Cluster analysis of Very-Long-Period events at Stromboli Volcano

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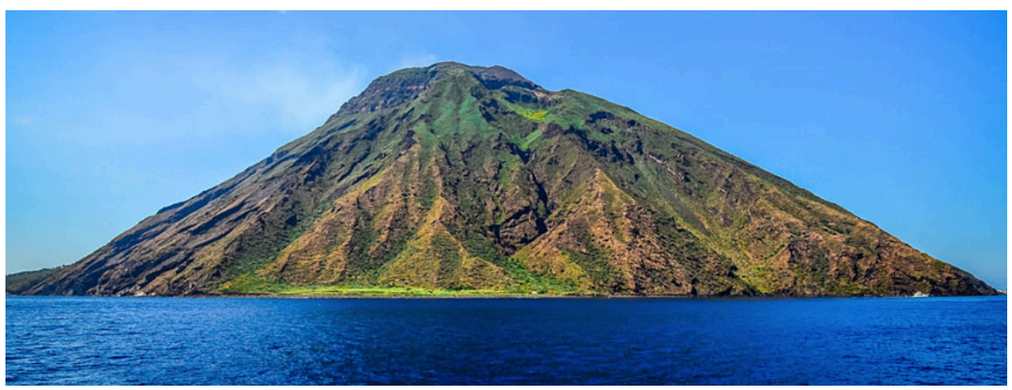
Stromboli Volcano

- **Open conduit volcano** with persistent explosive activity located in the Mediterranean Sea

- Activity characterized by **small explosions** occurring **repetitively** with a frequency ranging from five to more than 20 events per hour

- **Very-long-period (VLP) signals** associated with the Strombolian explosions

- **Rare** occurrence of **paroxysms** (violent explosions that produce eruptive columns often accompanied by pyroclastic flows) ~ **18 paroxysms over 110 years**



Paroxysms in 2019

- On **July 3, 2019** during a period of apparently moderate activity a **paroxysmal explosion** occurred

- The paroxysm gave rise to an **eruptive column** more than 5 km high and to a **pyroclastic flow**

- On **August 28**, **2019** a second **paroxysmal explosion** occurred similar to that of July 3 with another pyroclastic flow

- **Routinely monitored parameters by the INGV did not predict the July 3 paroxysm resulting in one fatality and some injuries**

The quest for new precursors

- To **reduce the risk of fatalities in the future** a wide range of parameters is analyzed to understand whether any of them show **anomalies** prior to the paroxysmal period to monitor them in the future

- Excellent analysis of various **promising parameters** recently published: *"Geophysical precursors of the July-August 2019 paroxysmal eruptive phase and their implications for Stromboli volcano (Italy) monitoring." (*Giudicepietro, F. *et al. Sci Rep* **10,** 10296 (2020). https://doi.org/10.1038/s41598-020-67220-1)

Very-Long-Period signal waveforms

- The first broadband seismic recordings have shown **differences in the waveforms** of the Very-Long-Period **VLP signals** associated with the Strombolian explosions (Chouet et al. 2003)

- Connection between the **VLP waveform** and the **physical state of the volcano** has been suggested (Esposito et al. 2008)

→ Cluster analysis of VLP waveforms (time series) in the paroxysmal period

Dataset

- The **Instituto Nazionale di Geofisica e Vulcanologia (INGV)** operates a permanent **broadband network** on Stromboli with thermal and infrared cameras

- The network consists of **7 digital stations** equipped with three-component **seismometers** and signals are recorded at a **sampling rate** of **50 samples/s**

- Signals that exceed a certain **amplitude threshold are selected** and signals from other sources (e.g. earthquakes) are removed manually

- **Final selection** consists of **~20.000 VLP events** in the period **15/05/19 to 19/09/19**

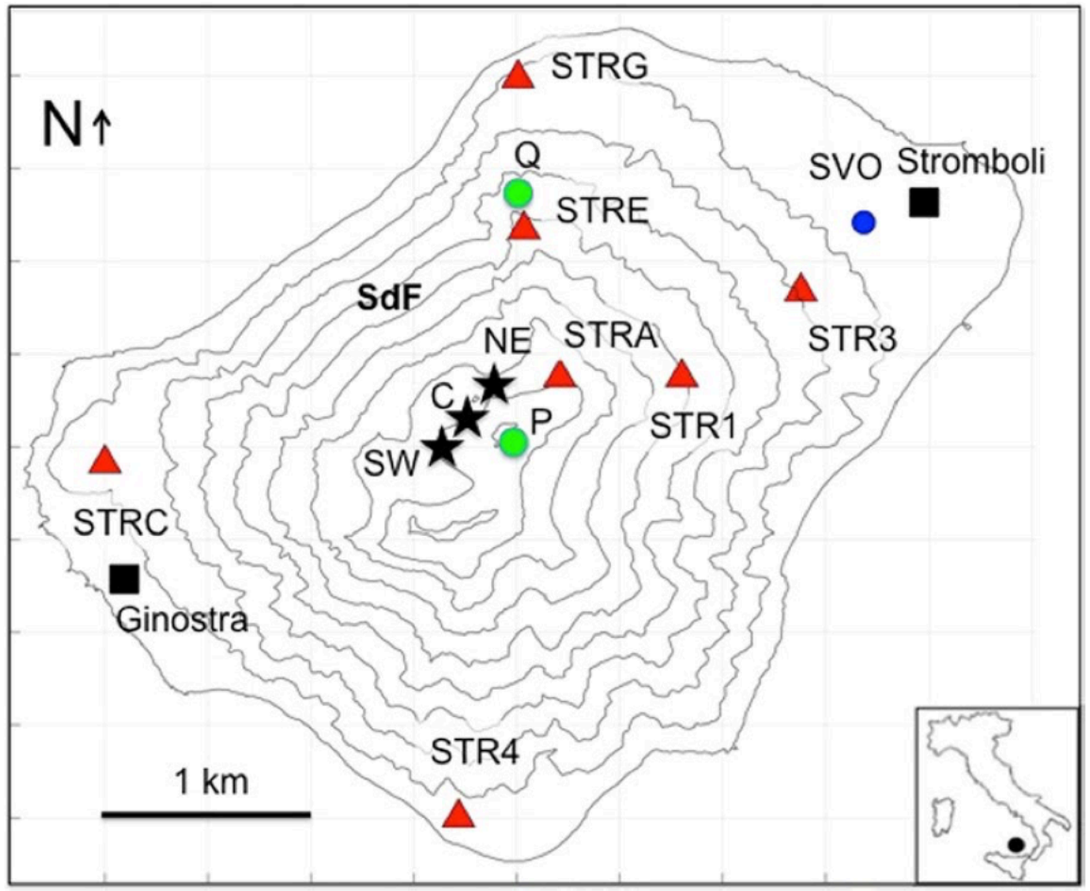
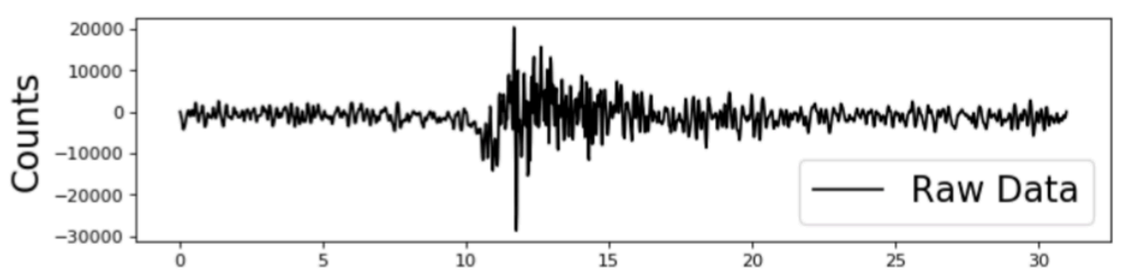


