

Long Short Term Memory

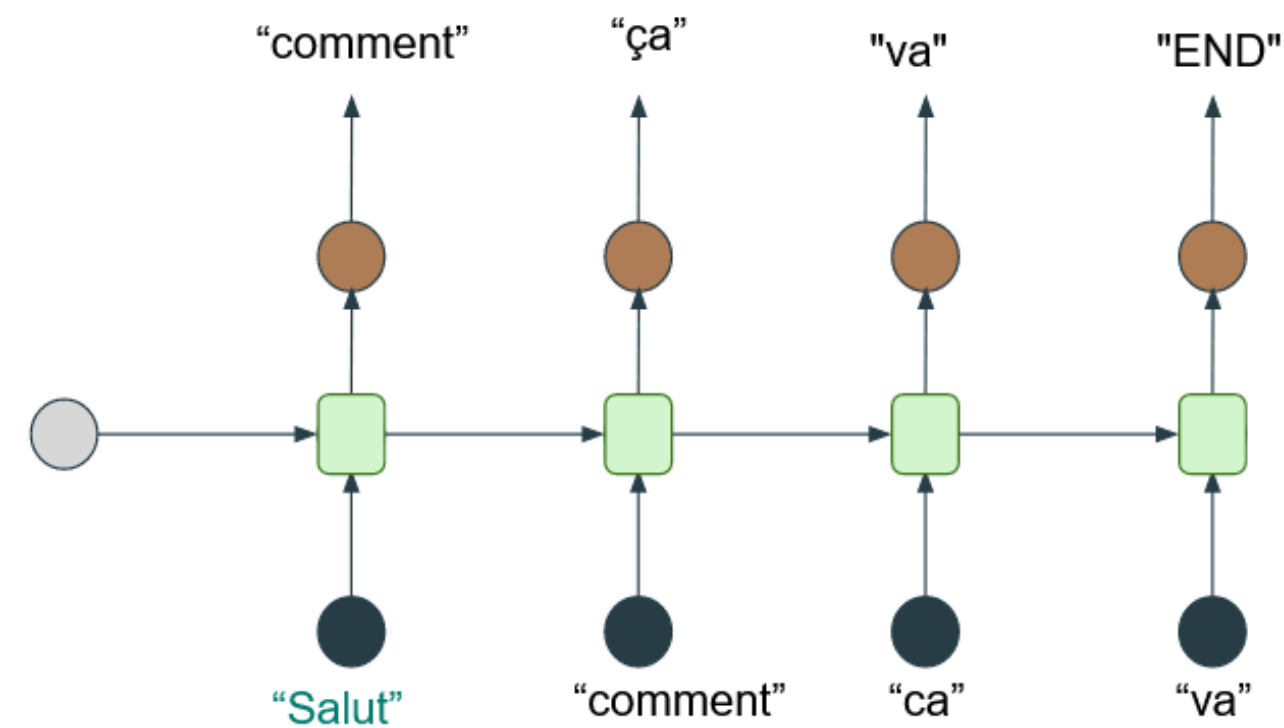
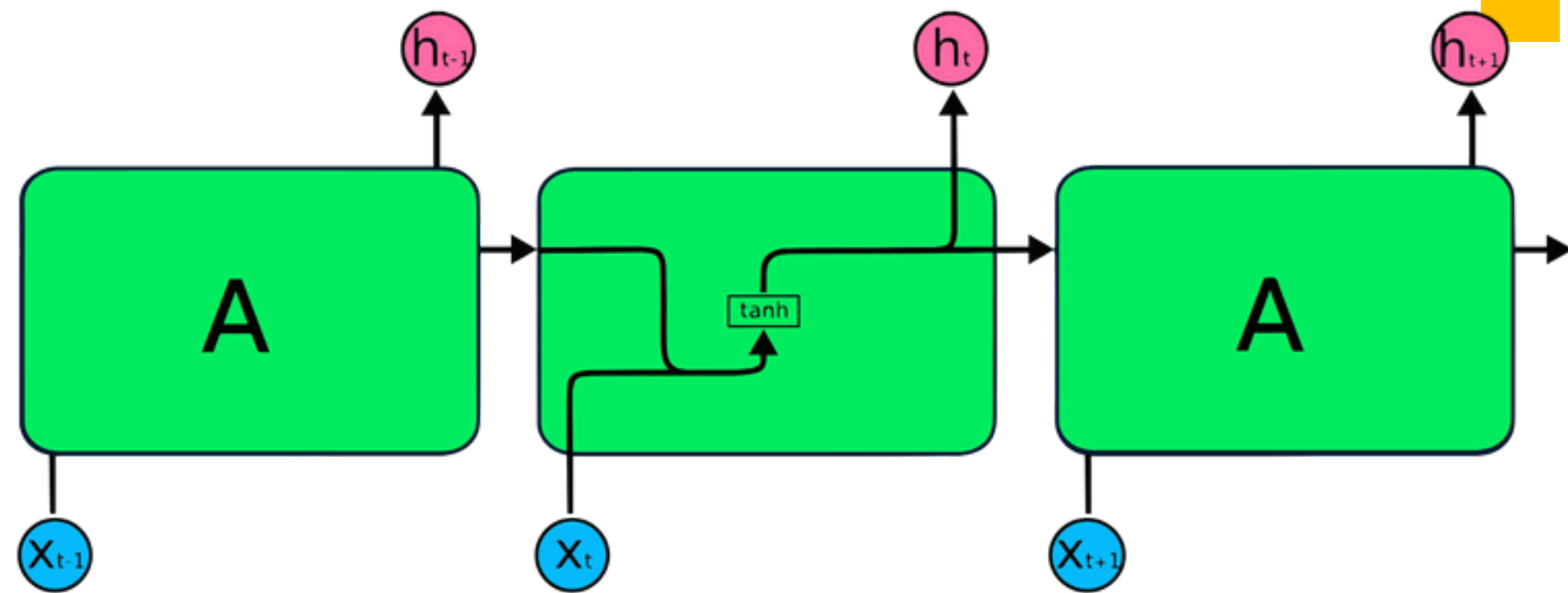
LSTM Networks for gravitational waves detection

