Leveraging geophysical time series forecasting for monitoring volcanic systems: can we use machine learning?

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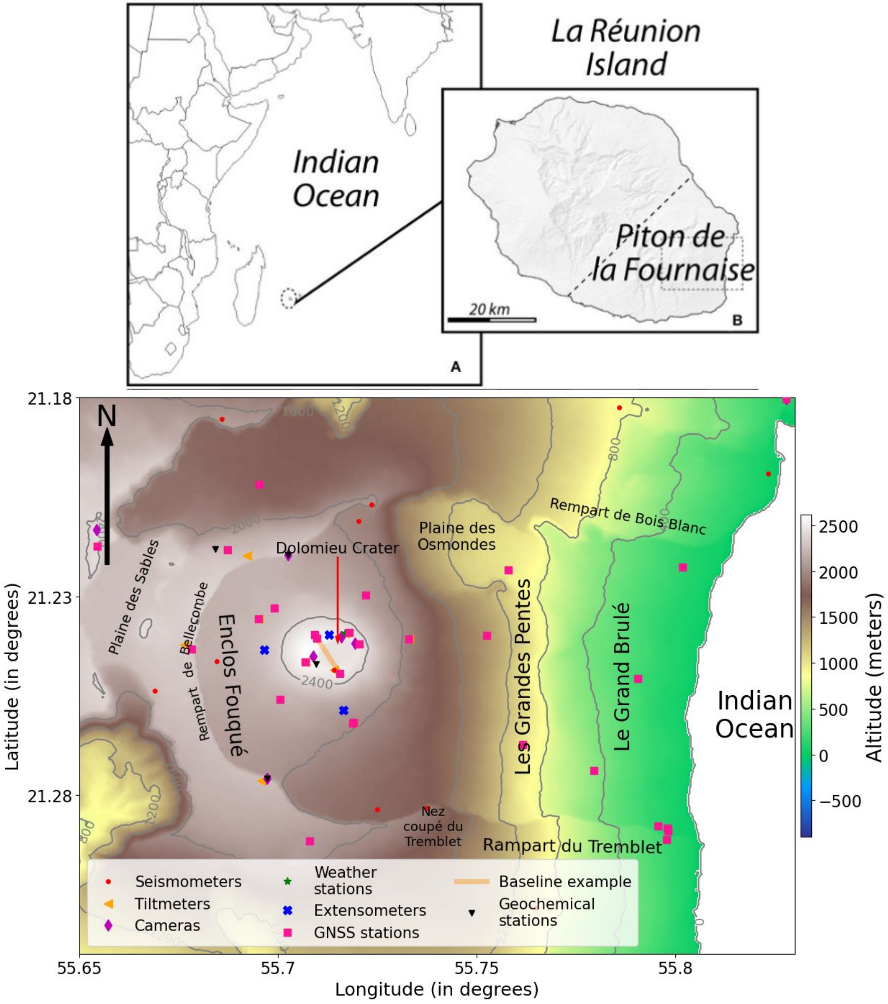
Objective

Volcanoes are dangerous to surrounding populations

Monitoring implies interpreting various data (seismicity, gas, deformation…)

Machine learning algorithms for multi-methods analysis

Piton de la Fournaise



Location of (A) La Réunion in the Indian Ocean, (B) Piton de la Fournaise on La Réunion Island. (C) Zoom on the Enclos Fouqué caldera.

Very active volcano (2 eruptions/year)
Densely monitored by OVPF-IPGP (112 stations)

April 2007

State at OVPF

Using seismic noise correlations to estimate volcano interior temporal seismic velocity changes. [*Brenguier et al., 2011*]

Using multiparameter (seismicity, extensometer and seismic velocity changes rate) for eruptions time predictability. *[Schmid et al., 2012*]

Automatic detection of eruptive tremor with machine learning [*Ren et al., 2020*]

Monitoring long-term deformation and CO_2 degassing and using a threshold on seismicity [*Peltier et al., 2021*]

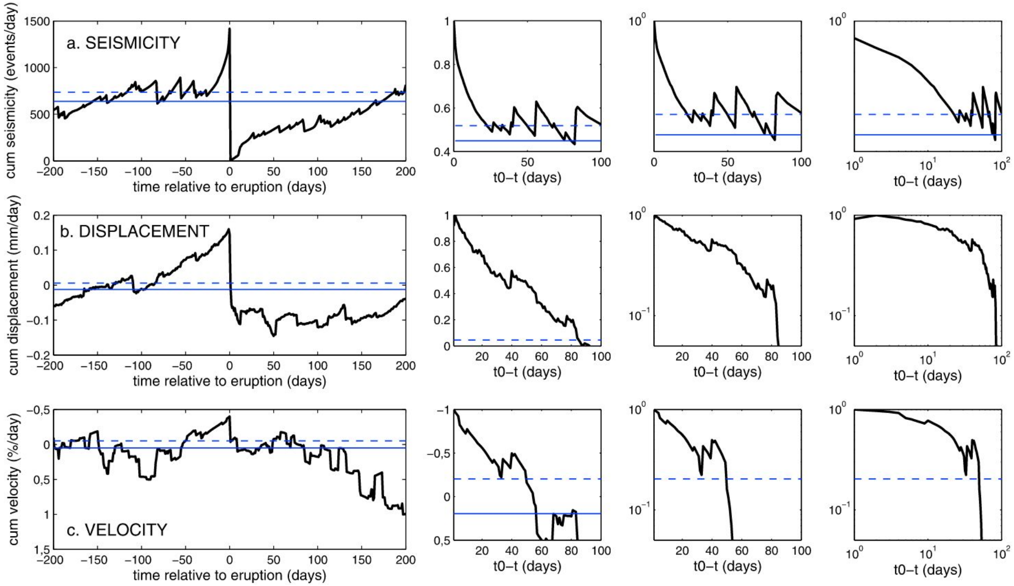


Figure 9 [A. Schmid et al. 2012]

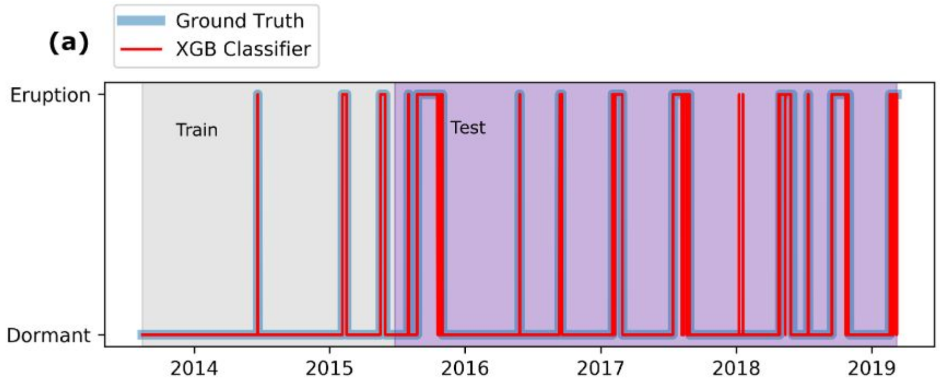


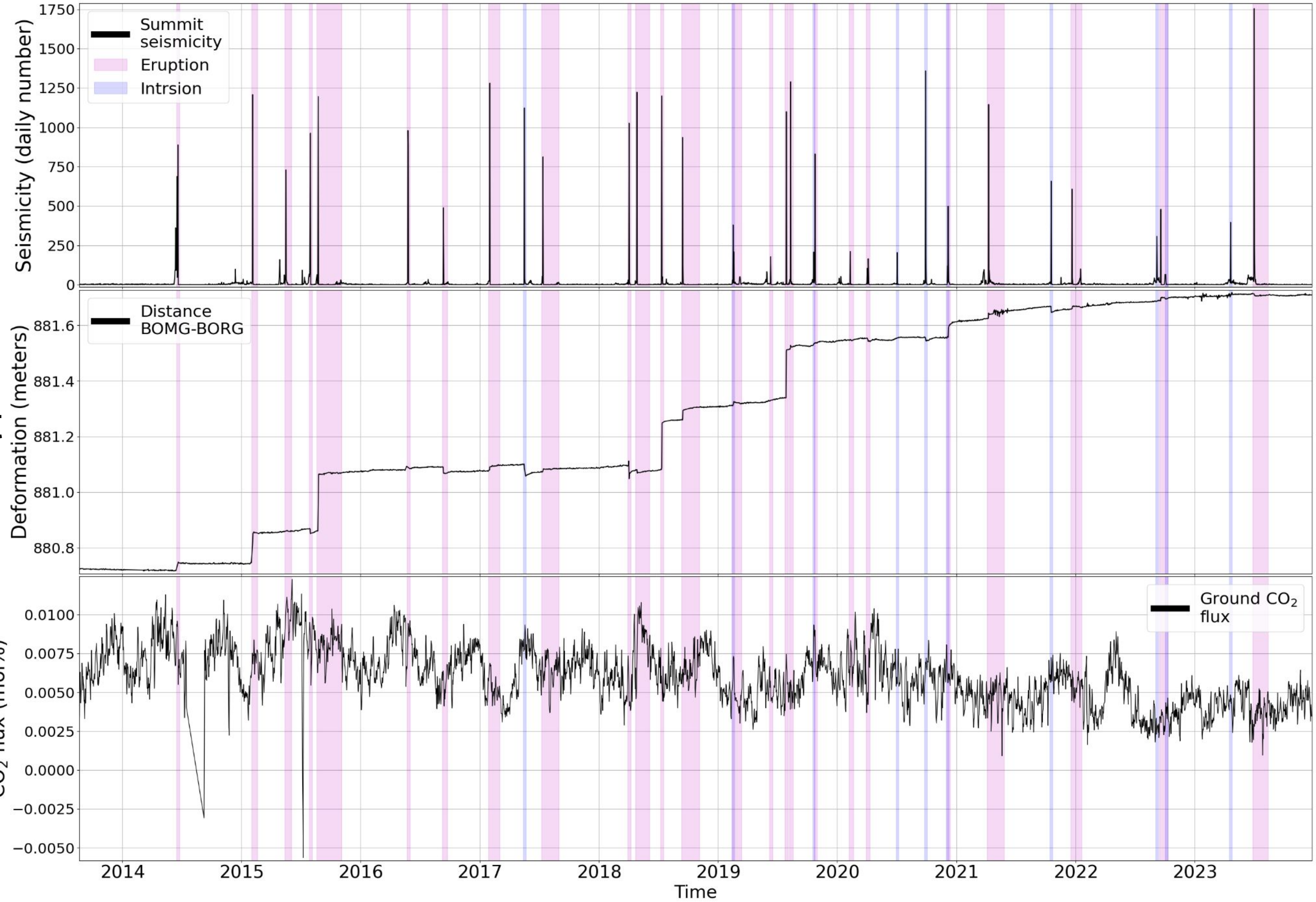
Figure 2. (a) [C. X. Ren et al. 2020] (modified)

Data : long term time series

Number of earthquakes

Surface displacement

Soil CO_2 flux



Machine learning (ML) algorithms

Algorithms with parameter trained on data to make decisions based on patterns observed.