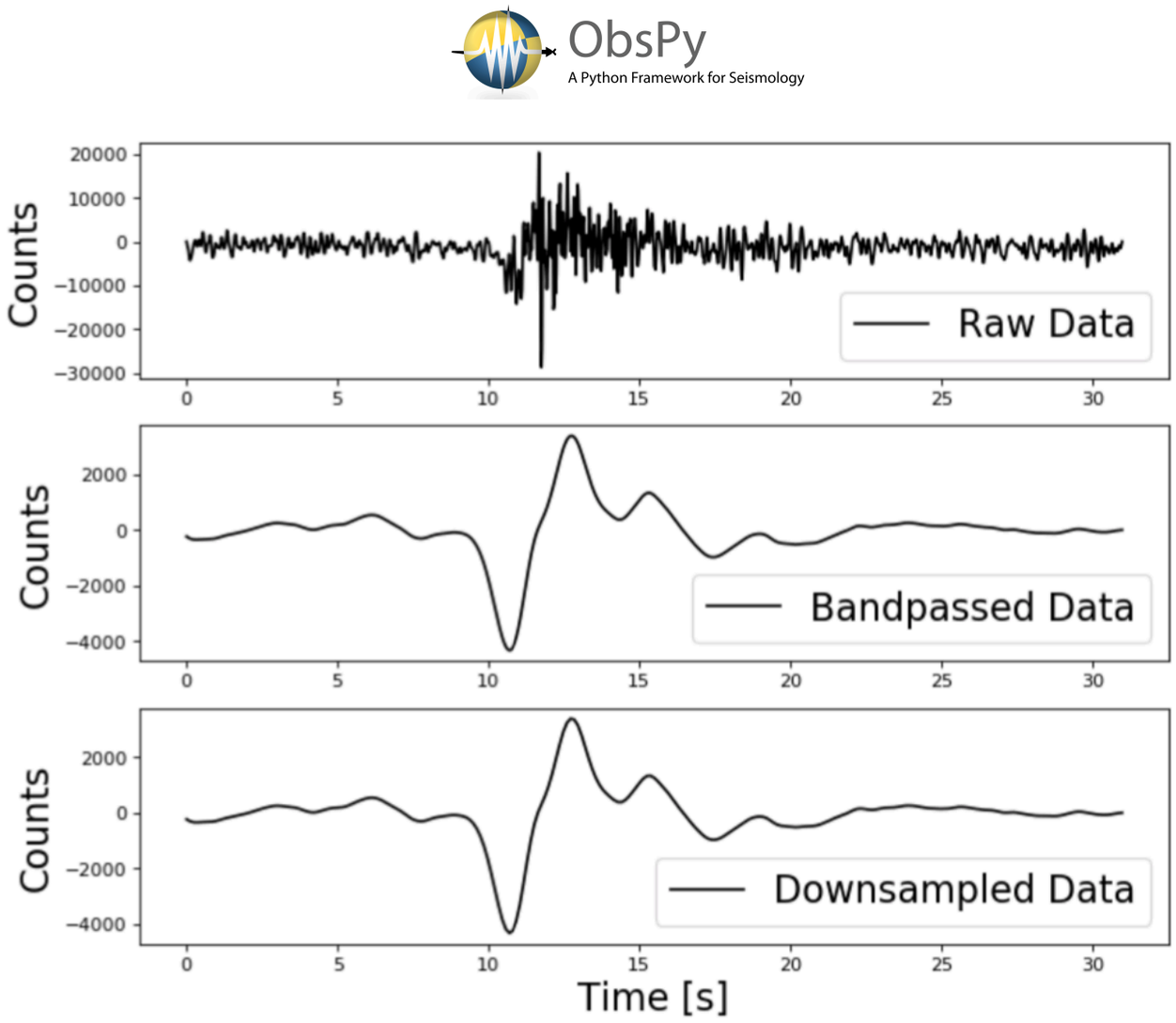
Figure taken from: https://doi.org/10.1038/s41598-020-67220-1



Preprocessing of the signals

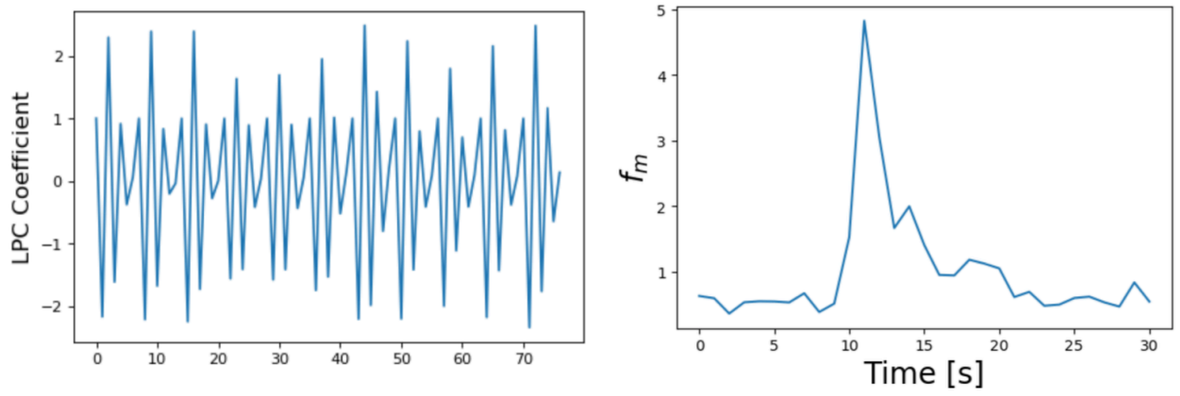
Filtering of the VLP signals

- Uses the python framework for seismology ***obspy***
- **Bandpass filter** in the VLP-frequency band (0.05–0.5 Hz)
- **Decimation** (downsampling) of the resulting signal by a factor of 6



