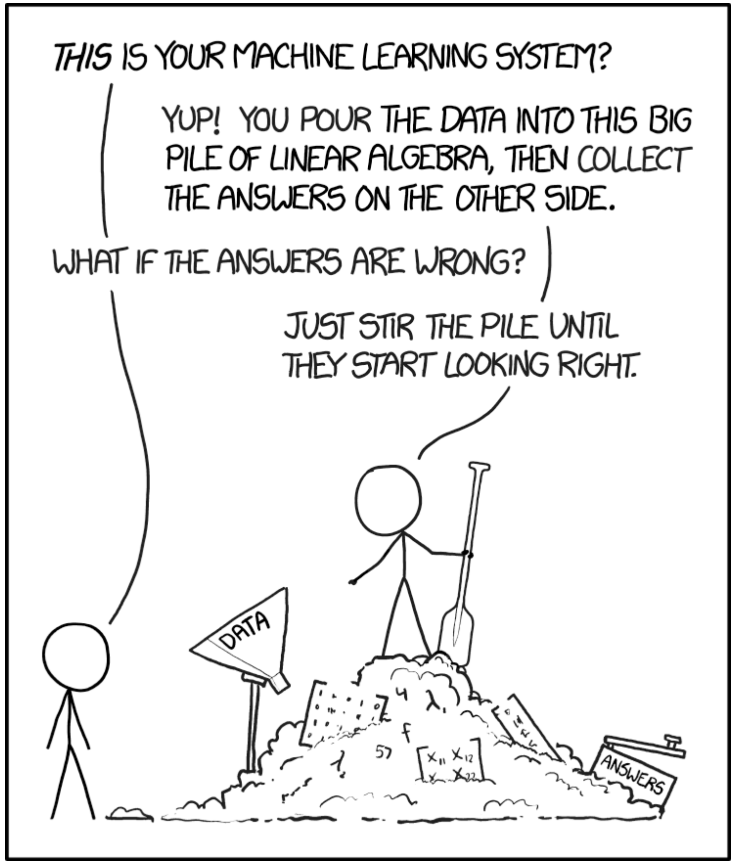
Three examples of applications using surf and swash zone data:

- 1. Timeseries classification
- 2. Wave-by-wave classification
- 3. Unsupervised data exploration

Artificial Intelligence and Machine Learning

“Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.”

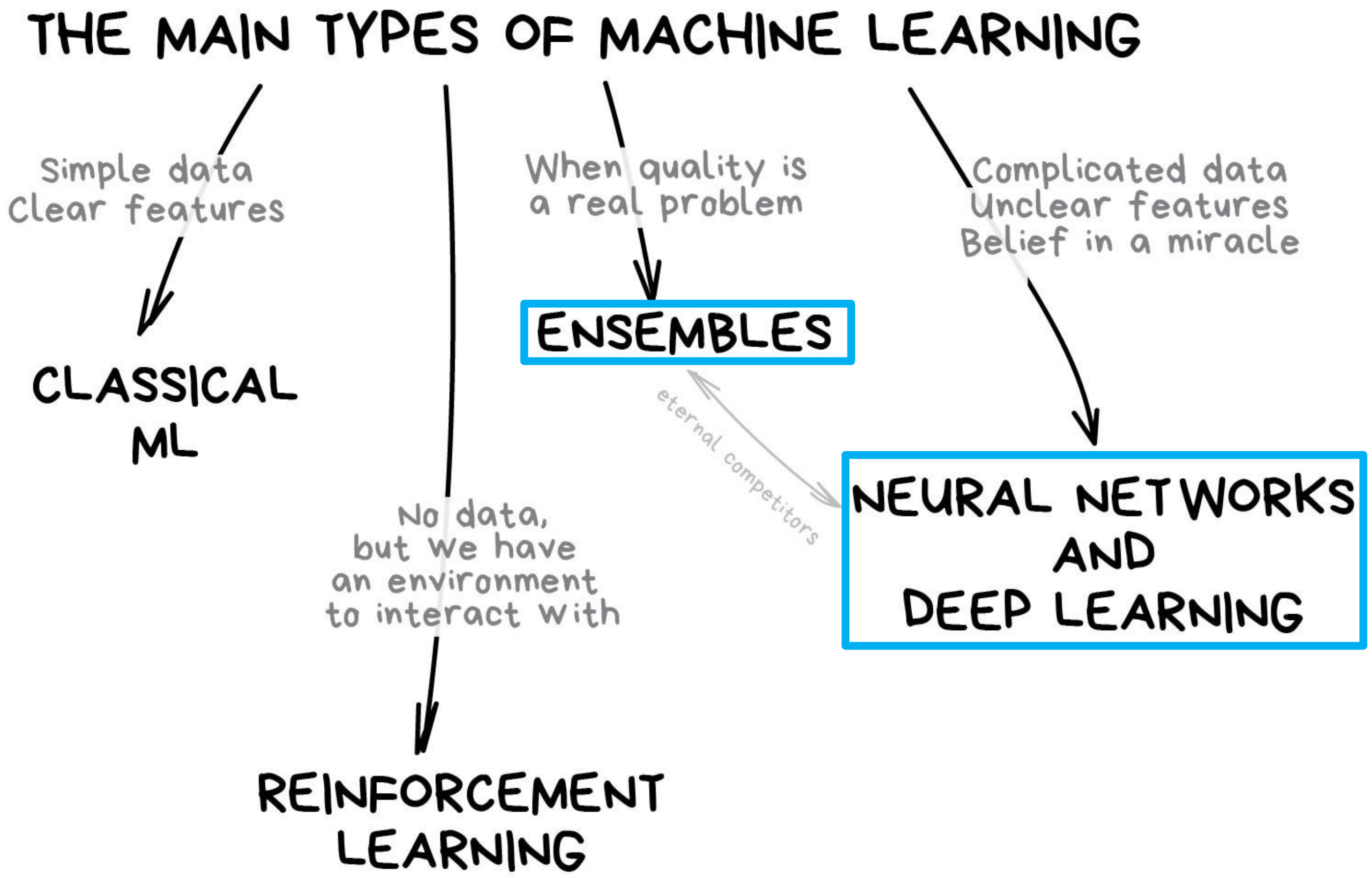
from: https://expertsystem.com/machine-learning-definition/