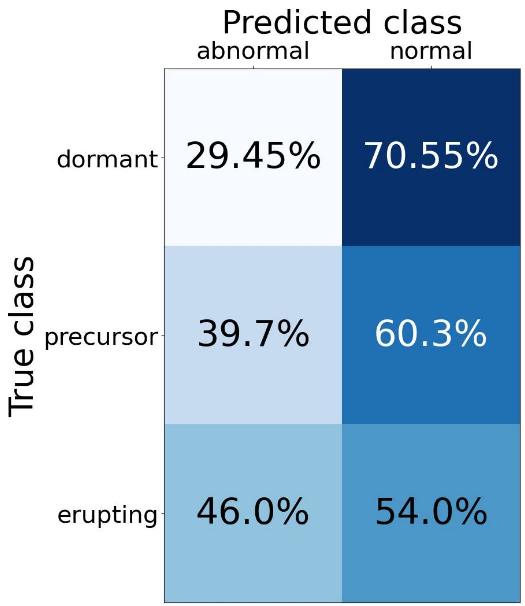
Artificial Neural Networks are **ML** algorithm that associate X data with Y_t observables, approximating an unknown function *f*.

Unsupervised:
What is the difference between those two pictures?

Supervised:
Which picture is a puppy and which one is a kitten?

Unsupervised and supervised classification

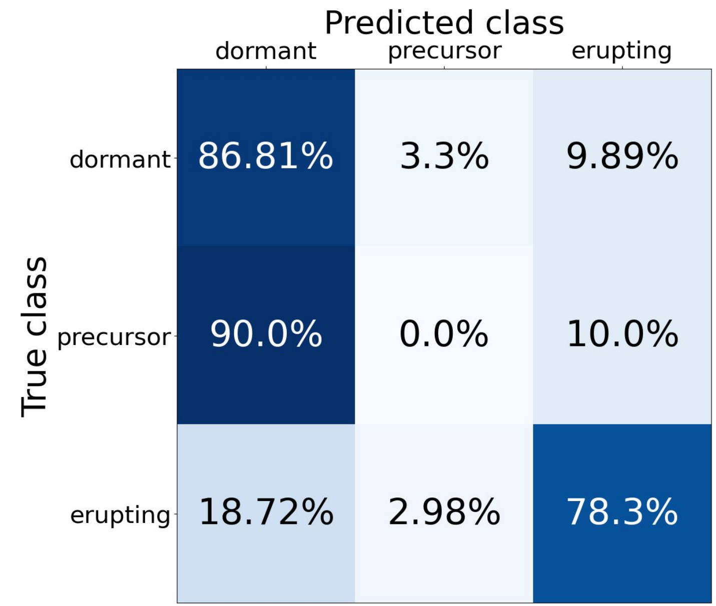
Unsupervised anomaly detection



Dormant state is more usually classified as normal.

Precursor and eruption states are not well detected.

Supervised signal classification

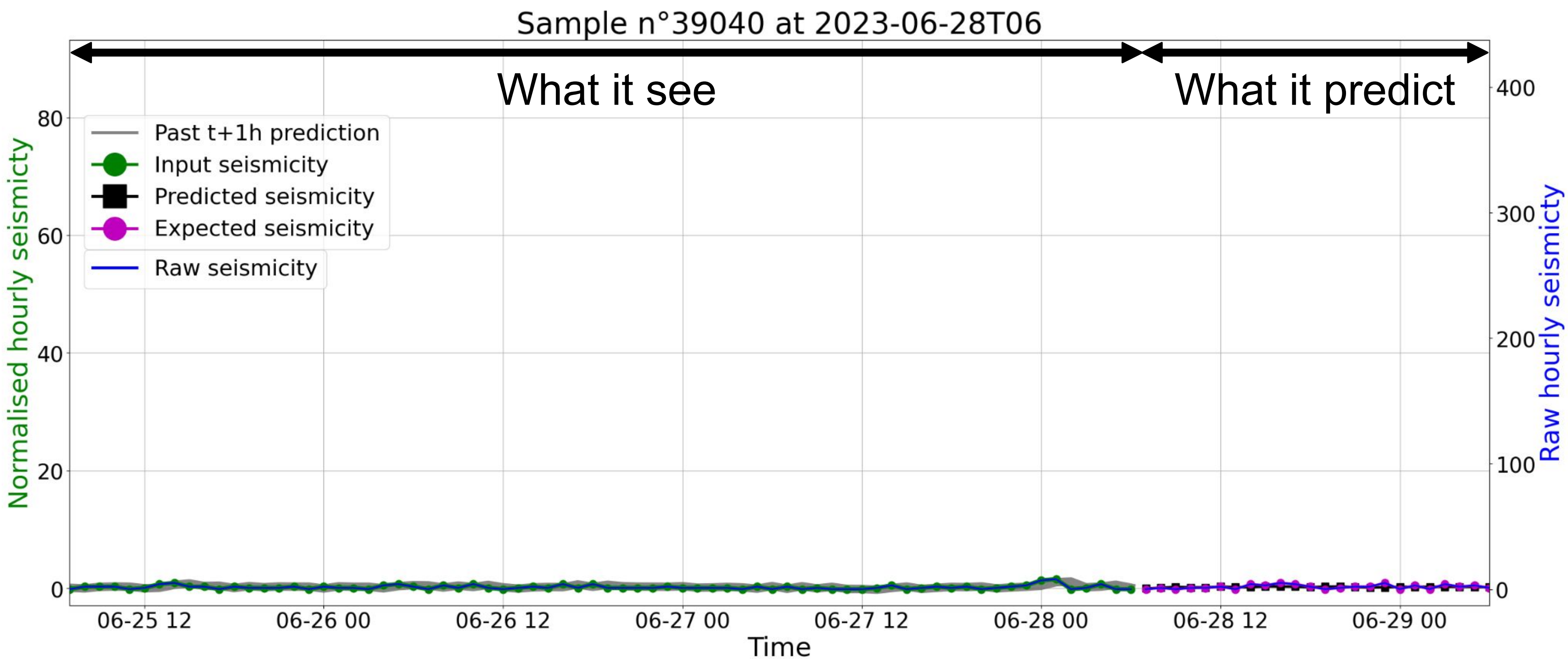


Dormant and eruption state are quite well classified.

Precursors are not well detected.

Human with lots of experience can do better, thus can we predict evolution of the channels and let humans do what they are strong in ?

Predicting the future seismicity



Forecasting the chanels

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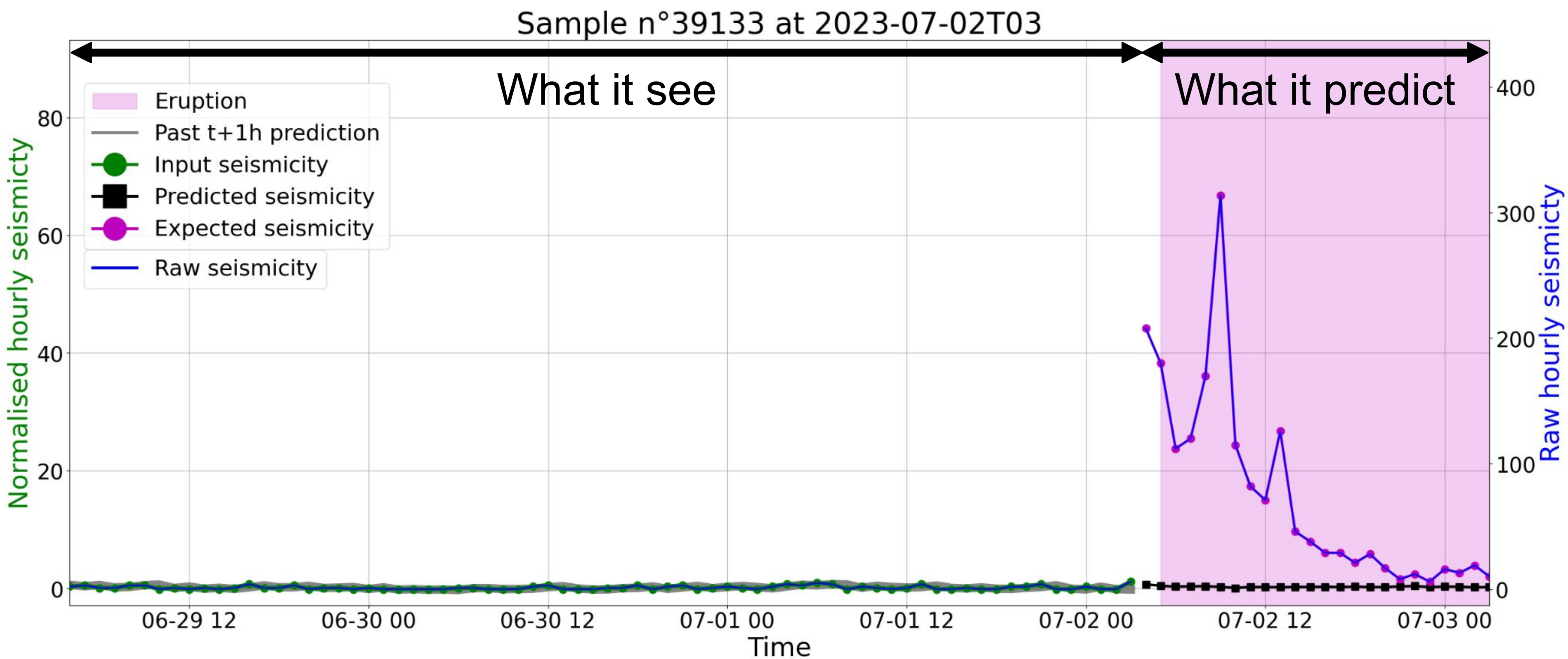