Additional features

- Extraction of **spectral information** with **Linear Predictive Coding**
- Extraction of **time domain information** by parametrizing the **amplitude**



Auto Encoders

LSTM Auto Encoder

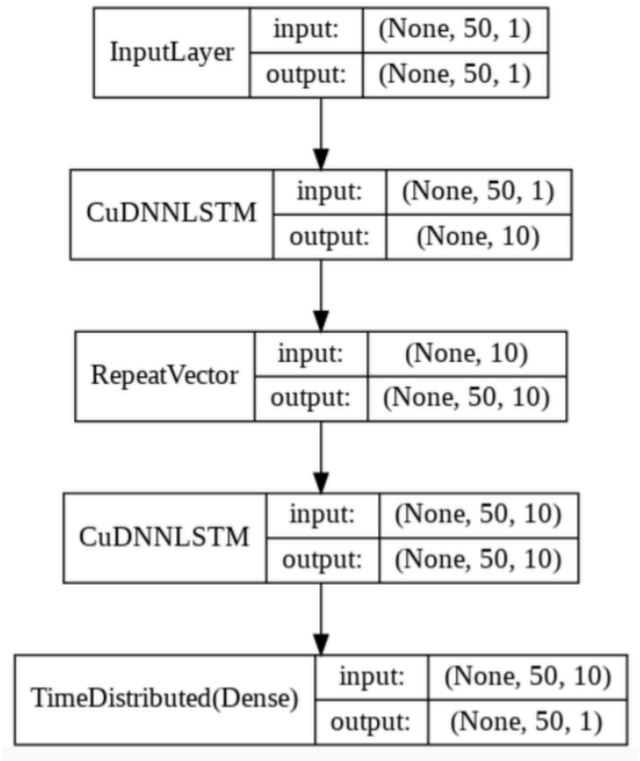
Keras

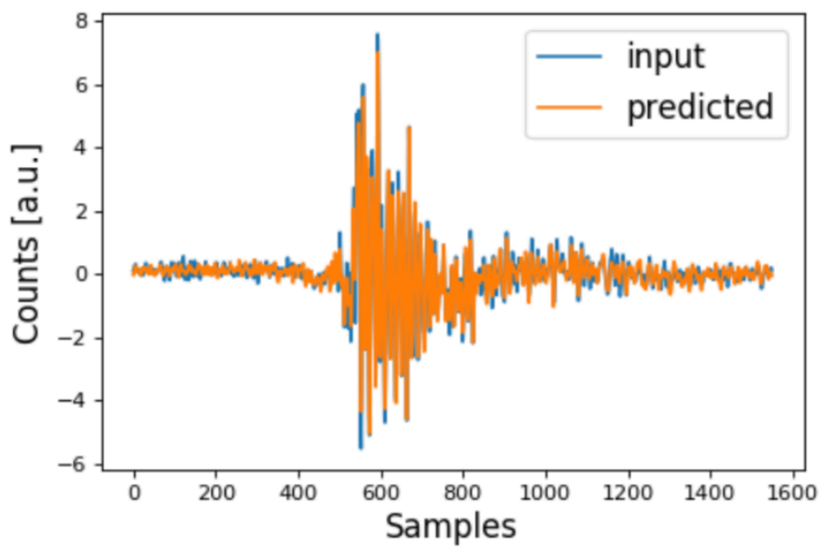
- Neural network used to learn efficient **data codings** in an **unsupervised** manner

- Consists of **encoder** that maps the input into a **code** and a **decoder** that maps the code to a reconstruction of the original input

- Training the network to **ignore** signal “**noise**” and **preserve** only the **most relevant aspects** of the data

- **LSTMs** are predestined for **sequential data** and thus promising for **time series**





Visualization of high dimensional vectors with Self Organizing Maps (SOM)

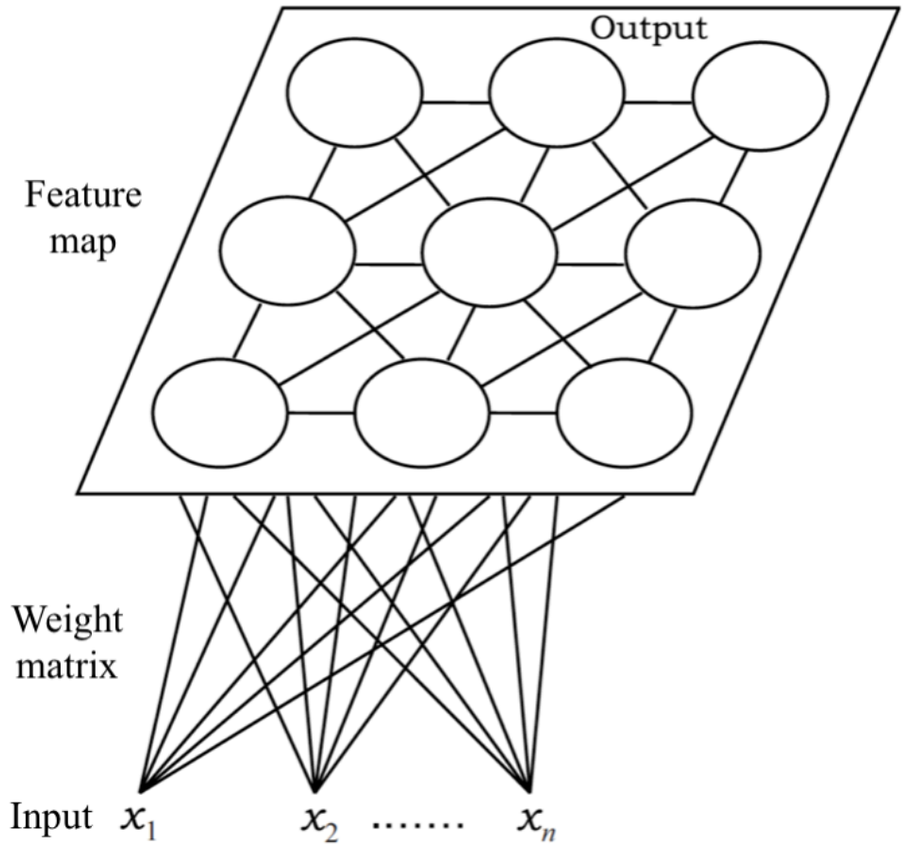
Self Organizing Maps

- Type of **neural network** that is trained using **unsupervised** learning to produce a low-dimensional discretized representation of the training samples → **dimensionality reduction**

- The **visible part** of a self-organizing map is the **map space**, which consists of components called **nodes**

- Each **node** is associated with a **weight vector** that has the same dimension as each input vector

- **Training** consists in moving **weight vectors** toward the input data - reducing a **distance metric** - without spoiling the **topology** induced from the map space