from https://xkcd.com/1838

→ ***We are Learning from Data***

Artificial Intelligence and Machine Learning



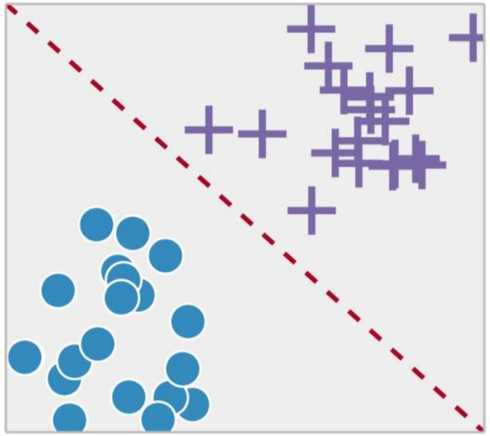
from https://xkcd.com/

Types of Machine Learning

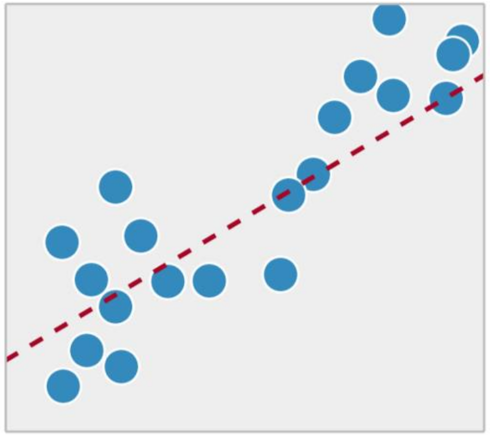
Supervised Learning:
known labels

Unsupervised Learning:
unknown labels

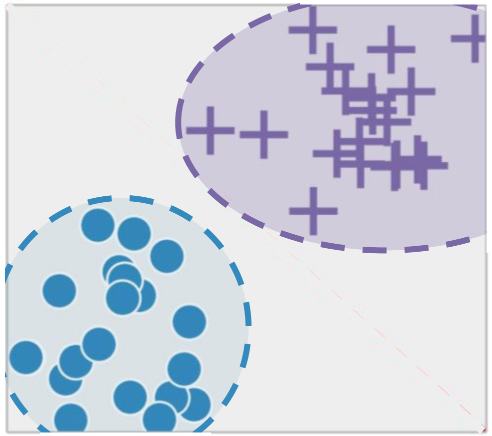
Classification



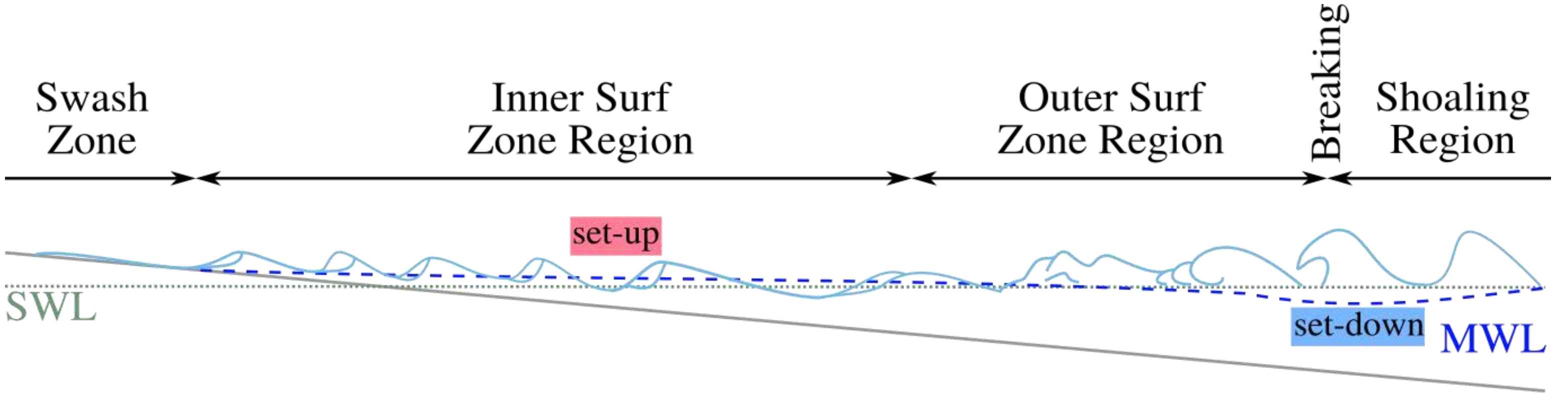
Regression

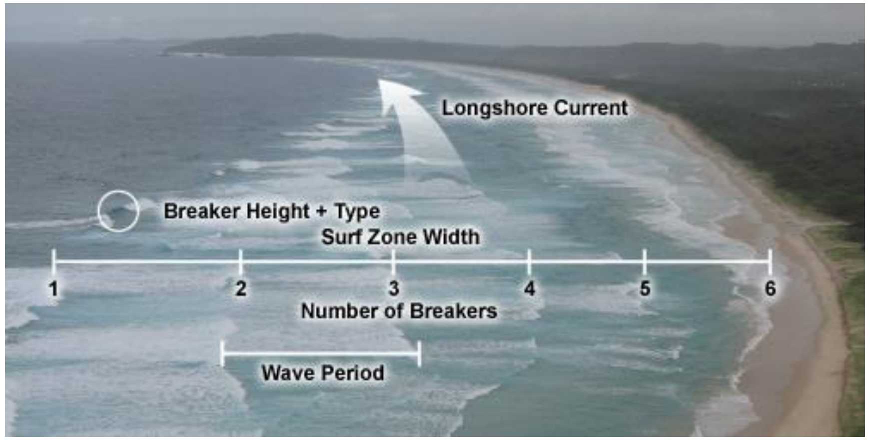


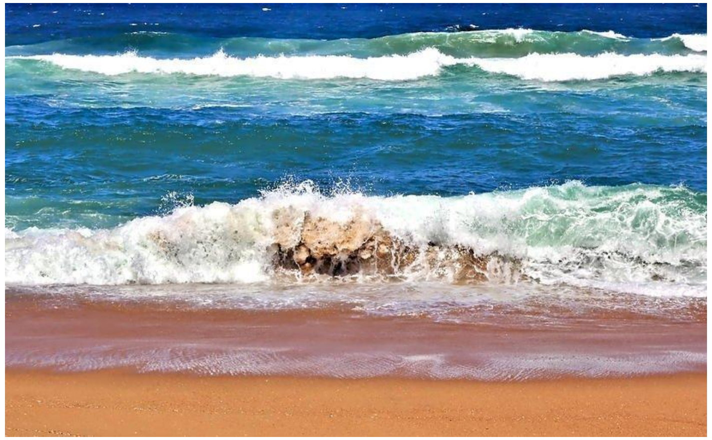
Clustering



First Step: Data Collection (Nearshore Example)