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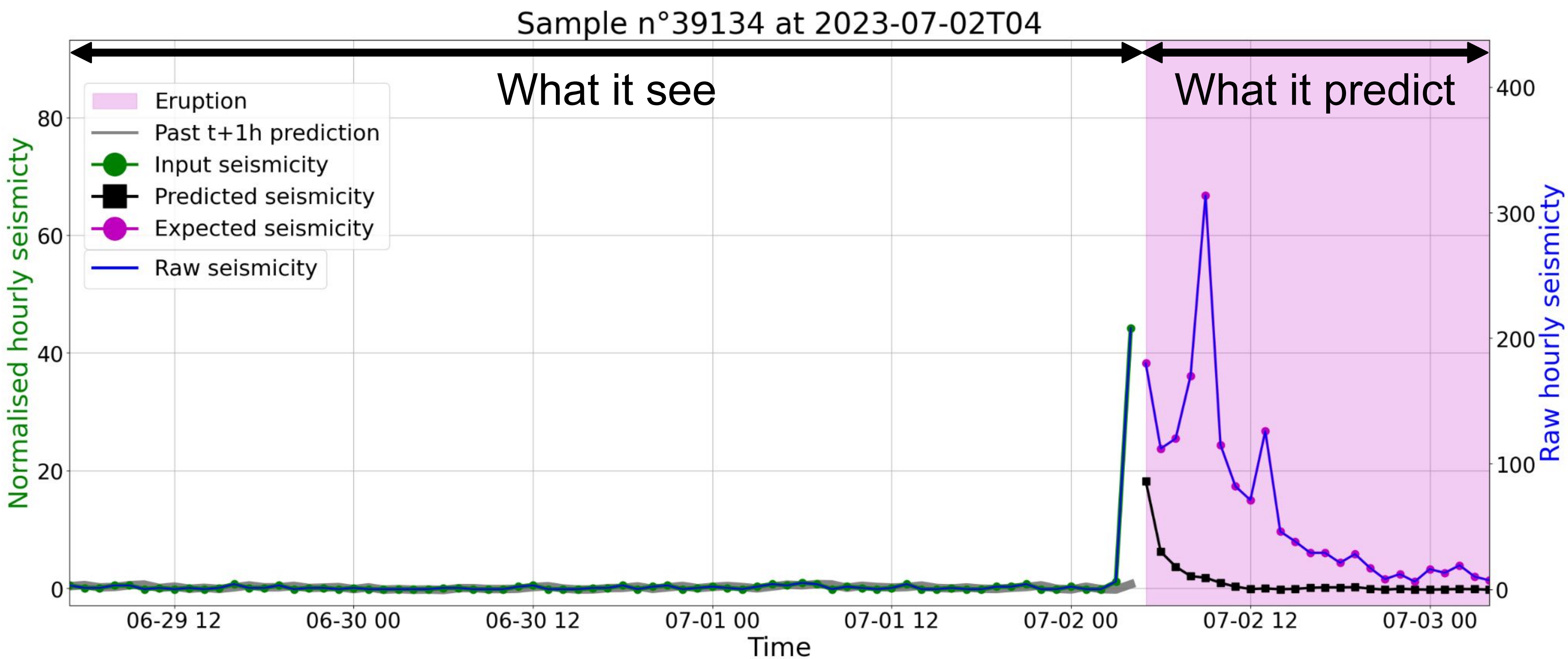

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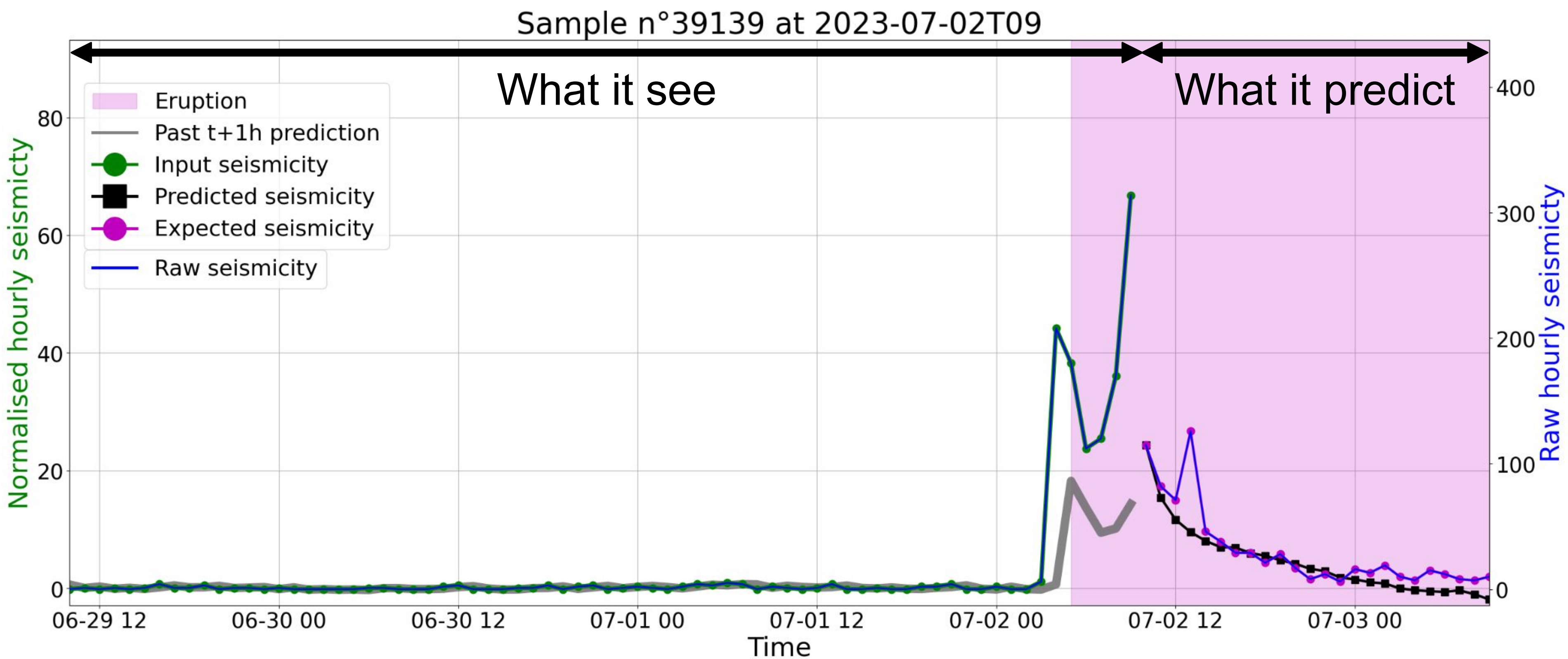

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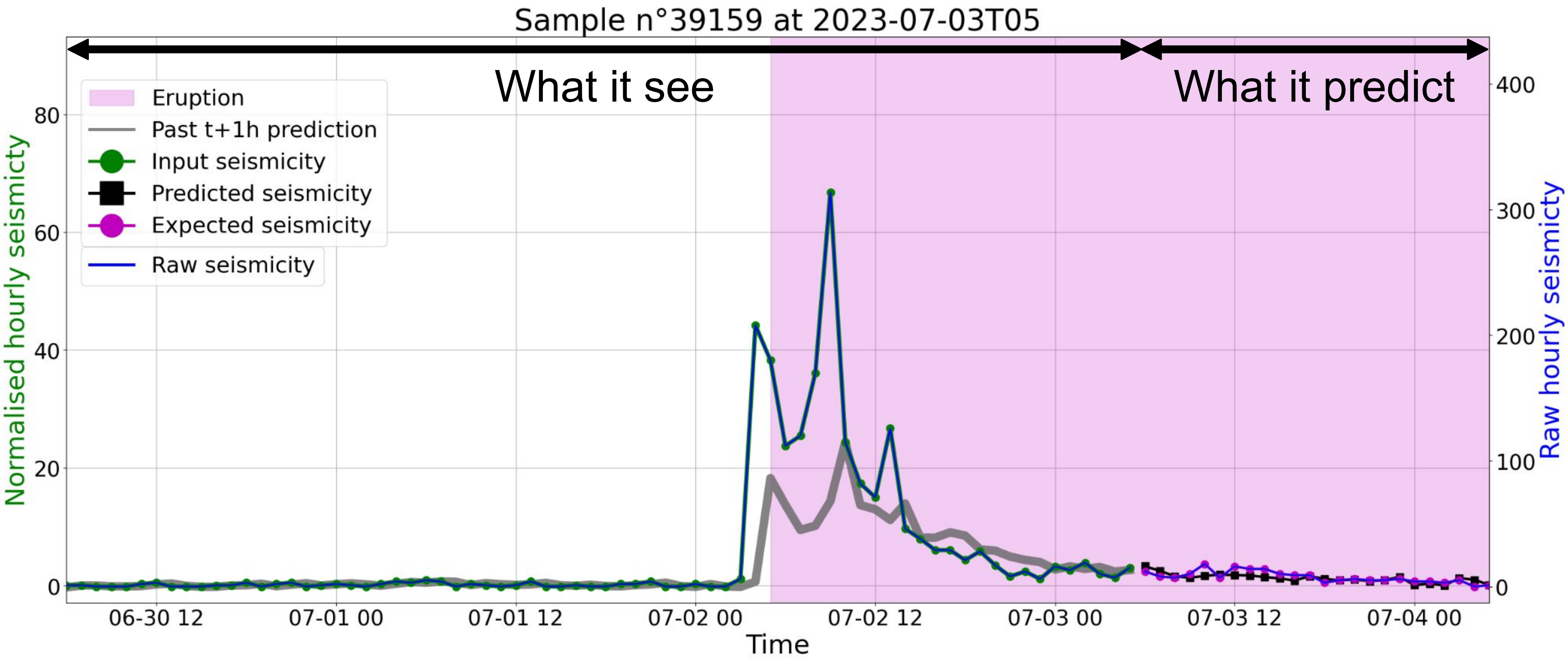

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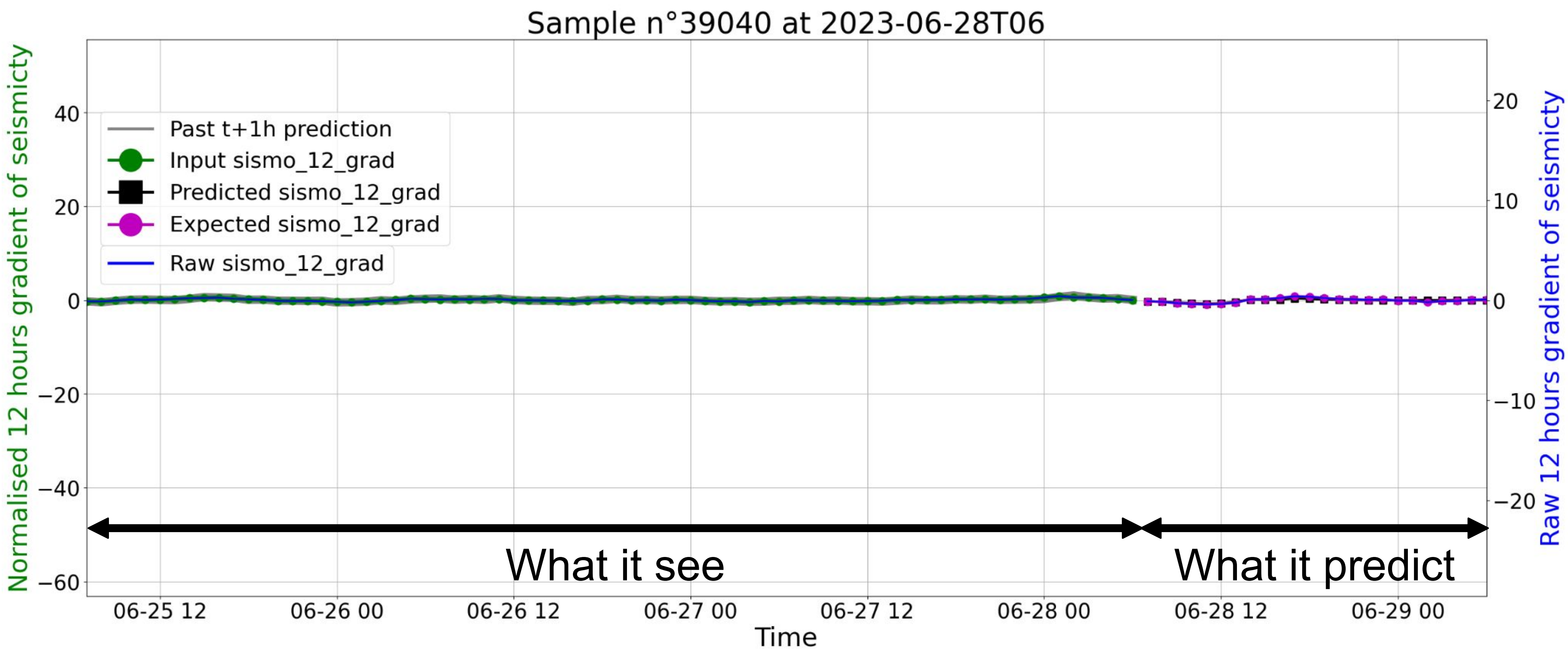
Predicting the future 12 hours gradient of the seismicity