Application of SOM to the VLP waveforms

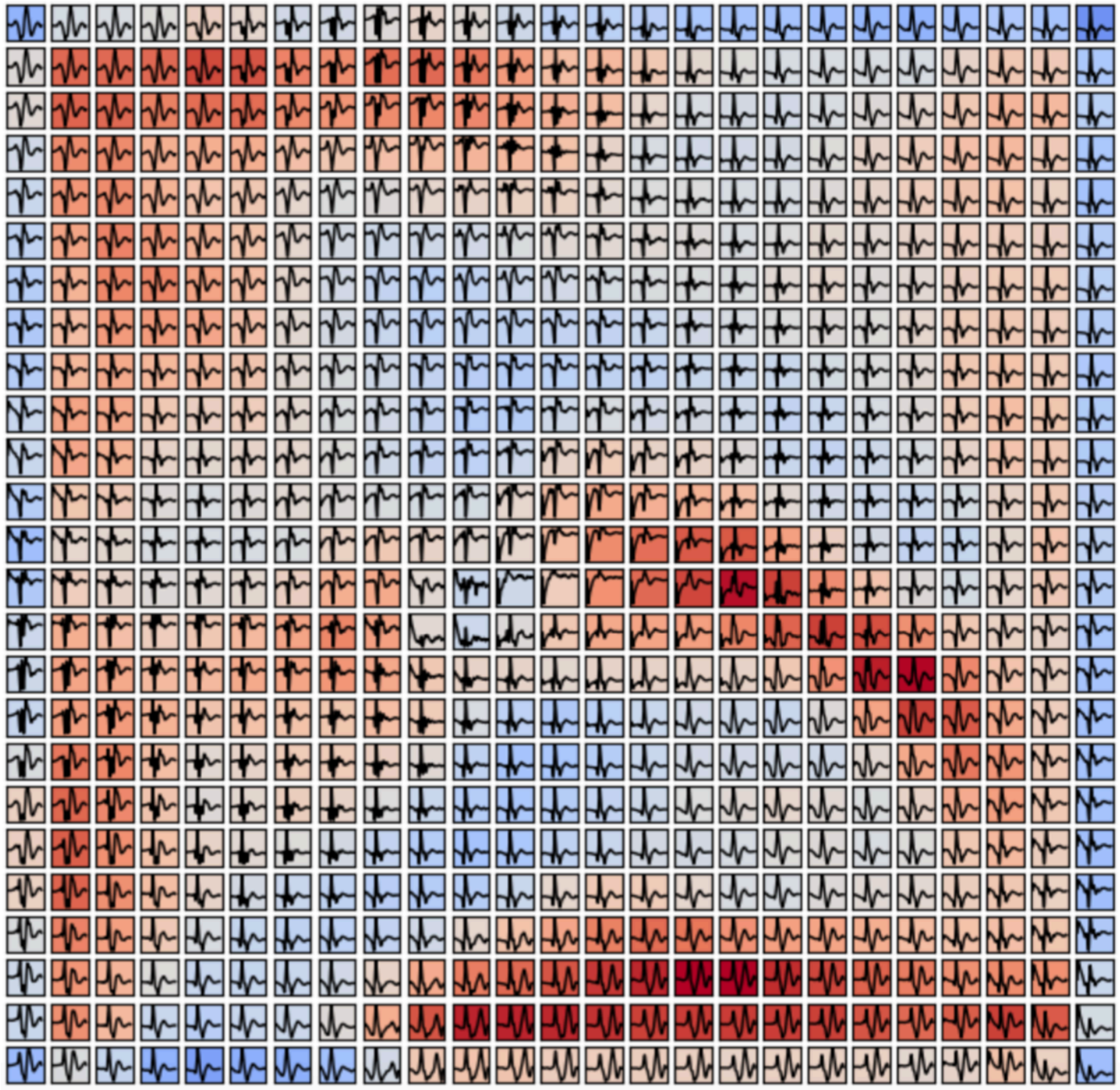
- **25x25 rectangular SOM** is used with **Euclidean distance** as distance metric implemented in python package ***minisom***

- Output of the SOM shows the **different signal forms** and the **distances** between neighboring nodes

- **Similar waveforms** are **close** in the map space

- Also the **frequencies** of signals in the nodes can be analyzed

Distance matrix of the 25x25 SOM



Blue = close to neighbors / Red = distant to neighbors

Visualization of the VLP waveform signals with the t-SNE algorithm

t-SNE

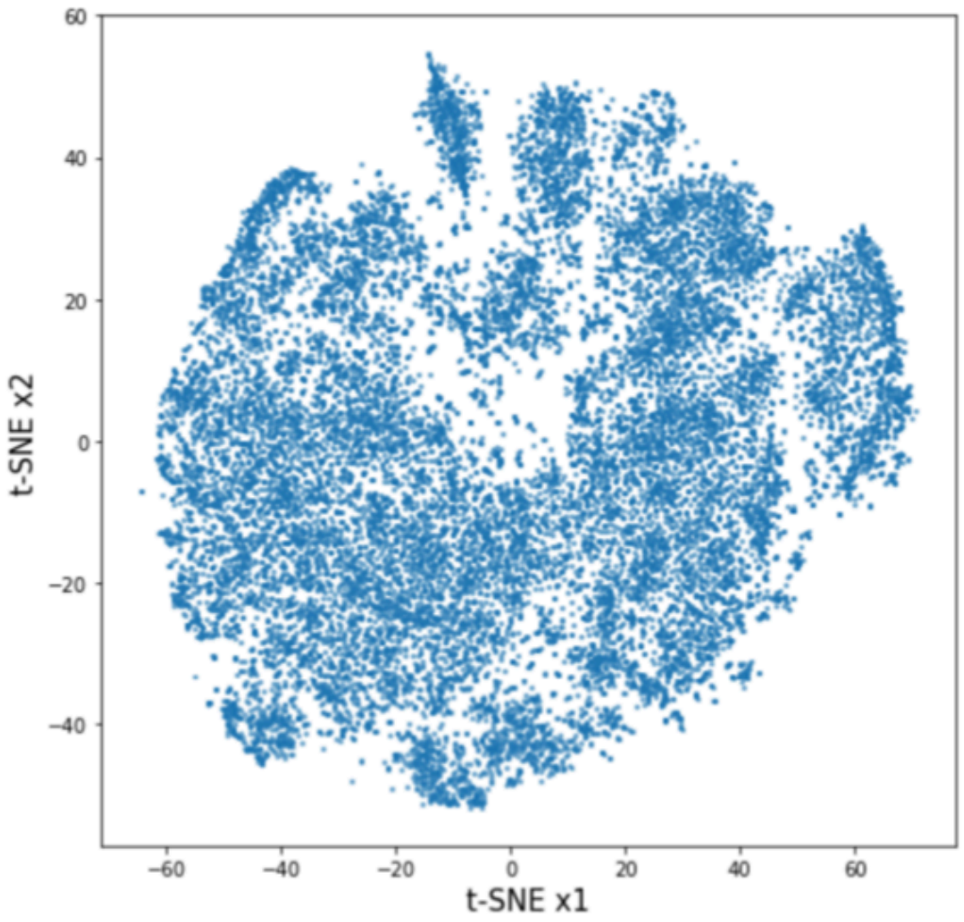
- **Nonlinear dimensionality reduction** for embedding high-dimensional data in a low dimensional space