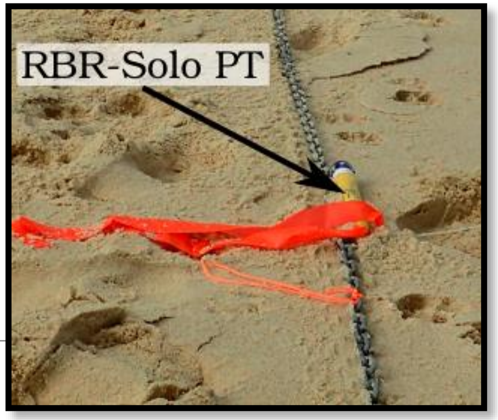


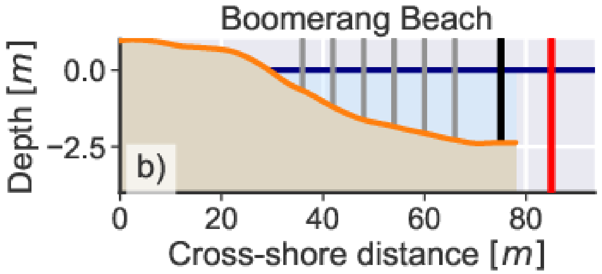


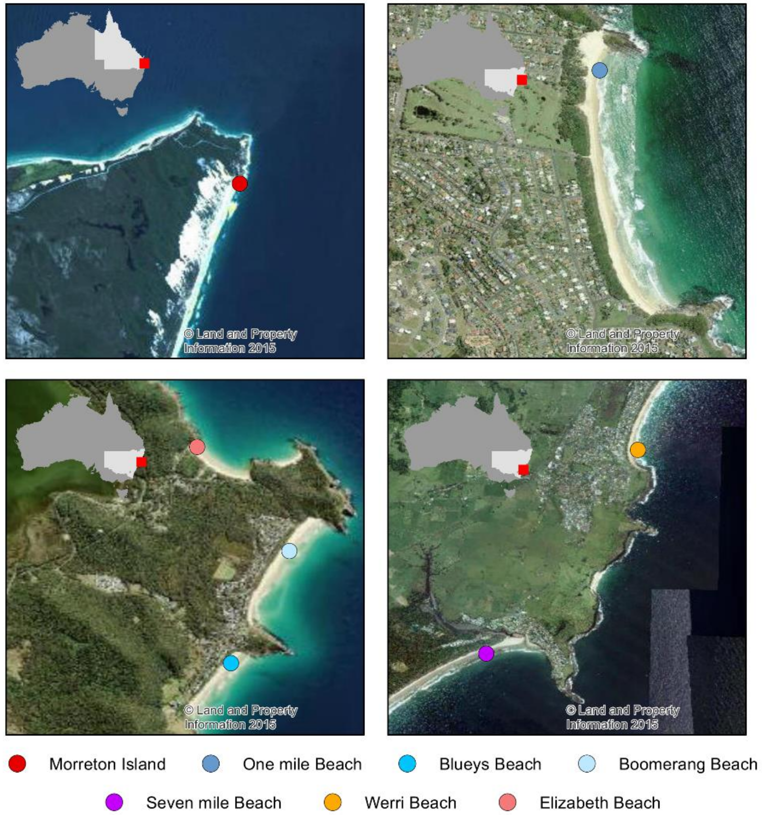


Source: http://stream1.cmatc.cn/pub/comet/MarineMeteorologyOceans/NearshoreWaveModeling/comet/oceans/nearshore_wave_models/print.htm