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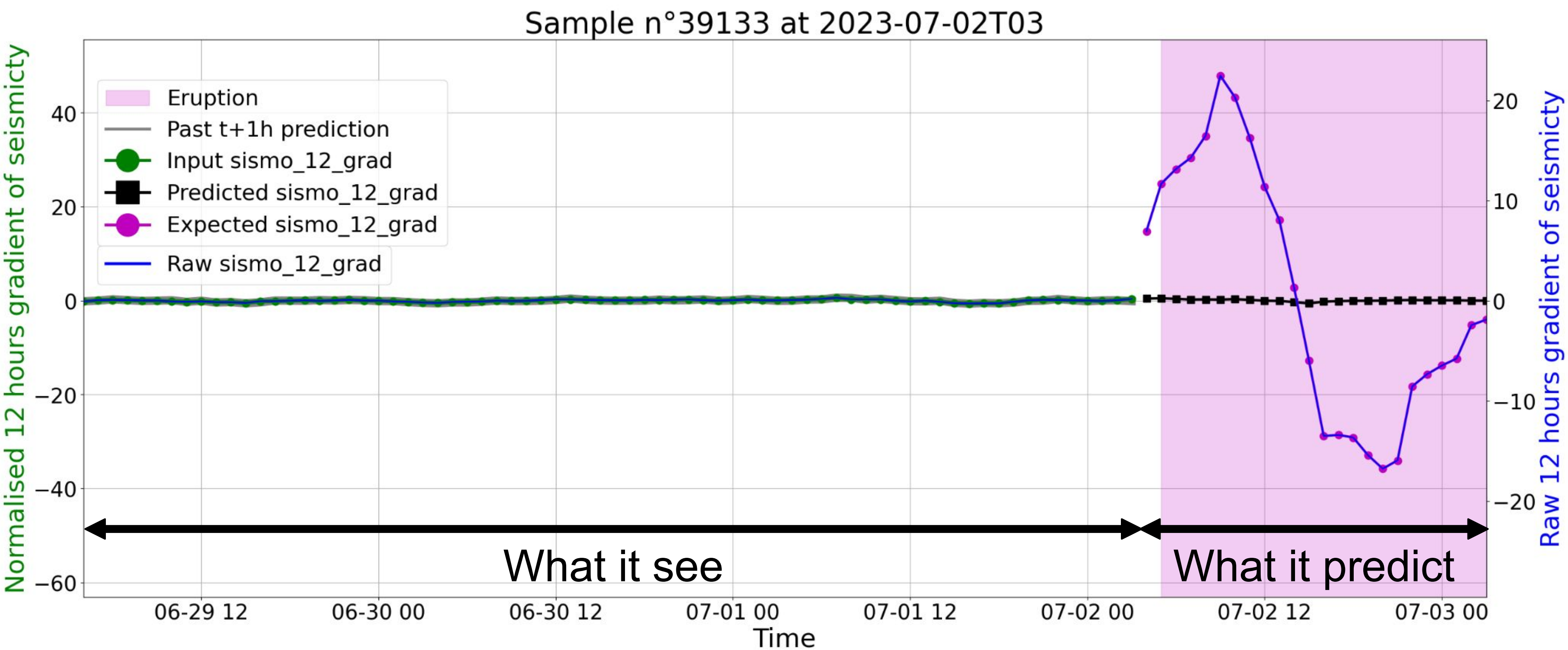

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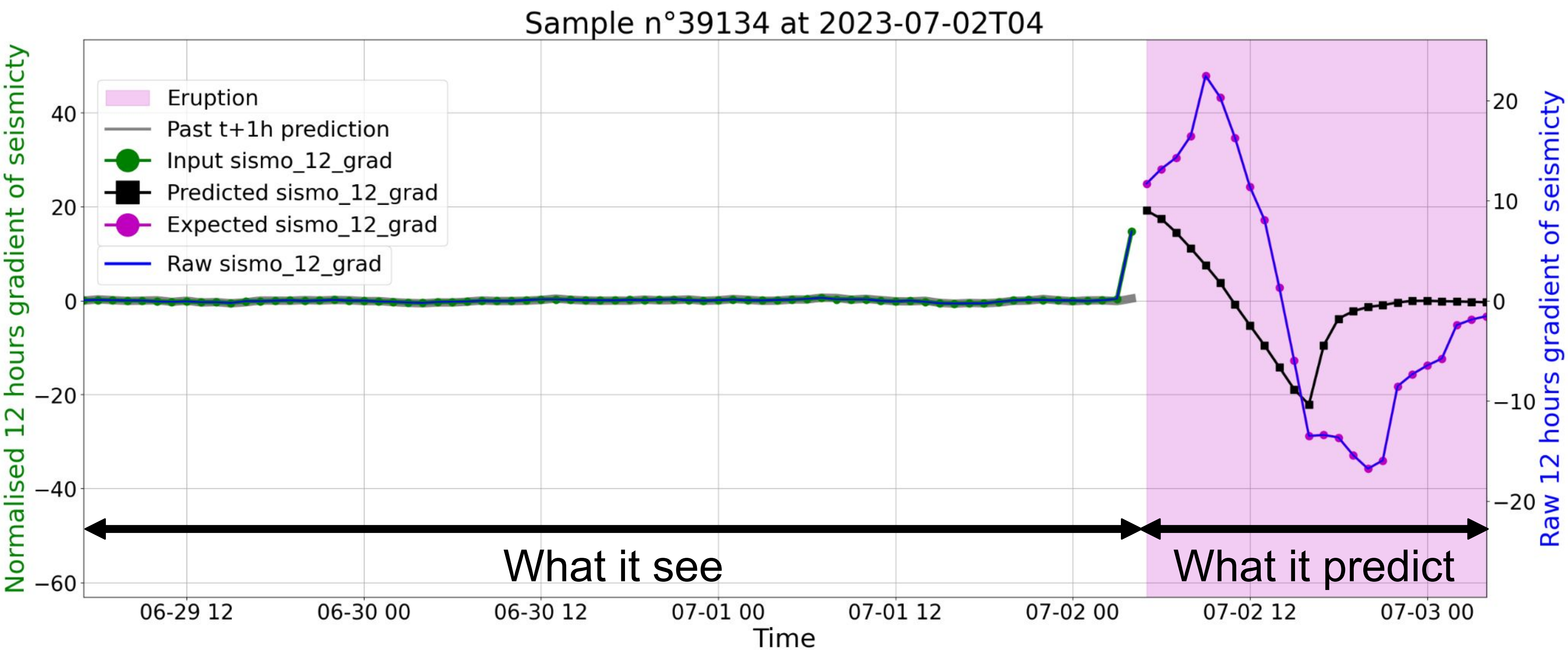

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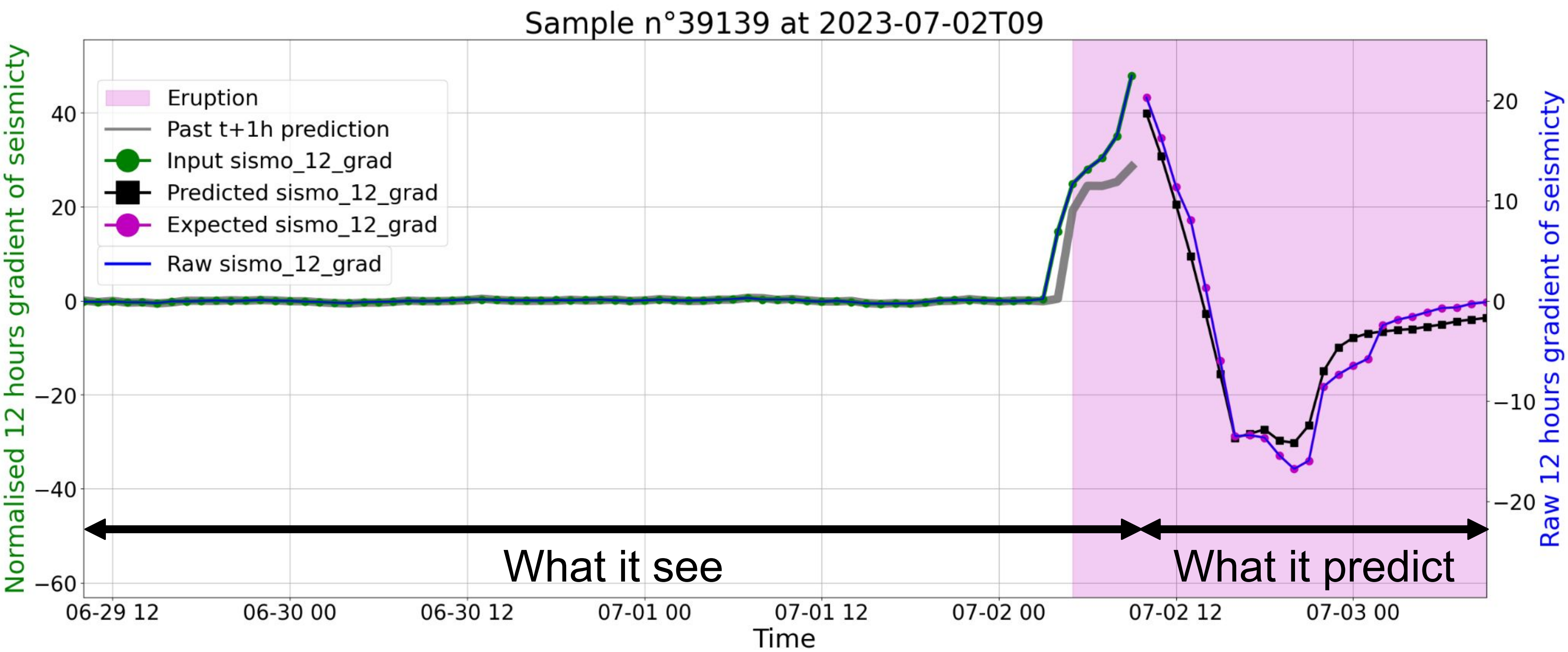