- First, t-SNE constructs a **probability distribution over pairs of high-dimensional objects** such that higher probabilities are assigned to similar objects

- Second, t-SNE defines a **similar probability distribution** over the points in the **low-dimensional map**, and it **minimizes** the **KL divergence** between the two distributions

- **Similar objects** are modeled by **nearby points** and **dissimilar objects** are modeled by **distant points** with high probability

t-SNE applied to the VLP waveforms



Structures are visible

Clustering of the VLP waveforms with K-Means

K-Means

- Clusters data by trying to **separate samples groups** of equal variance, **minimizing** a criterion called **within-cluster sum-of-squares**

- **Number** of clusters need to be **specified**

Silhouette analysis

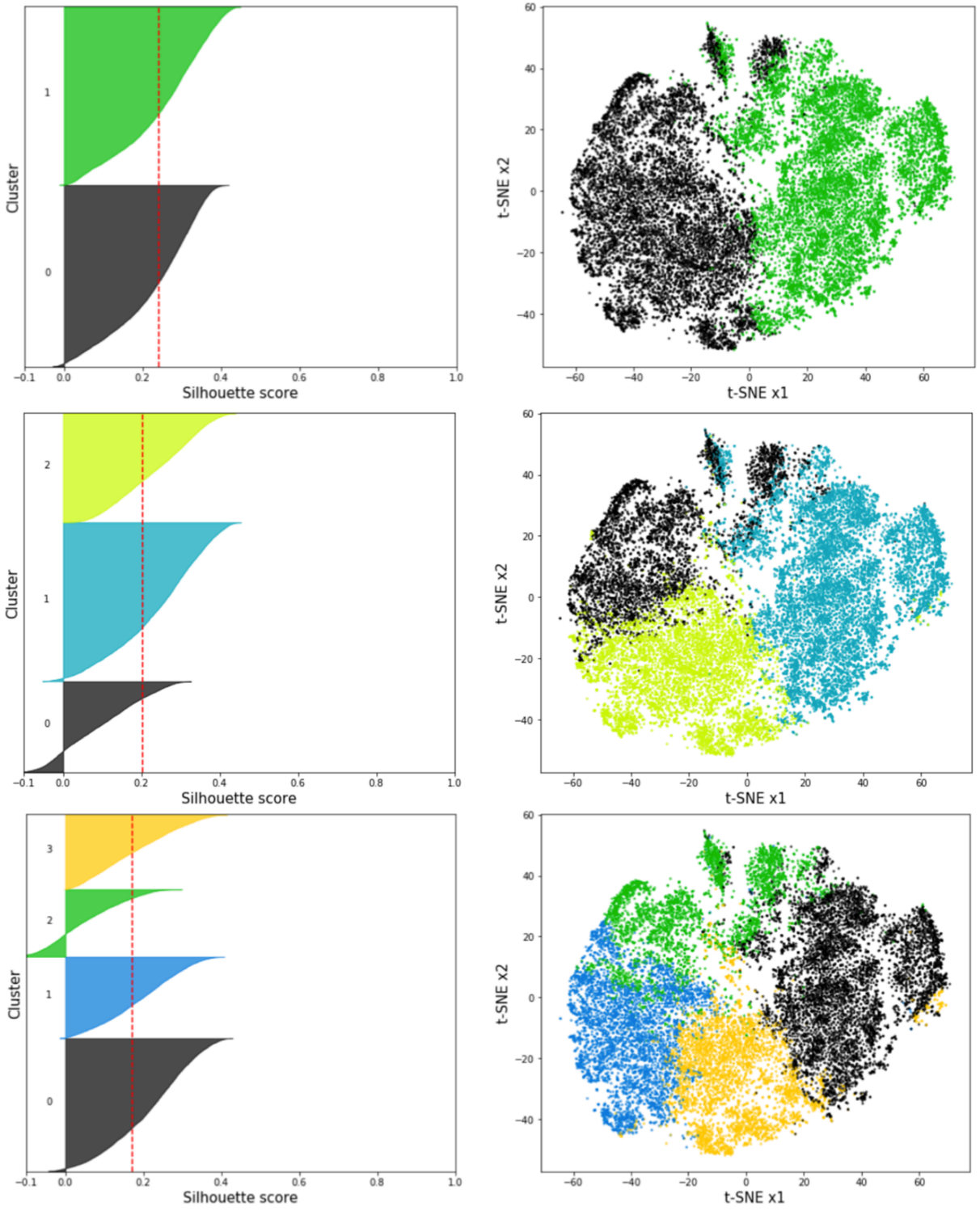
- **Optimal number** of clusters is **unknown** → performance has to be evaluated using the model itself

- **Silhouette scores** measure the **separation distance** between the resulting **clusters,** where **higher scores** relate to a model with **better defined clusters**

- Coefficients **near +1** → sample is **far away** from the neighboring cluster

- Coefficients **near 0** → sample **close to the decision boundary** between two neighboring clusters,

- Coefficients with negative values (max -1) → samples might have been **assigned to the wrong cluster**