First Step: Data Collection

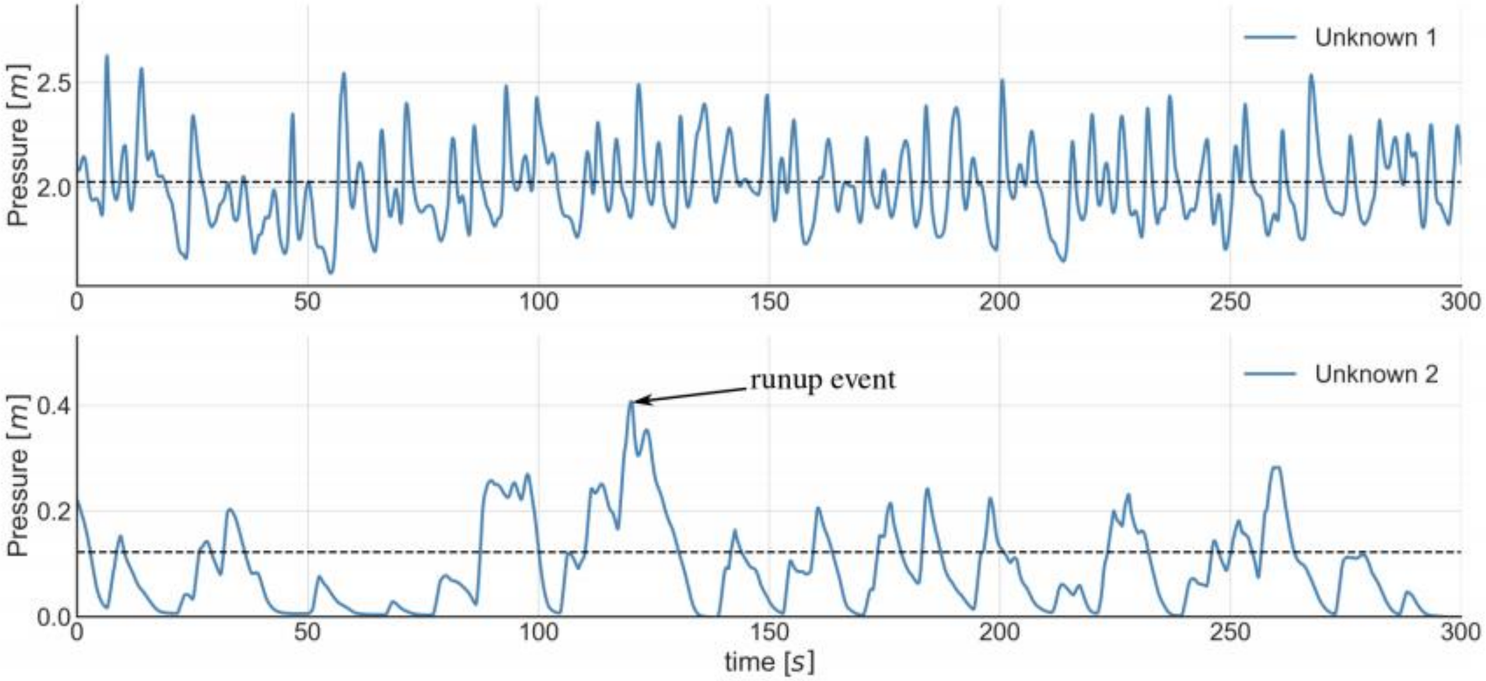






Example 1
Data Management: Timeseries Classification

Objective: define a model to classify timeseries into two groups

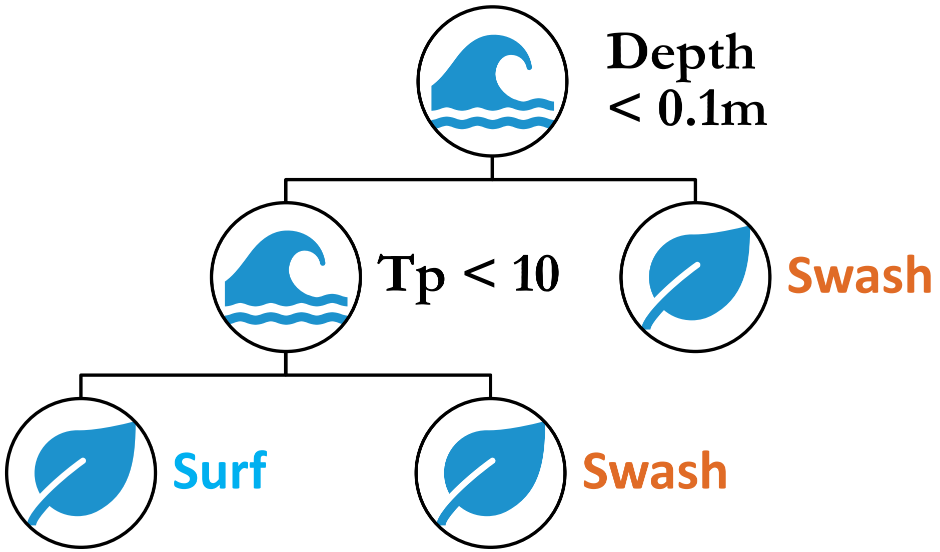


Unknown 1: Surf zone

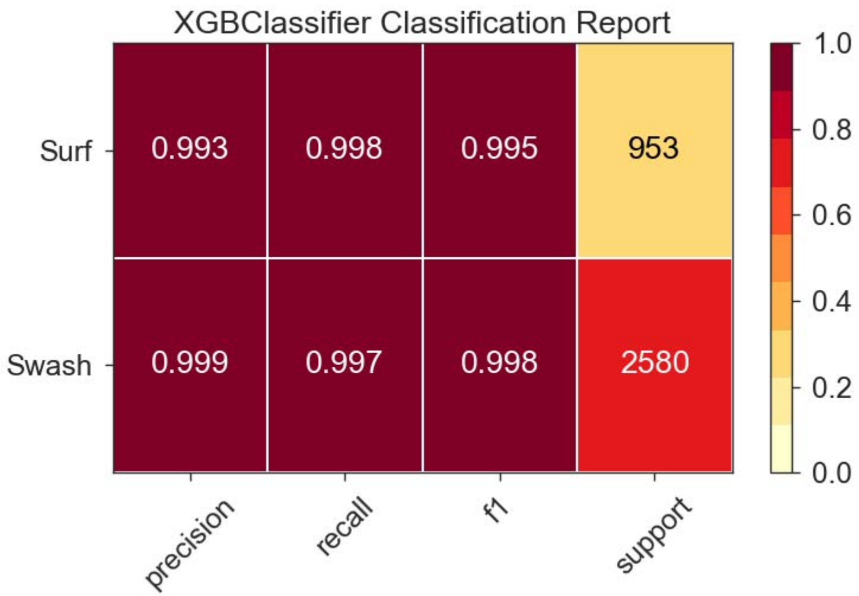
Unknown 2: Swash zone

Data Management: Timeseries Classification

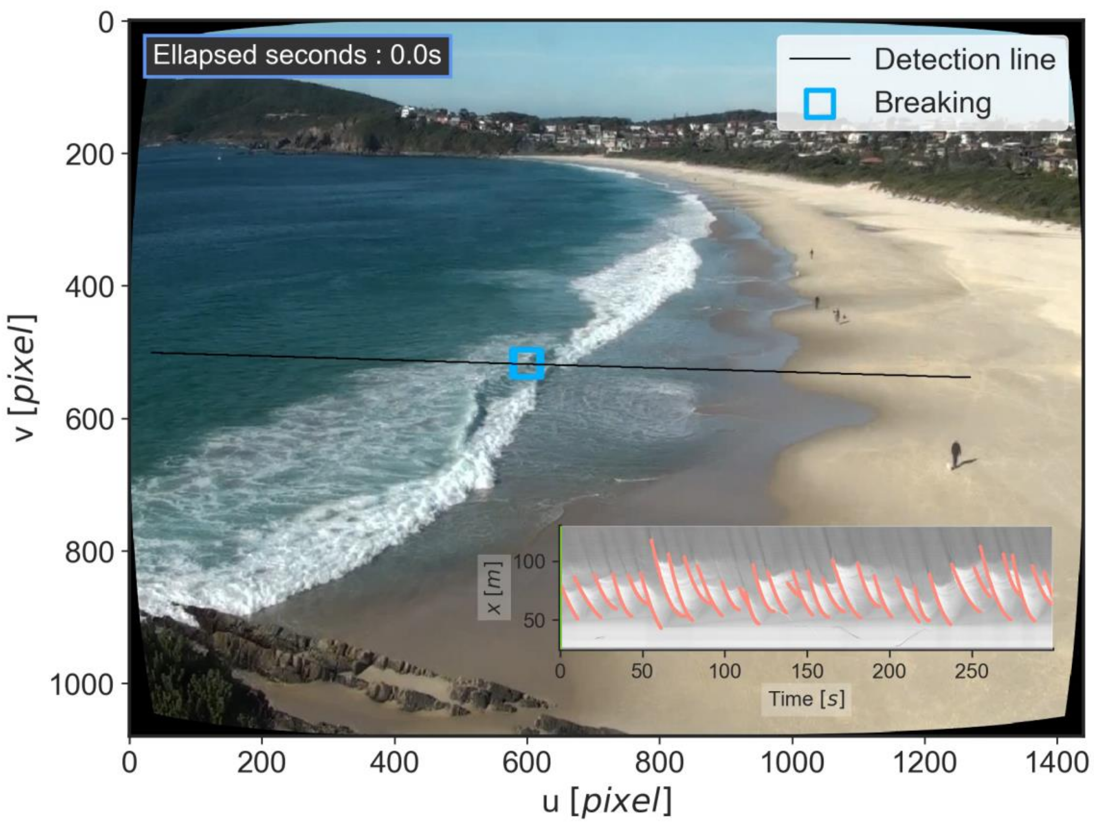
Model Definition:

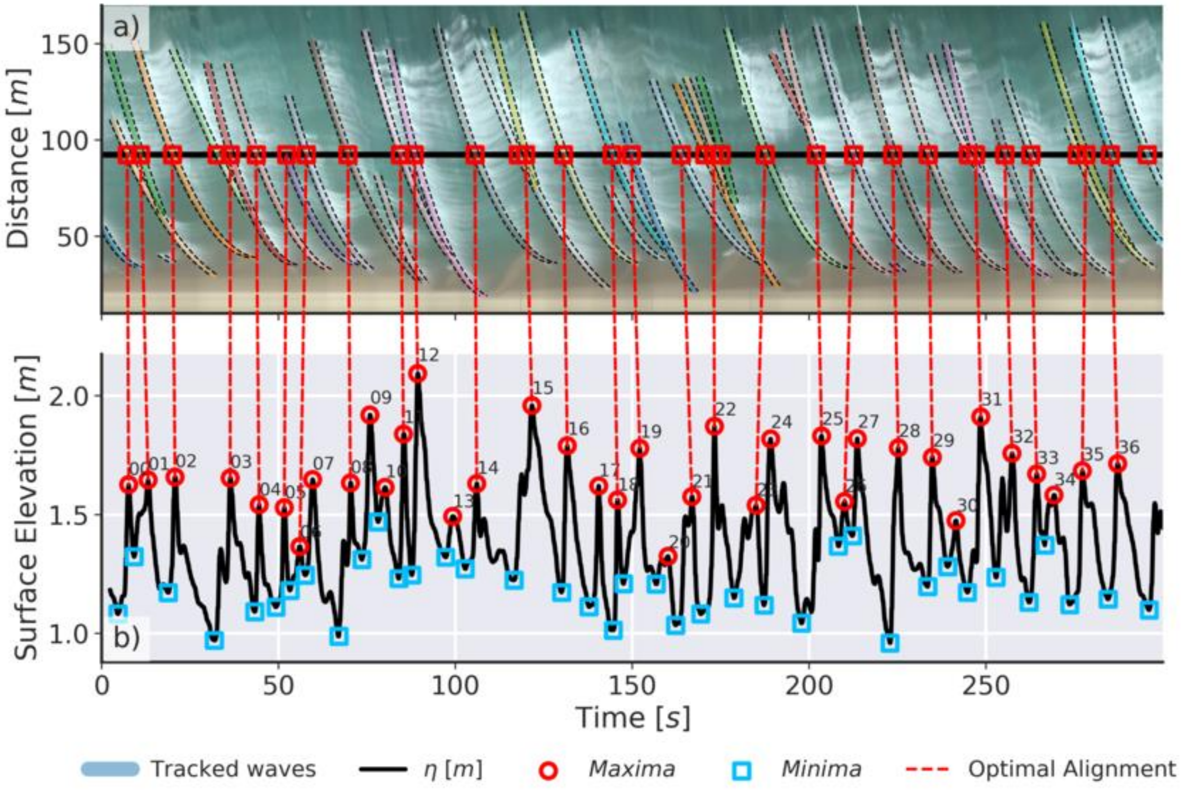


Results:



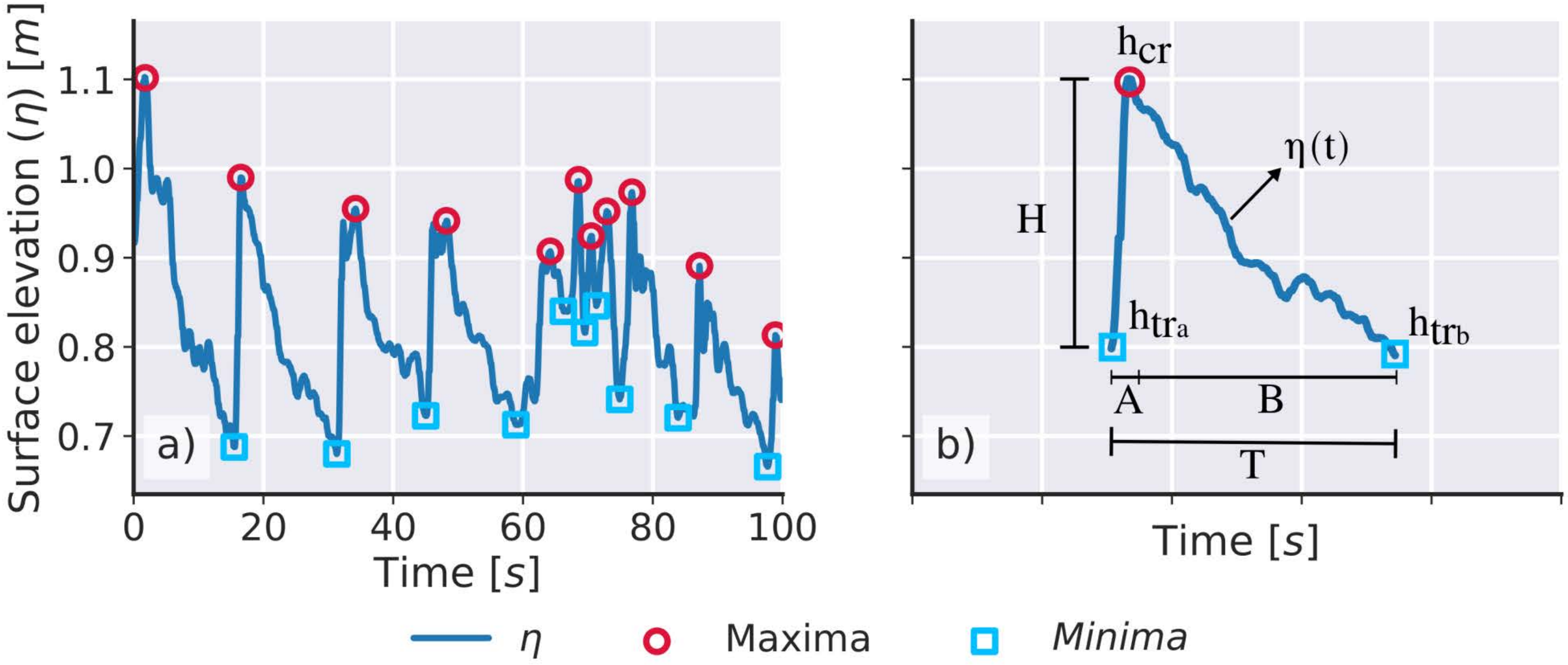
Example 2:
Answering Scientific Questions