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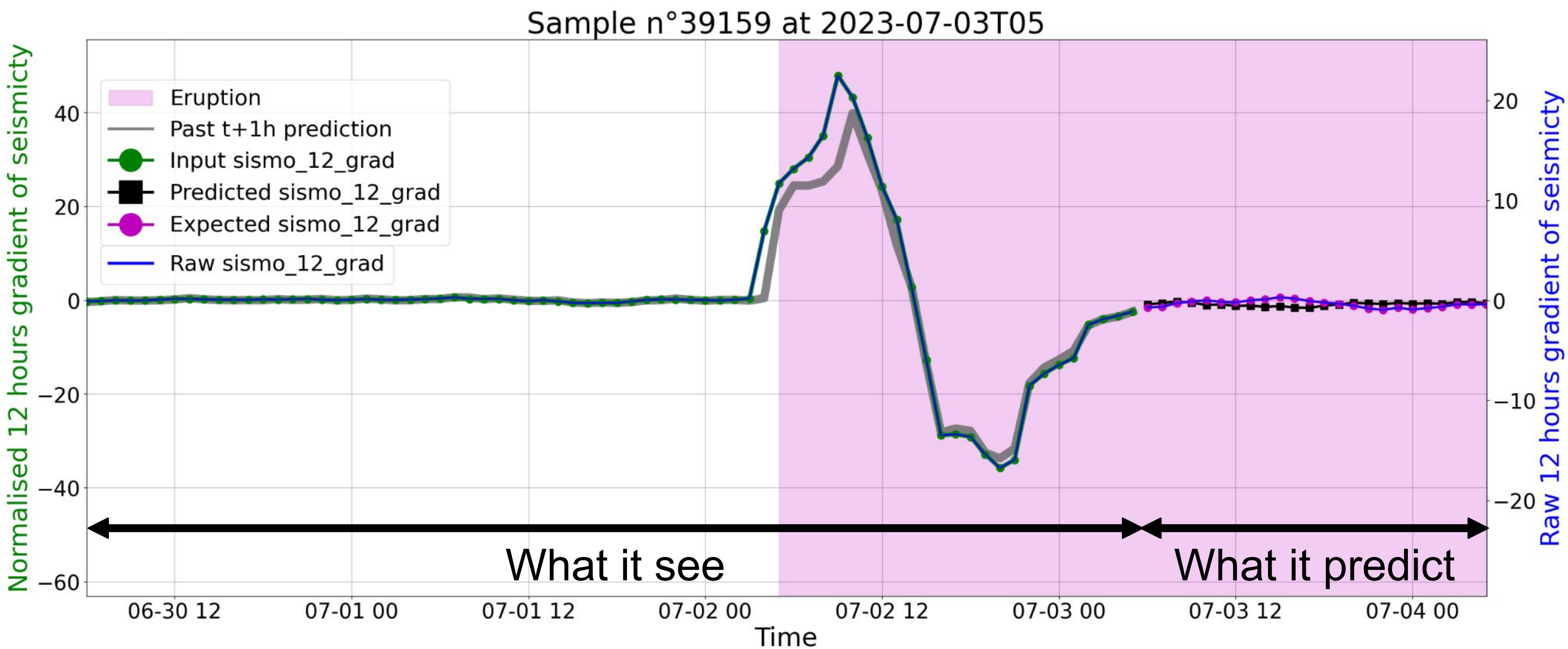
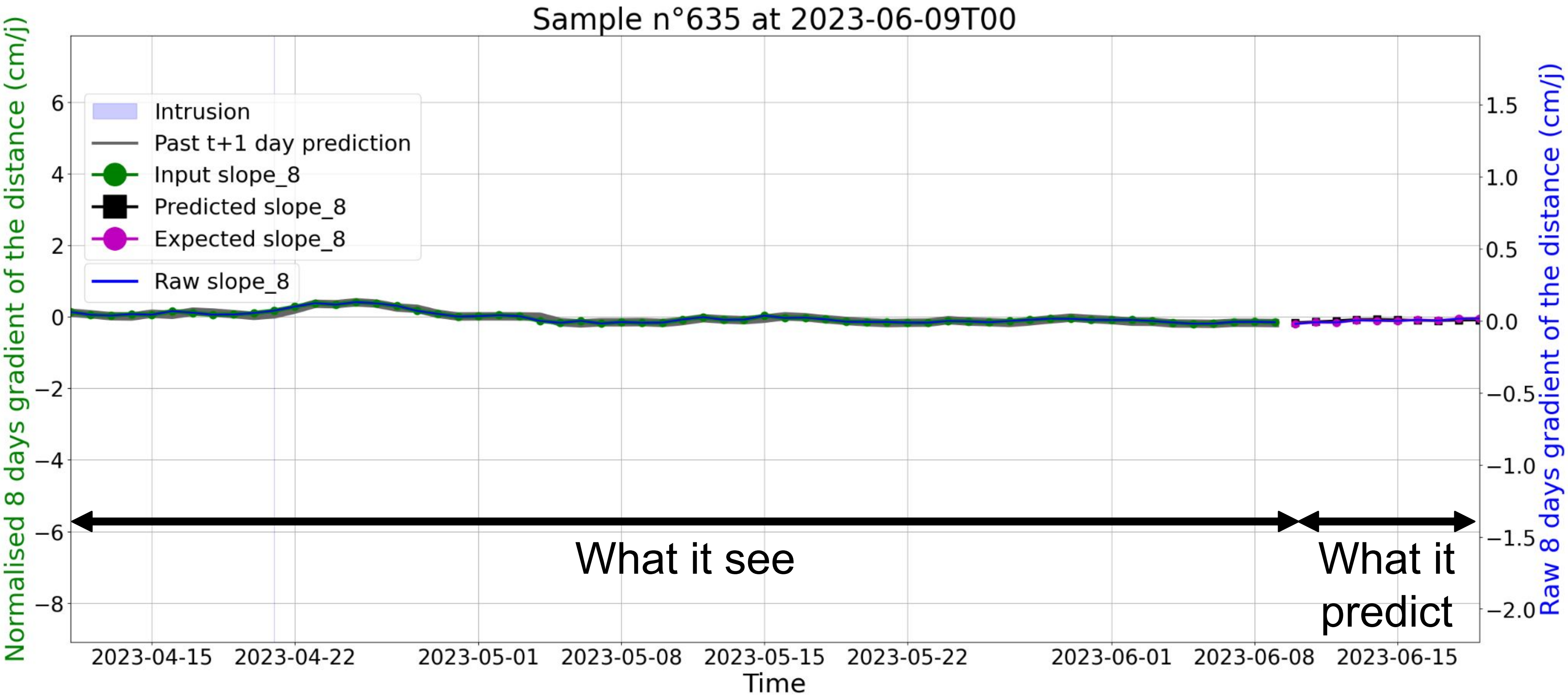


An other geophysical time series: the deformation

8 days gradient of the distance between two gnss stations



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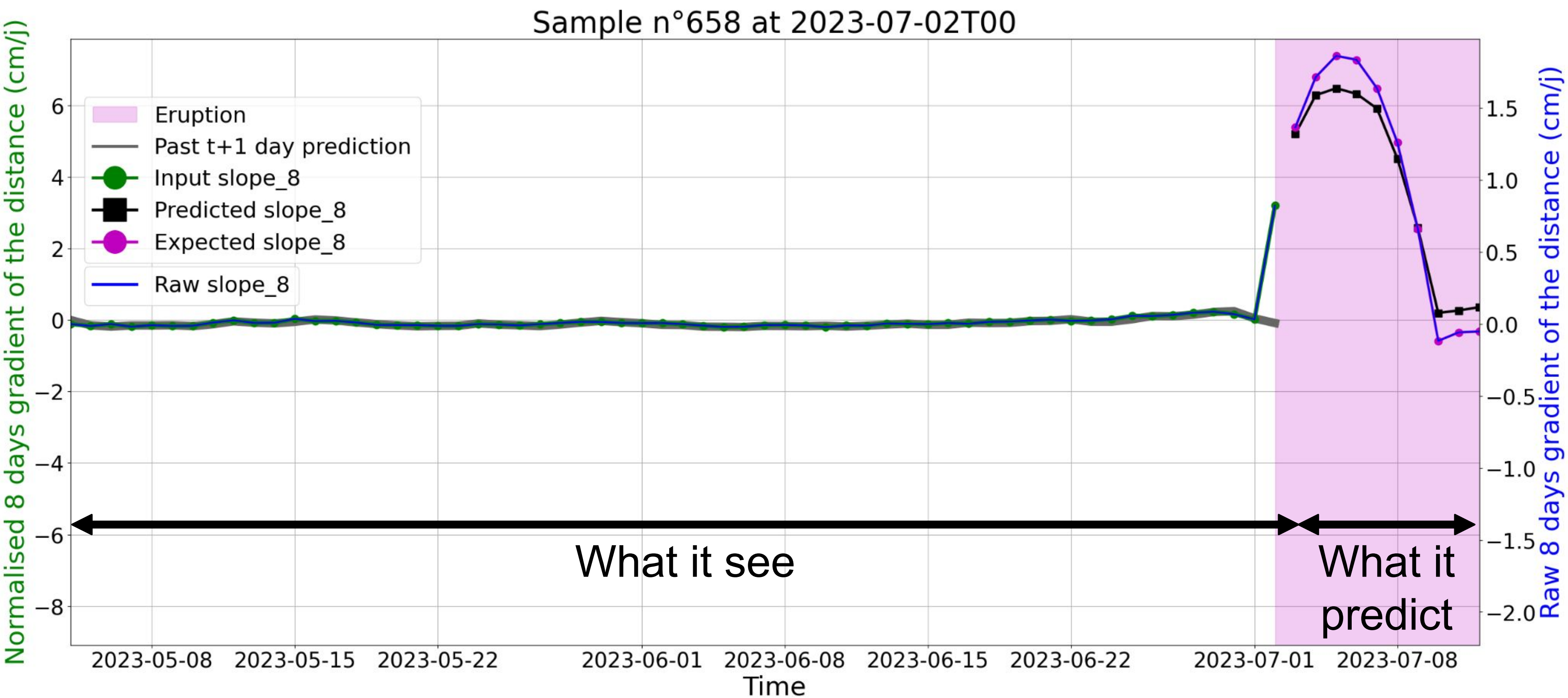