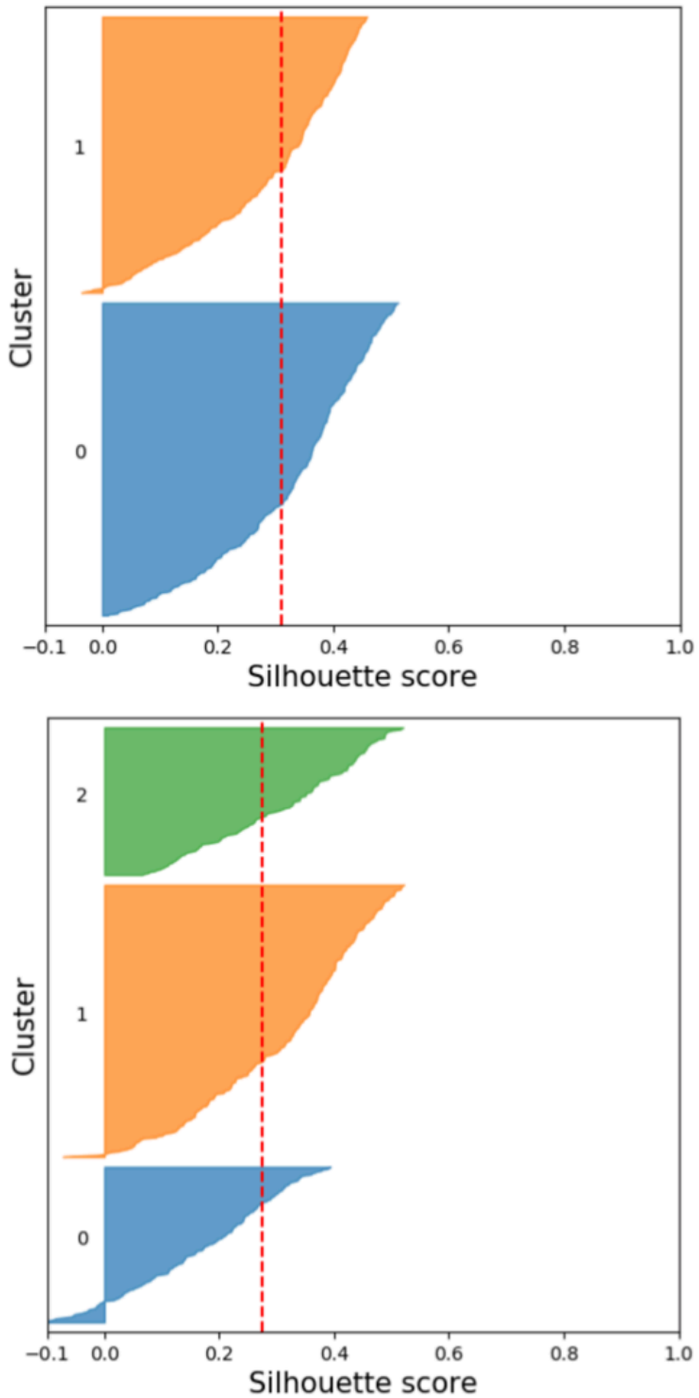
→ Best average silhouette score obtained for two clusters

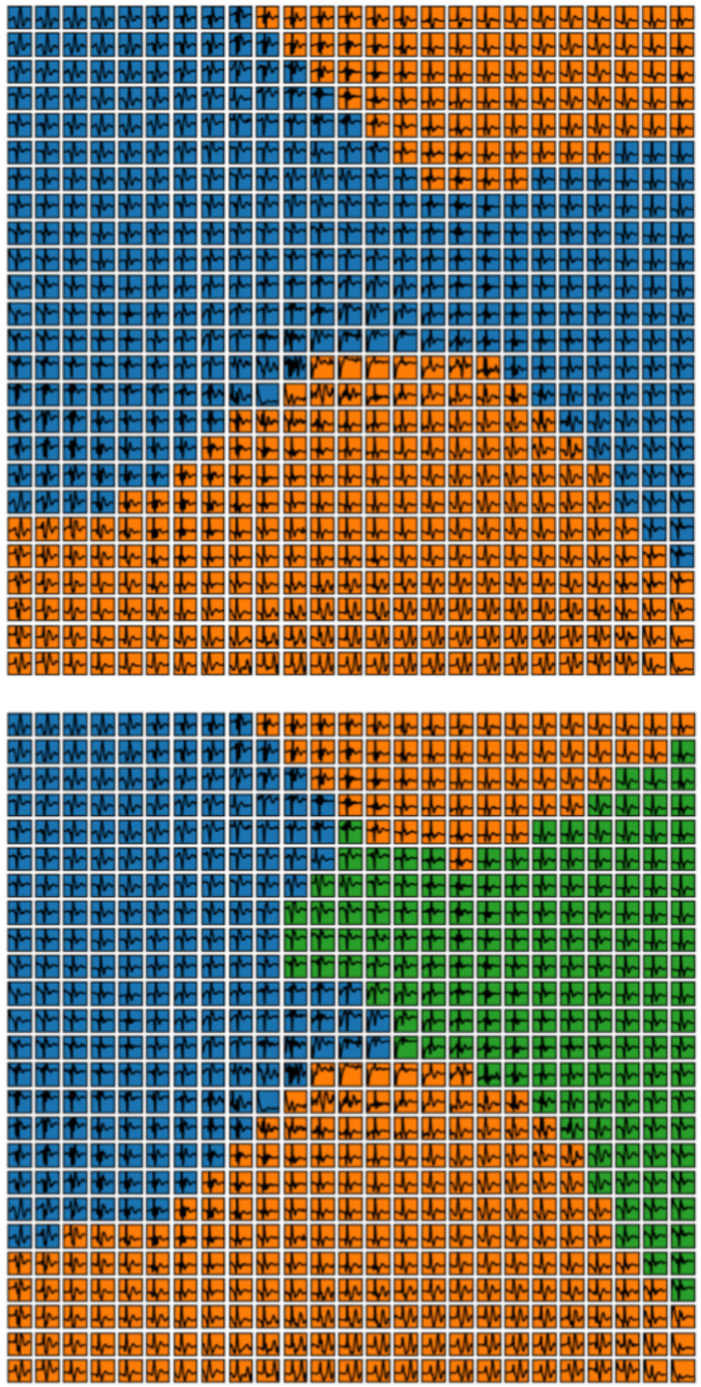
Clustering of the VLP waveform SOM with K-means

- K-means can also be applied to the **weight vectors** of the trained **SOMs → less noise** can be advantageous

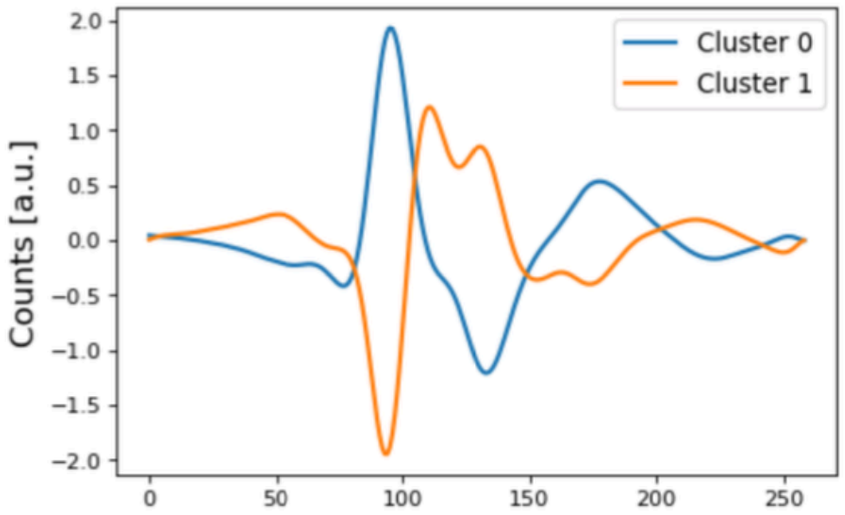
- **Analysis** of the silhouette scores is **repeated**