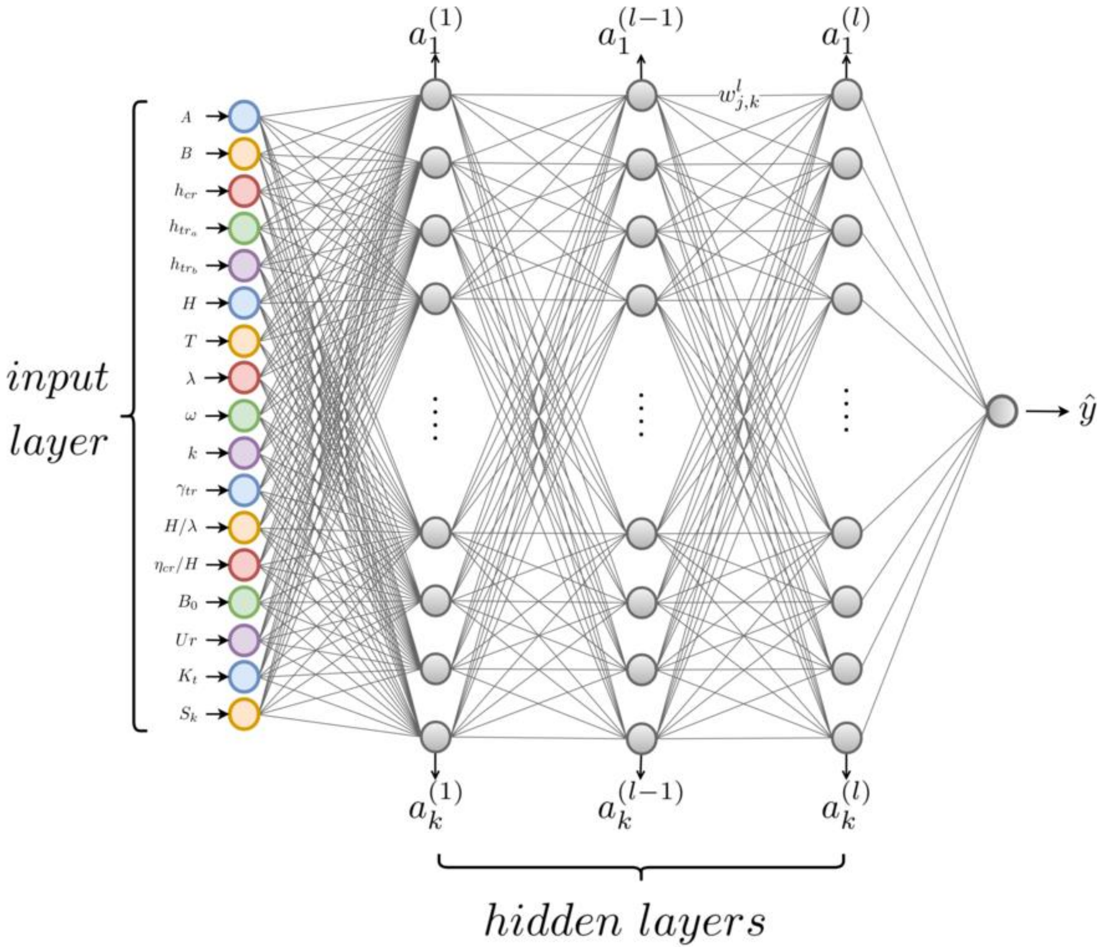
Stringari, C. E., and Power, H. E. (2019). "The Fraction of Broken Waves on Natural Beaches", *Journal of Geophysical Research: Oceans.*

Extracting Features From Pressure Data



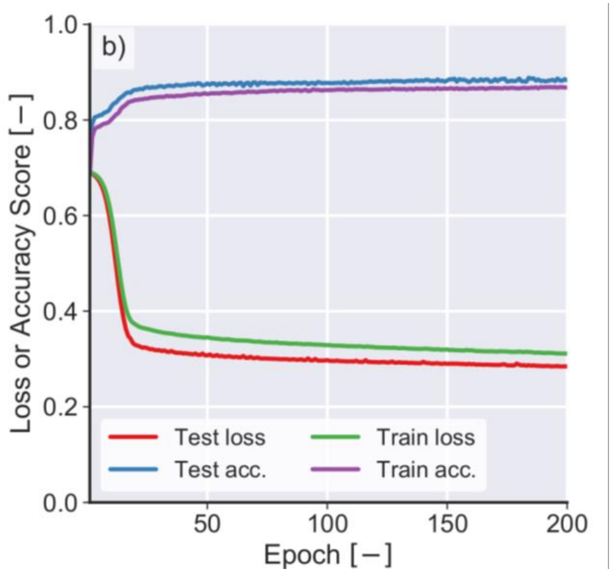
Stringari, C. E., and Power, H. E. (2019). "The Fraction of Broken Waves on Natural Beaches", *Journal of Geophysical Research: Oceans.*