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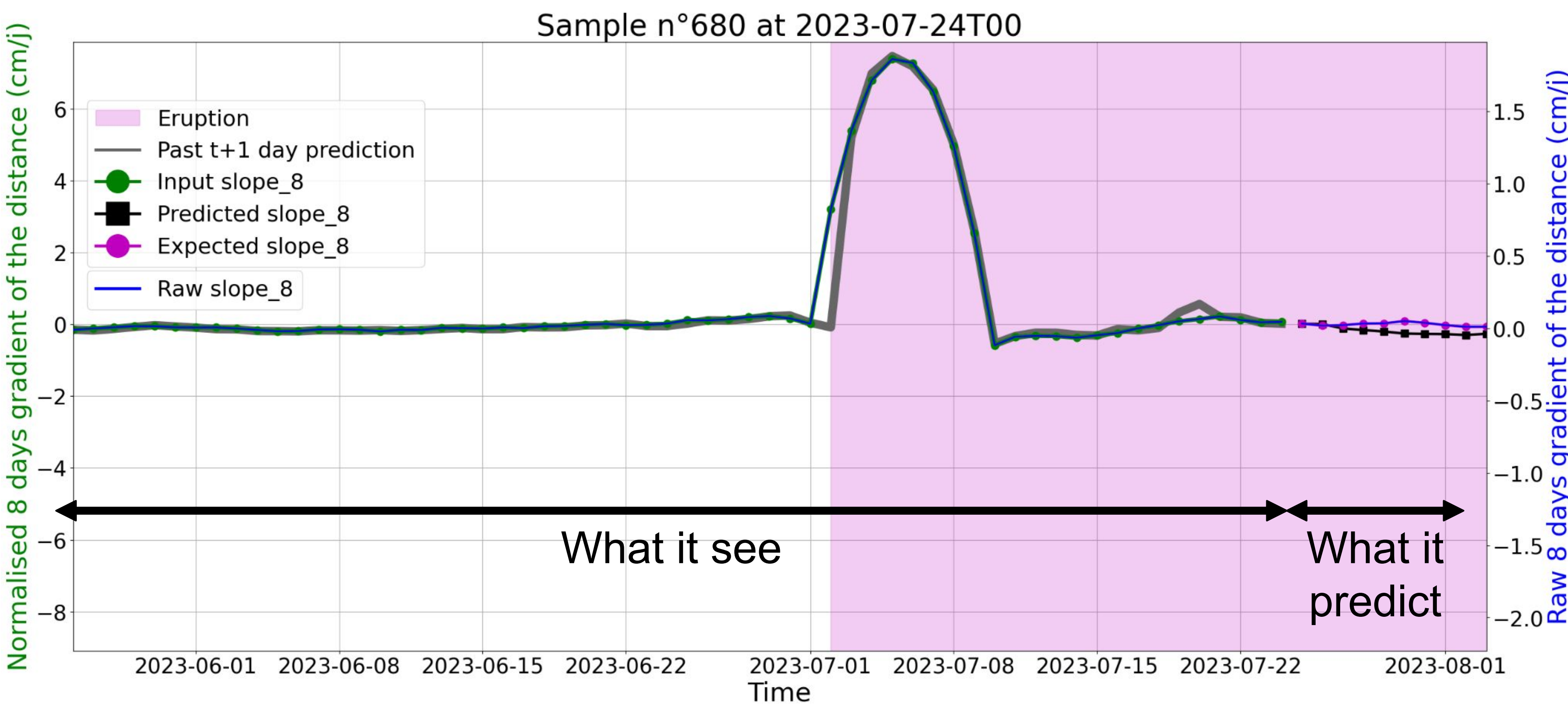

Conclusion

Unsupervised: detect changes in the data close to eruption, but lack accuracy.

Supervised: could predict the active or the rest state of the volcano but not the pre-eruptive state.

Forecasting: have difficulties to predict the augmentation of earthquakes and deformation, but works to predict how it will return to the rest state.

Nexts steps:

- Fine tuning and optimization of the forecasting models;
- Hourly deformation prediction;
- Predicting seismicity and deformation together;
- Can we predict CO_2 flux ?

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Thank you for your attention

References

A. Peltier, V. Ferrazzini, A. Di Muro, P. Kowalski, N. Villeneuve, N. Richter, O. Chevrel, J. L. Froger, A. Hrysiewicz, M. Gouhier, D. Coppola, L. Retailleau, François Beauducel, L. Gurioli, P. Boissier, C. Brunet, P. Catherine, F. Fontaine, F. Lauret, L. Garavaglia, J. Lebreton, K. Canjamale, N. Desfete, C. Griot, A. Harris, S. Arellano, M. Liuzzo, S. Gurrieri, and M. Ramsey. Volcano crisis management at Piton de la Fournaise (La Reunion) during the COVID-19 lockdown. Seismological Research Letters, 92 :38–52, 2021. ISSN 0895-0695. doi:10.1785/0220200212. URL https://www.documentation.ird.fr/hor/{PAR}00022131.

G. Boudoire, A. Di Muro, M. Liuzzo, V. Ferrazzini, A. Peltier, S. Gurrieri, L. Michon, G. Giudice, P. Kowalski, and P. Boissier. New perspectives on volcano monitoring in a tropical environment: Continuous measurements of soil co2 flux at piton de la fournaise (la réunion island, france). Geophysical Research Letters, 44(16) :8244–8253, 2017a. doi:https ://doi.org/10.1002/2017GL074237. URL: https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017GL074237.

F. Brenguier, D. Clarke, Y. Aoki, N. M. Shapiro, M. Campillo, V. Ferrazzini. Monitoring volcanoes using seismic noise correlations. Comptes Rendus. Géoscience, Volume 343 (2011) no. 8-9, pp. 633-638. doi : 10.1016/j.crte.2010.12.010. https://comptes-rendus.academie-sciences.fr/geoscience/articles/10.1016/j.crte.2010.12.010/

A. Schmid, J. R. Grasso, D. Clarke, V. Ferrazzini, Patrick Bachèlery, and T. Staudacher. Eruption forerunners from multiparameter monitoring and application for eruptions time predictability (Piton de la Fournaise). Journal of Geophysical Research, 117 :B11203, 2012. doi:10.1029/2012JB009167. URL https://hal.archives-ouvertes.fr/hal-00793995.

C. X. Ren, A. Peltier, V. Ferrazzini, B. Rouet-Leduc, P. A. Johnson, & F. Brenguier, (2020). Machine learning reveals the seismic signature of eruptive behavior at Piton de la Fournaise volcano. Geophysical Research Letters, 47, e2019GL085523. https://doi.org/10.1029/2019GL085523

W. Zhu, G. C. Beroza, PhaseNet: a deep-neural-network-based seismic arrival-time picking method, Geophysical Journal International, Volume 216, Issue 1, January 2019, Pages 261–273, https://doi.org/10.1093/gji/ggy423

C. Corradino, G. Ganci, A. Cappello, G. Bilotta, S. Calvari, and C. Negro. Recognizing eruptions of mount etna through machine learning using multiperspective infrared images. Remote Sensing, 12 :970, 03 2020. doi:10.3390/rs12060970.

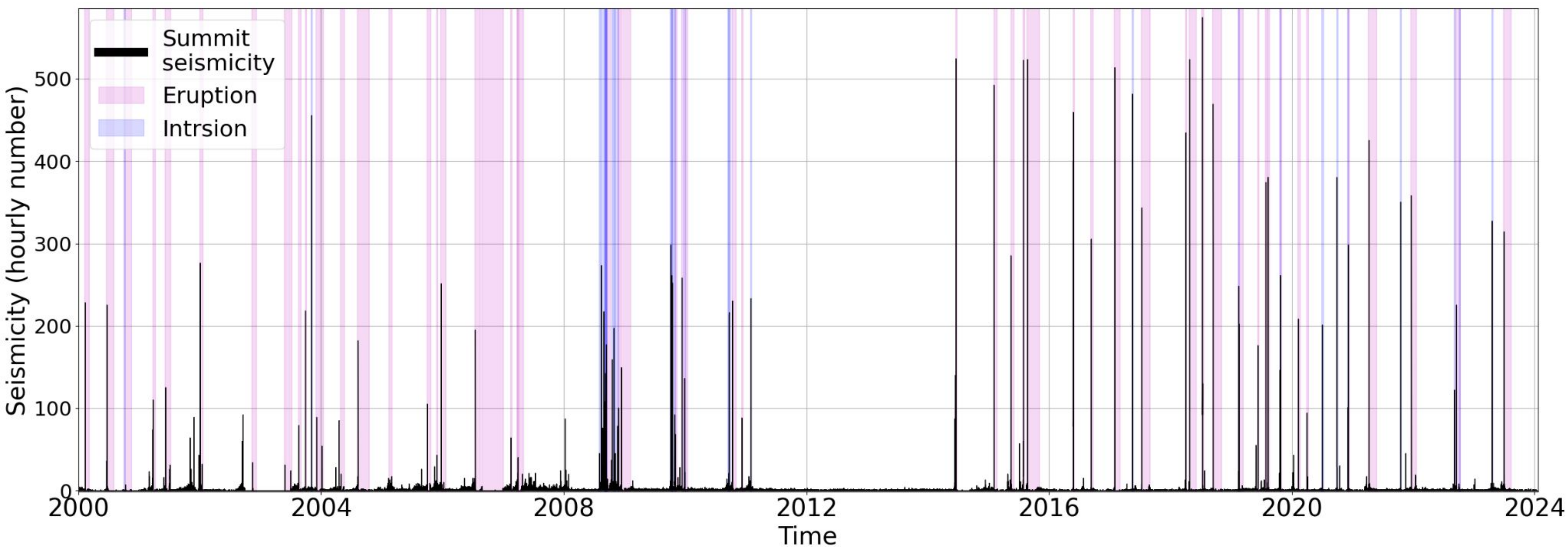
B. C. Dye and G. Morra. Machine learning as a detection method of strombolian eruptions in infrared images from mount erebus, antarctica. Physics of the Earth and Planetary Interiors, 305 :106508, 2020. ISSN 0031-9201. doi:https ://doi.org/10.1016/j.pepi.2020.106508. URL https://www.sciencedirect.com/science/article/pii/S0031920119301608.

N. Anantrasirichai, J. Biggs, Fabien Albino, and D. Bull. A deep learning approach to detecting volcano deformation from satellite imagery using synthetic datasets. Remote Sensing of Environment, 230, 09 2019. doi:10.1016/j.rse.2019.04.032.

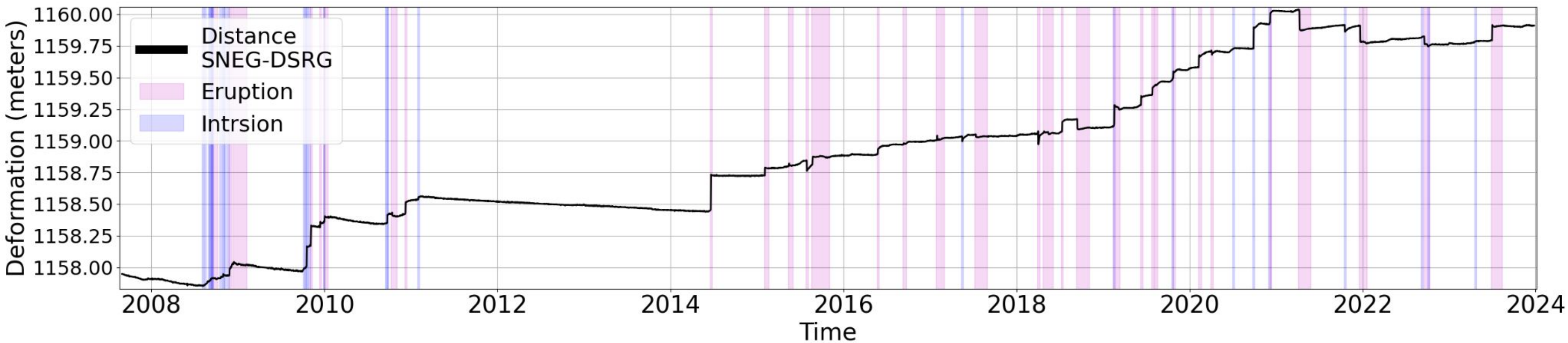
M. Malfante, M. D. Mura, J.-P. Métaxian, J. I. Mars, O. Macedo, and A. Inza. Machine Learning for Volcano-Seismic Signals : Challenges and Perspectives. IEEE Signal Processing Magazine, 35(2) :20 – 30, March 2018. doi:10.1109/MSP.2017.2779166. URL https://hal.archives-ouvertes.fr/hal-01742506.