- Same result as before: the **highest average score** is obtained with **two clusters**





Time evolution of the two main clusters

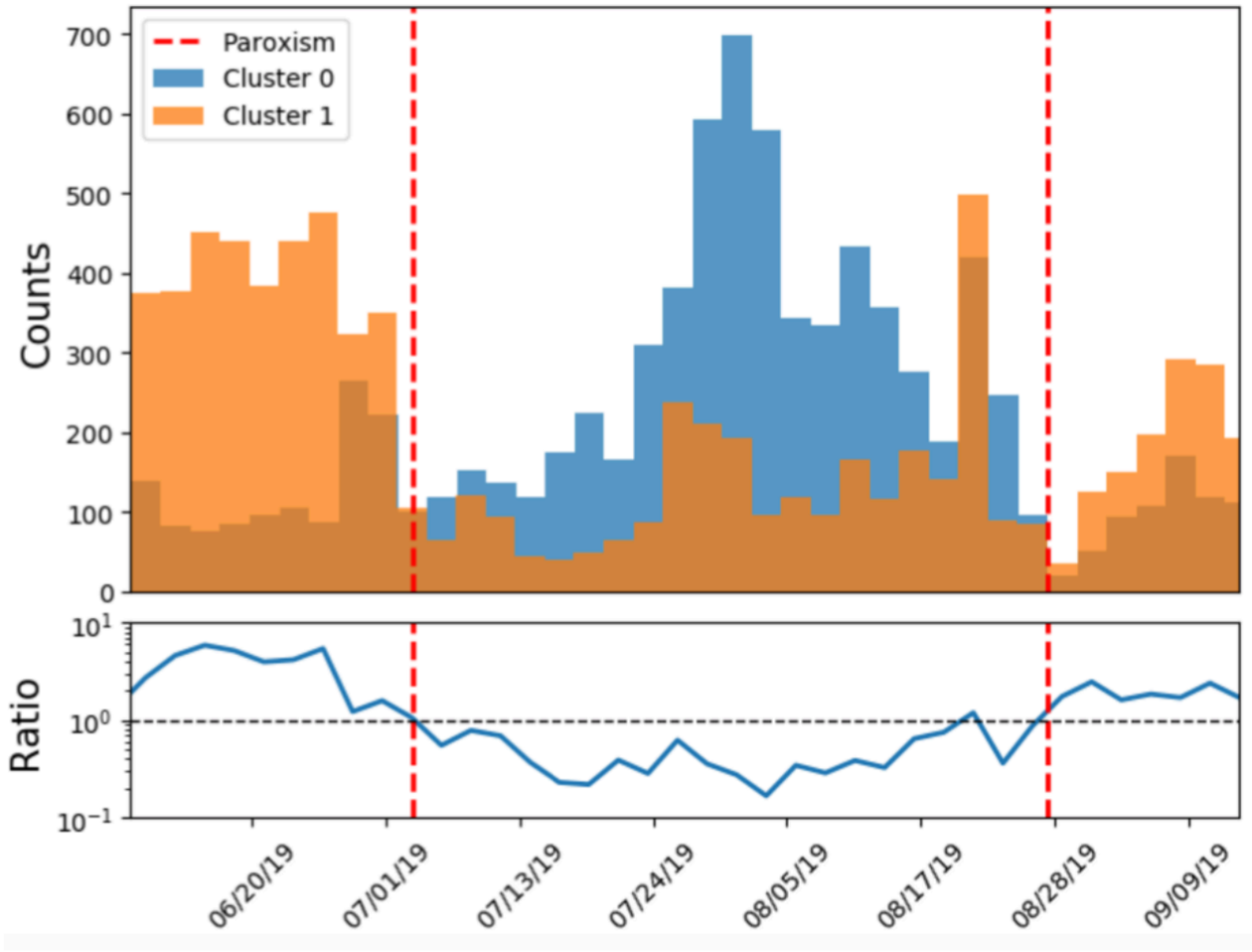


Visible difference in the shape of the centroids of the two clusters

- **Time stamps** of the signals allow to display the **time evolution** of the **signal counts** in the two main clusters

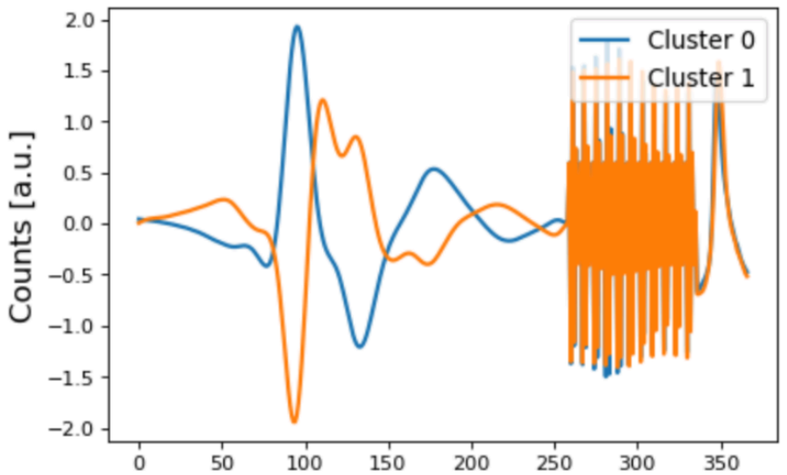
- **Strong imbalance of the two clusters** in the analyzed period of the paroxysms