Defining an AI/ML Model



Input (X): wave parameters

Output (y): broken or unbroken



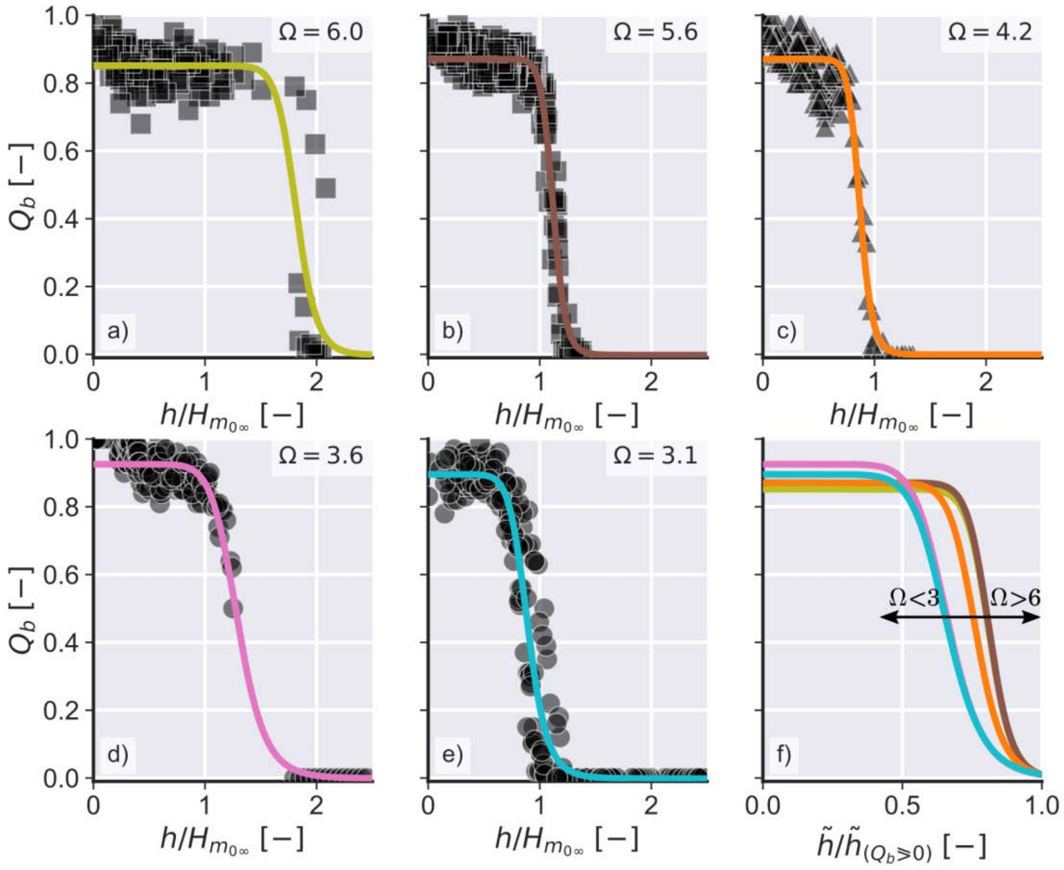
Inference and Interpretation

Probability of Wave Breaking:

$$Q_b = N_{br}/N$$

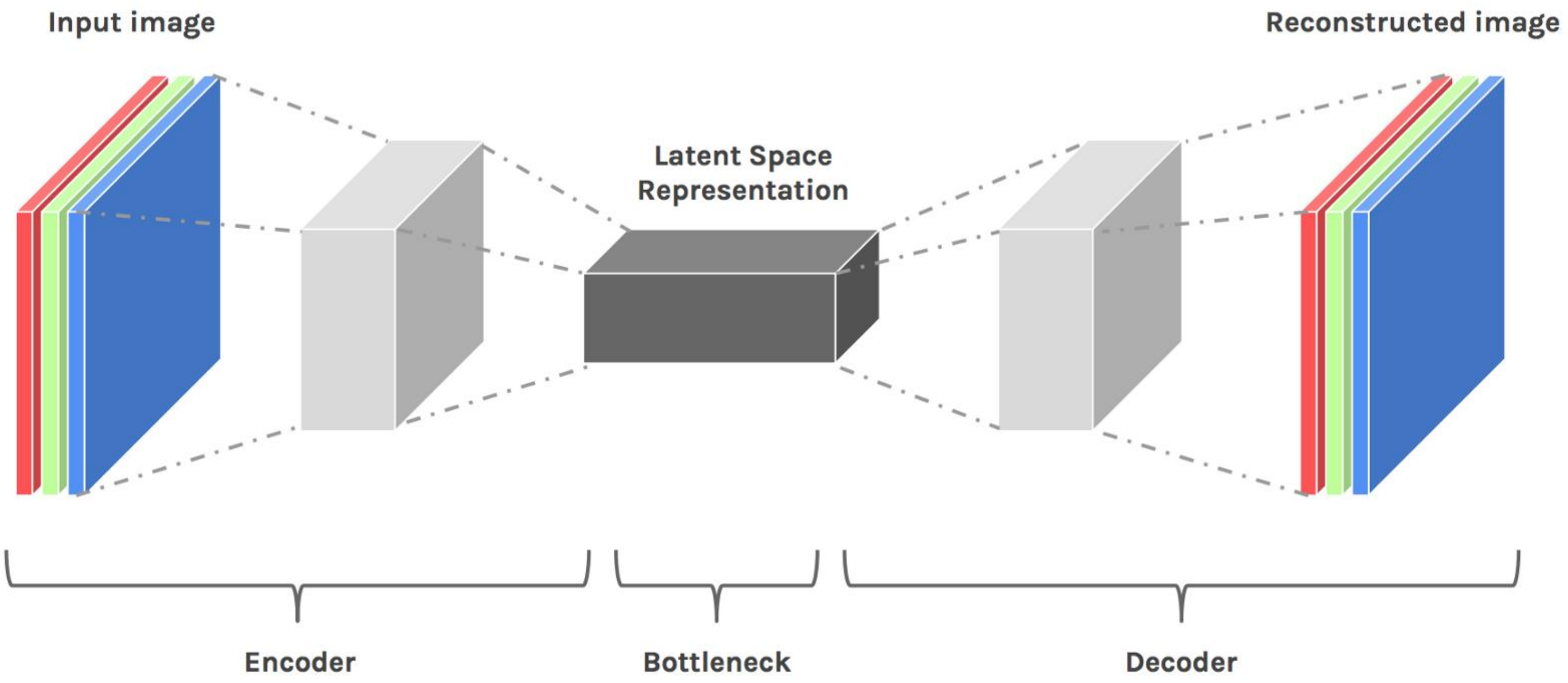
N = Total number of waves

N_{br} = Number of broken waves



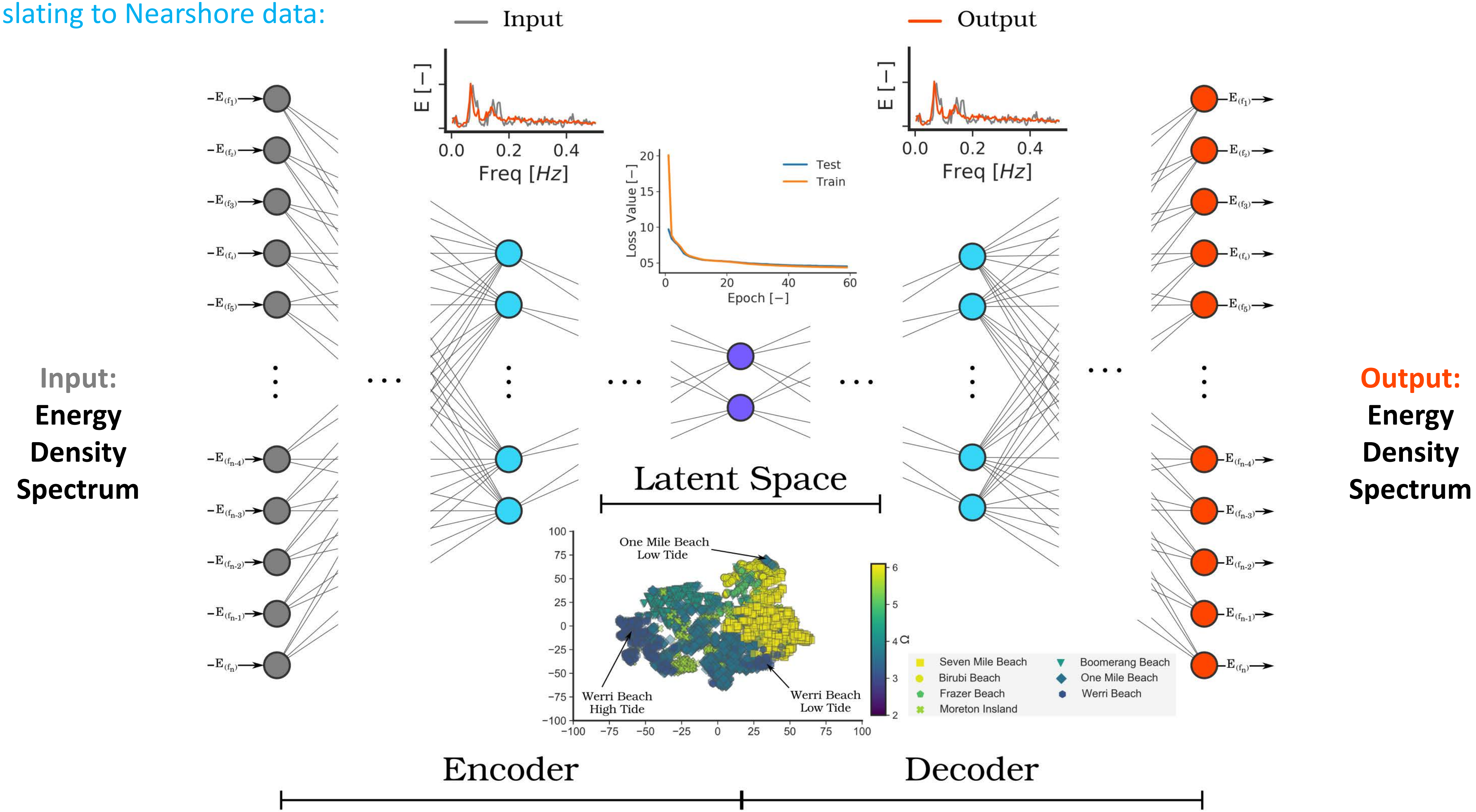
Stringari, C. E., and Power, H. E. (2019). "The Fraction of Broken Waves on Natural Beaches", *Journal of Geophysical Research: Oceans.*

Example 3
Data Exploration: Unsupervised Deep Learning

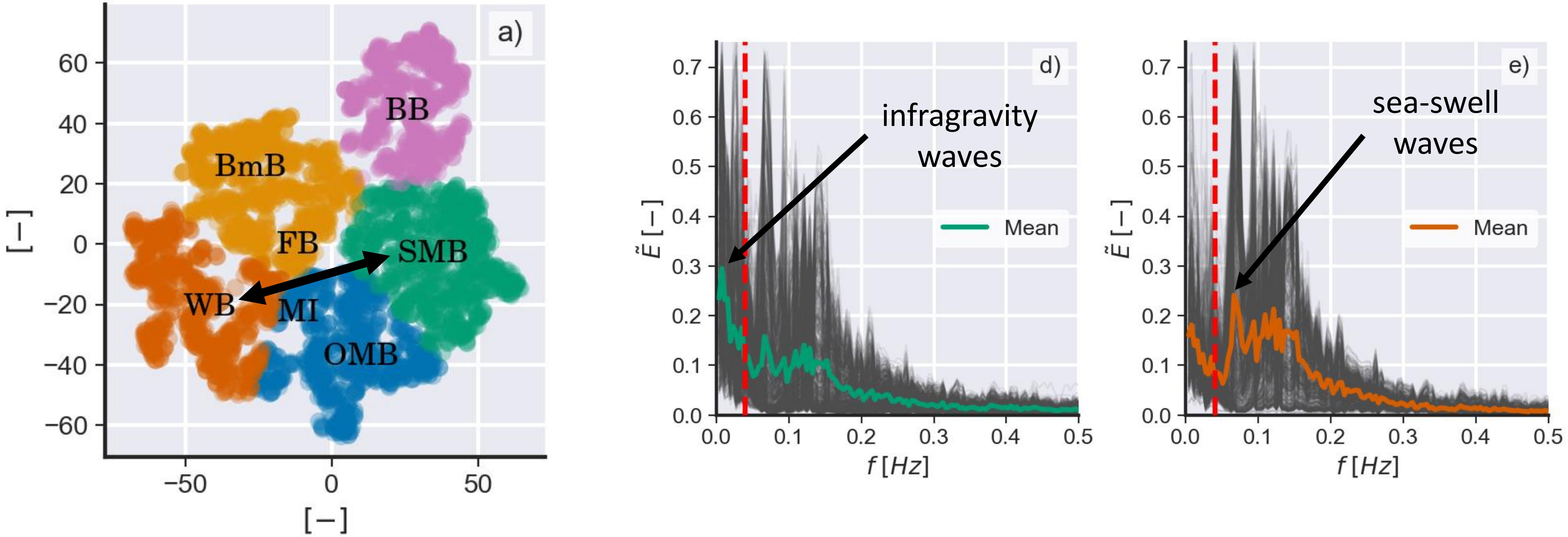


https://hackernoon.com/latent-space-visualization-deep-learning-bits-2-bd09a46920df

Translating to Nearshore data:



Data Exploration: Clustering Spectral Signatures



Clear separation between Dissipative (SMB) and more reflective (WB) beaches

Final Considerations

We can adapt AI/ML methods to Pressure Sensors relatively easily.

Three main applications are:

- Timeseries classification
- Feature prediction
- Data exploration

Great potential to be extended do solve another environmental problems related to pressure sensor timeseries.

Pressure sensors in the age of artificial intelligence

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