Diederik P Kingma and Max Welling. Auto-Encoding Variational Bayes. arXiv e-prints, art. arXiv :1312.6114, December 2013.

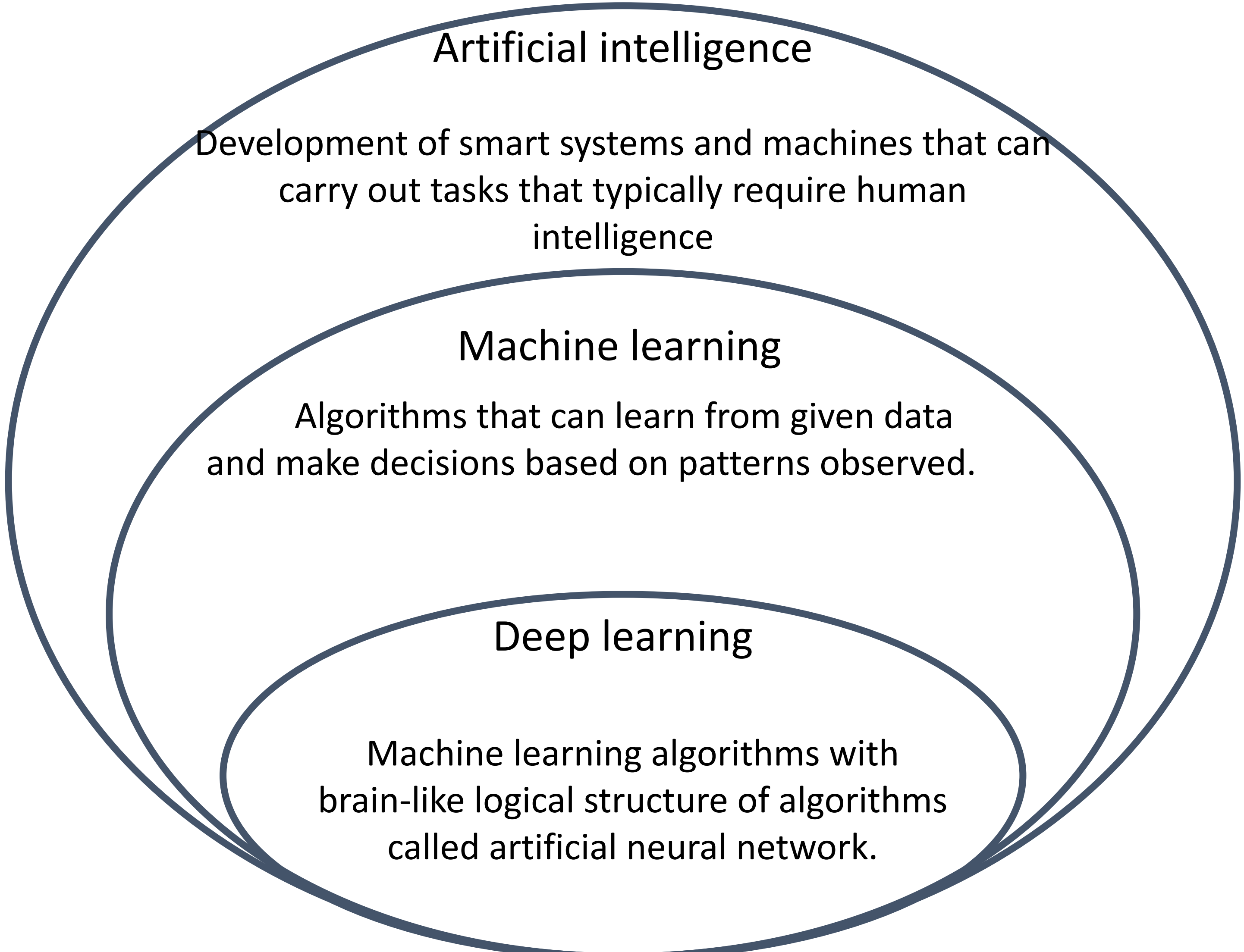
Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. Isolation forest. 2008 Eighth IEEE International Conference on Data Mining, pages 413–422, 2008. doi:10.1109/ICDM.2008.17.



Summit seismicity
Eruption
Intrsion
Seismicity (hourly number)
0
100
200
300
400
500
2000
2004
2008
2012
2016
2020
2024
Time



Distance SNEG-DSRG
Eruption
Intrsion
Deformation (meters)
1160.00
1159.75
1159.50
1159.25
1159.00
1158.75
1158.50
1158.25
1158.00
2008
2010
2012
2014
2016
2018
2020
2022
2024
Time



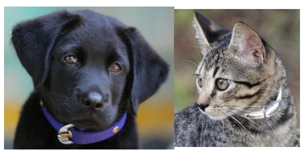
https://www.scs.org.sg/articles/machine-learning-vs-deep-learning & https://levity.ai/blog/difference-machine-learning-deep-learning

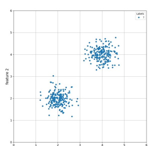
Machine learning (ML) is a field of **Artificial Intelligence (AI)** based on mathematics and informatics to solve problems without having a human to explicitly create a program for it. Thus, the algorithms will have to ‘find’ the relation between the observable.

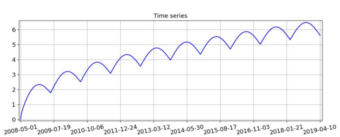
Observables
X and y

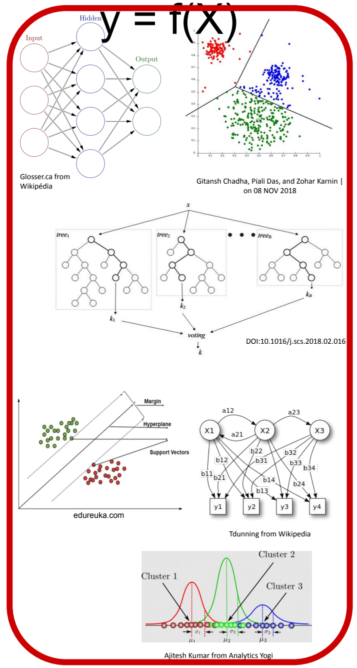
Unknown
function
y = f(X)

f being the ML algorithm









PUPPY v.s
KITTEN

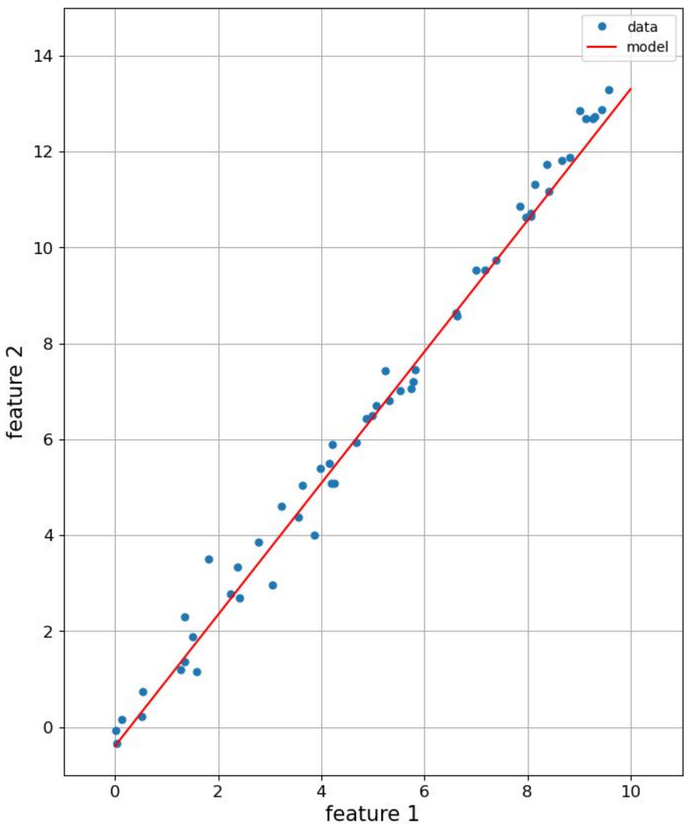
Number and center of
blobs

Stock and prices
predictions

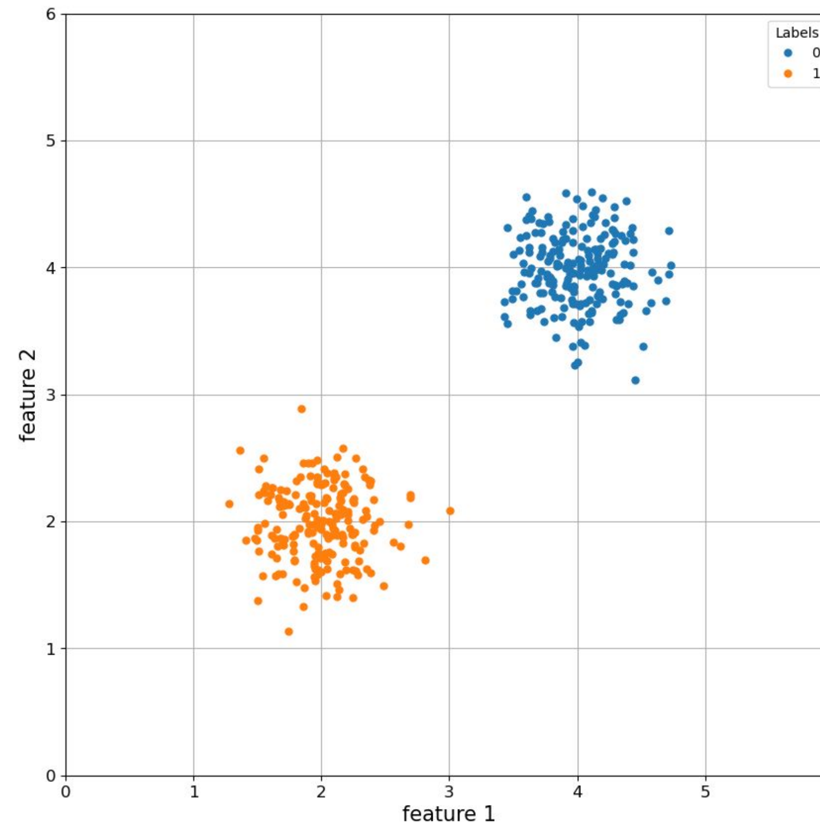
…

Mainly use for task of:

Regression



Classification



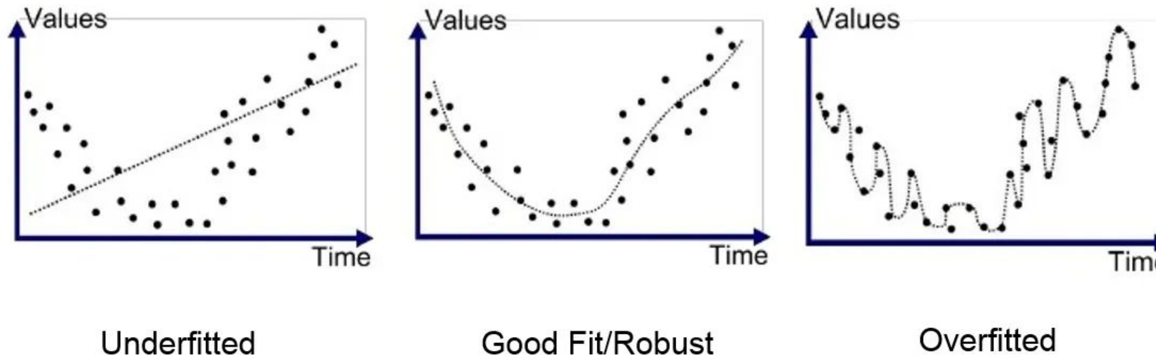
Under, good and overfitting:

Under = The model did not learn

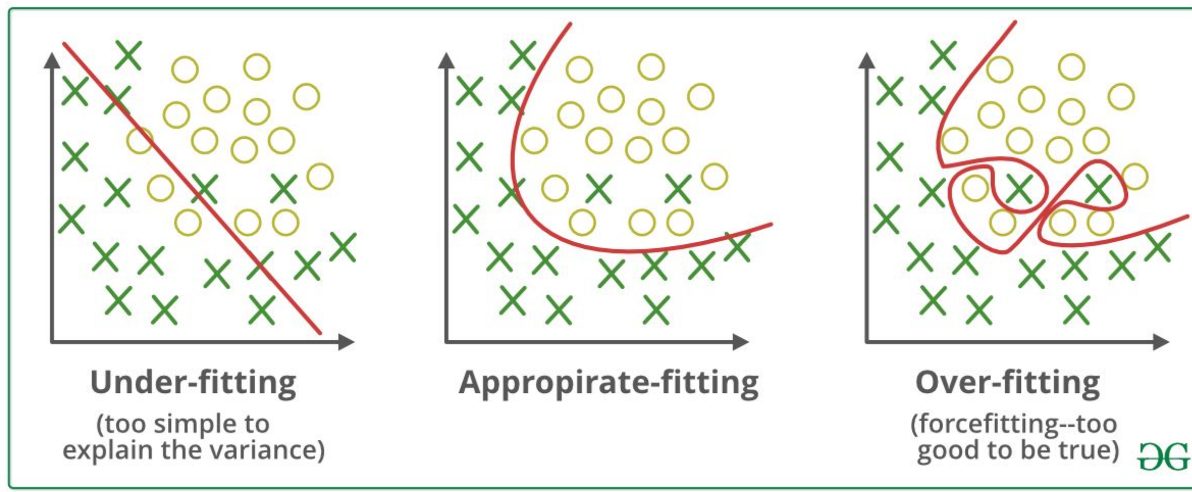
Good = The model learned the x and y relation and is able to generalize to unseen samples.

Over = The model only memorized the given samples

Your model is what it eat !



https://medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning-and-how-to-deal-with-it-6803a989c76



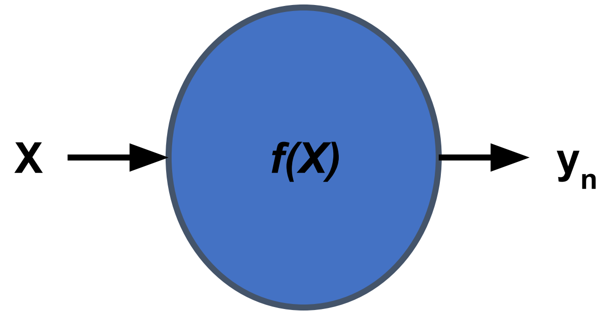
https://www.geeksforgeeks.org/underfitting-and-overfitting-in-machine-learning/

Artificial neural networks:

Simple neuron:

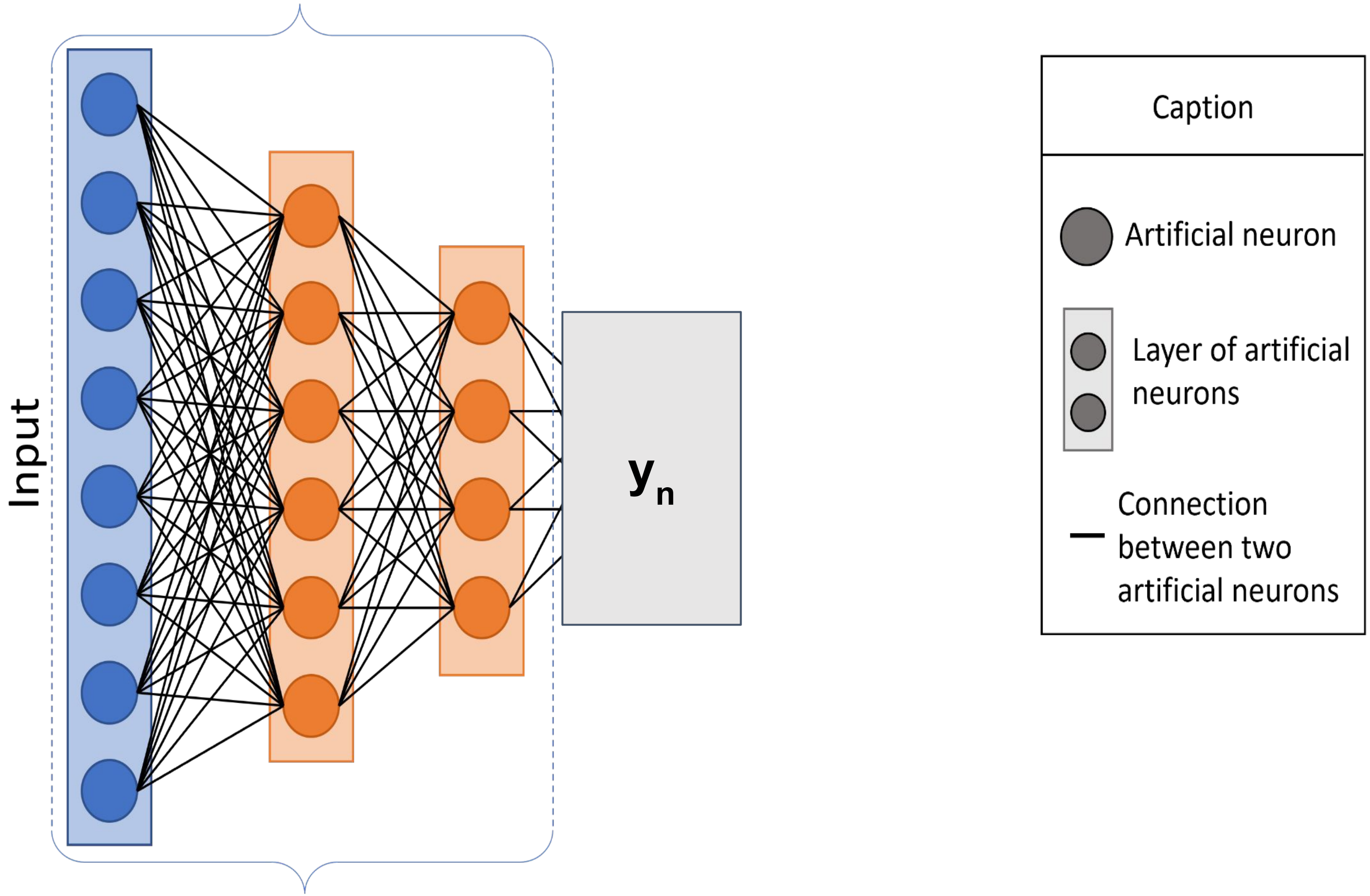
A type of **machine learning algorithm** that associate **X** data with $\mathbf{y_t}$ observables, thus approximating an unknown function ***f*** such as $\boldsymbol{f(X) = y_n \sim y_t}$.

Neuron = function f(x) = y



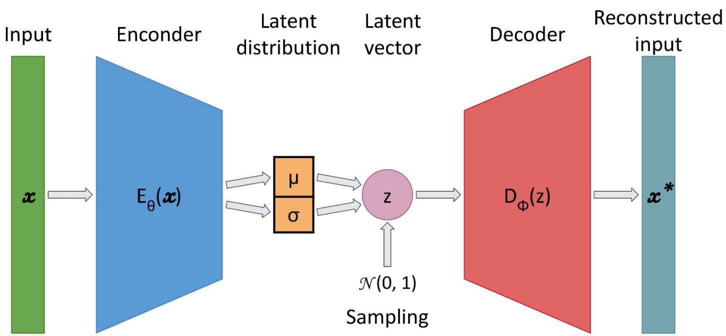
Artificial neural networks:

artificial neural networks = Several functions aggregated in network $F(\ldots, f_i(x), \ldots) = y_n$

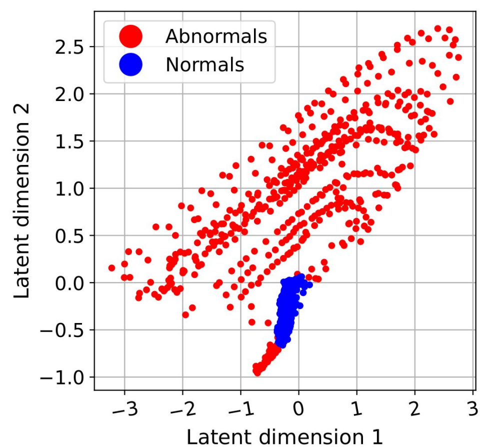


Unsupervised anomaly detection

1) Data dimension's reduction

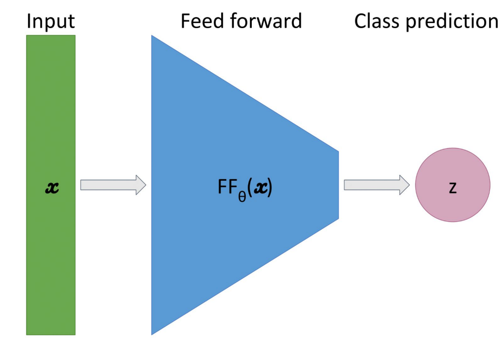


2) Automatic anomaly detection in latent space



Supervised signal classification

Convolutional feed forward network



Classes prediction

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{dormant, precursors, erupting}