Indicates a connection between the state of the volcano and the VLP signals



Clustering with additional information

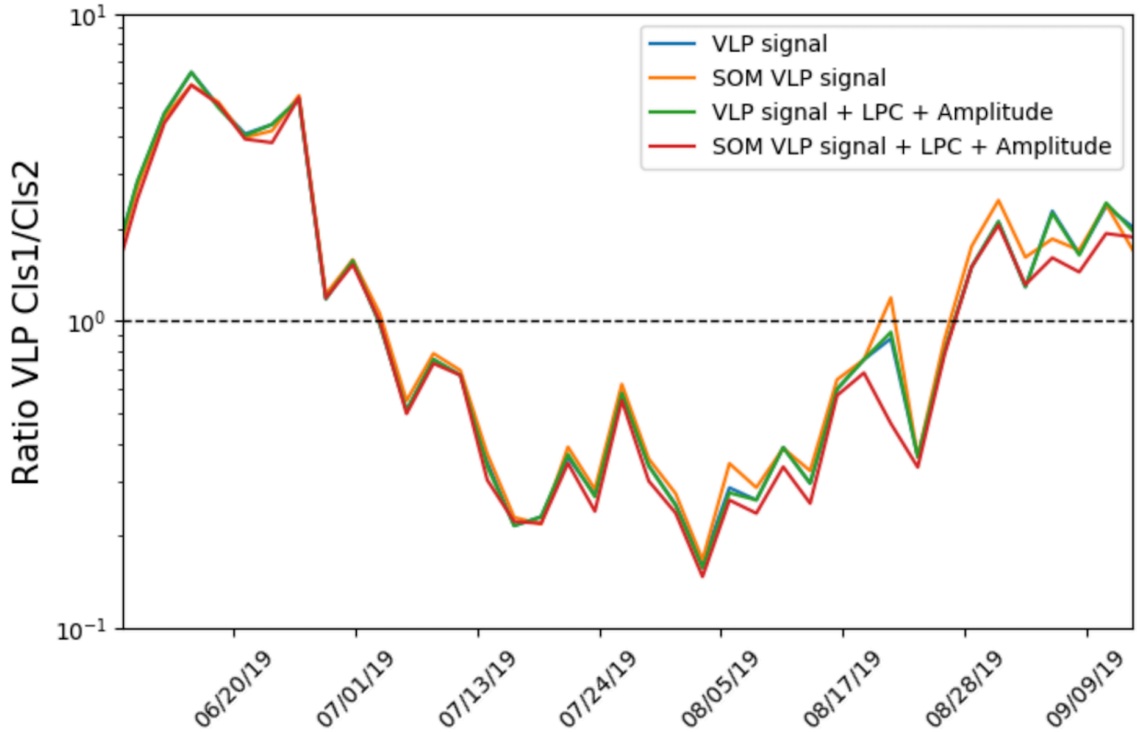
- Goal: add information to obtain **better defined clusters**
- Different **features** are **scaled** to the global standard deviation to **preserve the relative size** between the samples
- **LPC coefficients** and the **parametrized amplitude** / latent representation of the **Auto Encoder** are added



Comparison of the clustering results

- **Repeating the analysis** with additional information gives very **similar results** → dominating feature is the VLP waveform
- Obtained **ratio** of the two main clusters is **similar** for clustering directly with K-Means and first applying a SOM

→ Ratio of the two main clusters is stable



Summary

Conclusions

- **Visualization** and **Clustering analysis** of **time series** with unsupervised Machine Learning methods is a powerful tool to define **parameters** that **characterize the state of a system**

- The **ratio of the two main cluster** of the Very-Long-Period **waveforms of Stromboli** may constitute an **important parameter** to **characterize** the **state** of the volcano that can be **monitored in real time**

Outlook

- Analysis of a **larger time period** is in progress to understand whether the VLP waveforms have the potential to **predict anomalous behavior** of the volcano

- Analysis of **signals from controlled experiments** to better understand how the results of **clustering** and **visualization** with Machine Learning are **linked to the physical conditions** of the system


Thank you!

BACKUP

LPC and amplitude parametrization

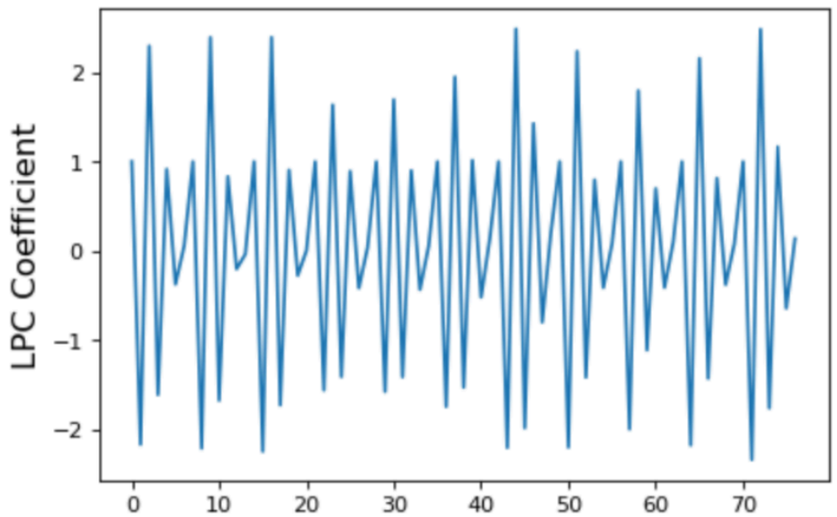
Linear predictive coding

$$\hat{x}(n) = \sum_{i=1}^{p} a_i x(n-i)$$

- **LPC** tries to **predict** a signal **sample** by means of a **linear combination** of **previous** signal **samples** → extracts **spectral information** (e.g. heavily used in speech analysis)

- **Converts** segments of a real time signal into a small set of **predictor coefficients {a_i}**

- **6 LPC coefficients** are extracted in 256-sample **windows**, with an **overlap** of 128 samples with the python audio library ***librosa***

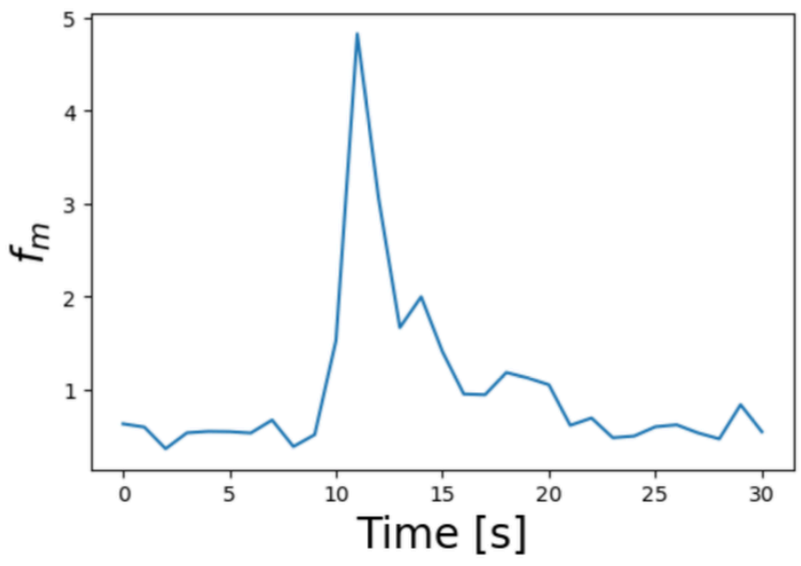


Amplitude parametrization

$$f_m = \frac{(max(A_{i,m}) - min(A_{i,m})) \cdot N}{\sum_{m=0}^{N}(max(A_{i,m}) - min(A_{i,m}))}$$

- **Time-domain information** is added by **parametrizing** the **amplitude** of the signal

- The function f_m is defined as the **normalized difference between the maximum and minimum signal amplitudes** within a 1 second window



Silhouette coefficient

- Calculated using the mean intra-cluster distance *a* and the mean nearest-cluster distance *b* for each sample,

- *a* is the mean distance between a sample and all other points in the same class

- *b* is the mean distance between a sample and all other points in the next nearest cluster

- The Silhouette Coefficient for a single sample is:

$$s = \frac{b - a}{max(a, b)}$$