Joubert
Gaspard

Recurrent Neural Networks



- RNN remembers past inputs due to an internal memory
- Unidirectional recurrent neural networks cannot account for future events in their predictions
- Vanishing Gradient Problem



<https://plainenglish.io/community/vanishing-gradient-problem-in-rnns-9d8e14>

<https://penseeartificielle.fr/comprendre-lstm-gru-fonctionnement-schema/gif-rnn-fonctionnement-cellule-rnn/>

https://www.ibm.com/topics/recurrent-neural-networks?mhsrc=ibmsearch_a&mhq=recurent%20neural%20network

Long Short Term Memory

Forget Gate

Determines which information from the previous cell state should be discarded or forgotten.

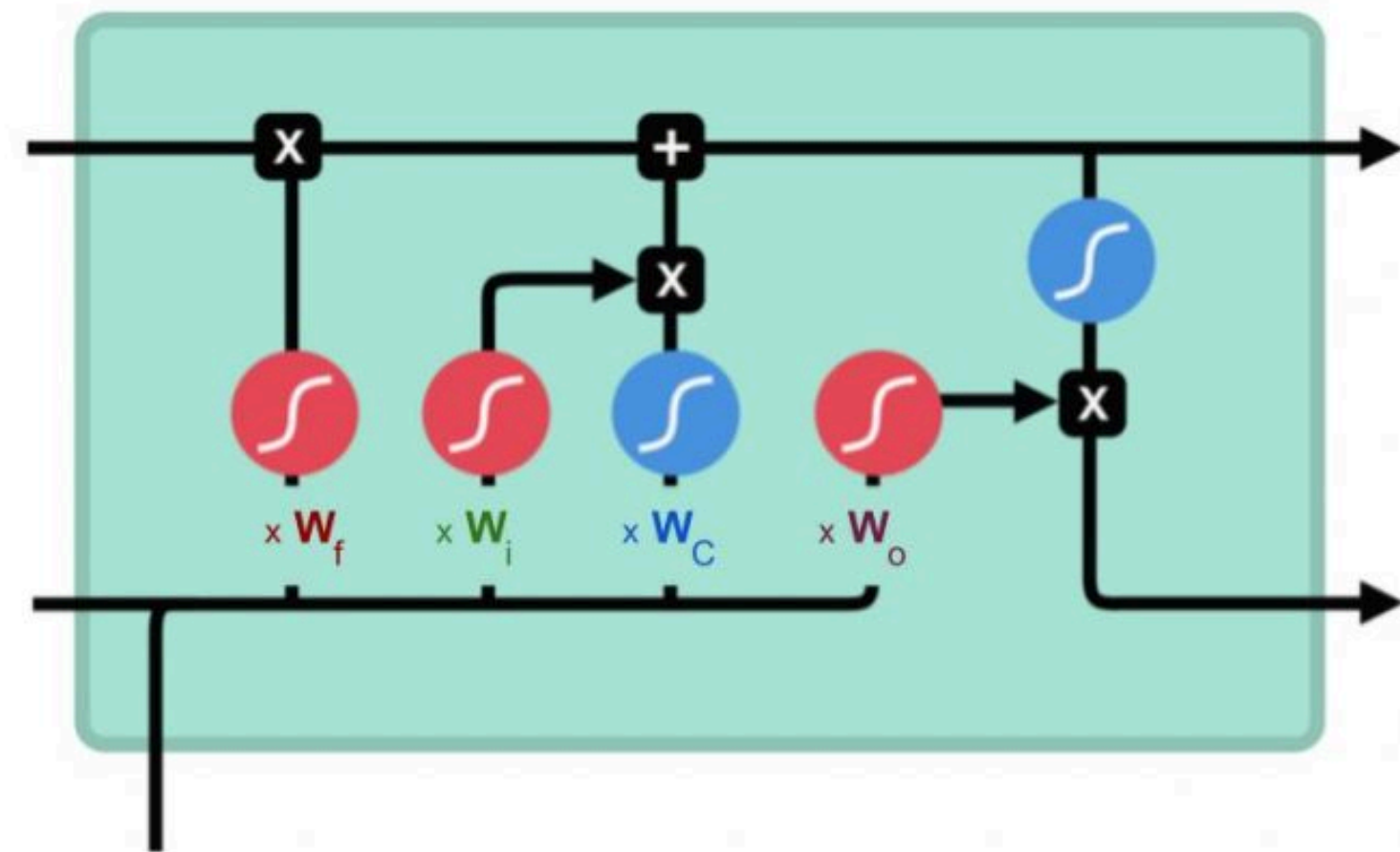
Input Gate

Determines which new information should be stored in the cell state.

Cell State

Output Gate

Determines what part of the cell state should be exposed as the output.




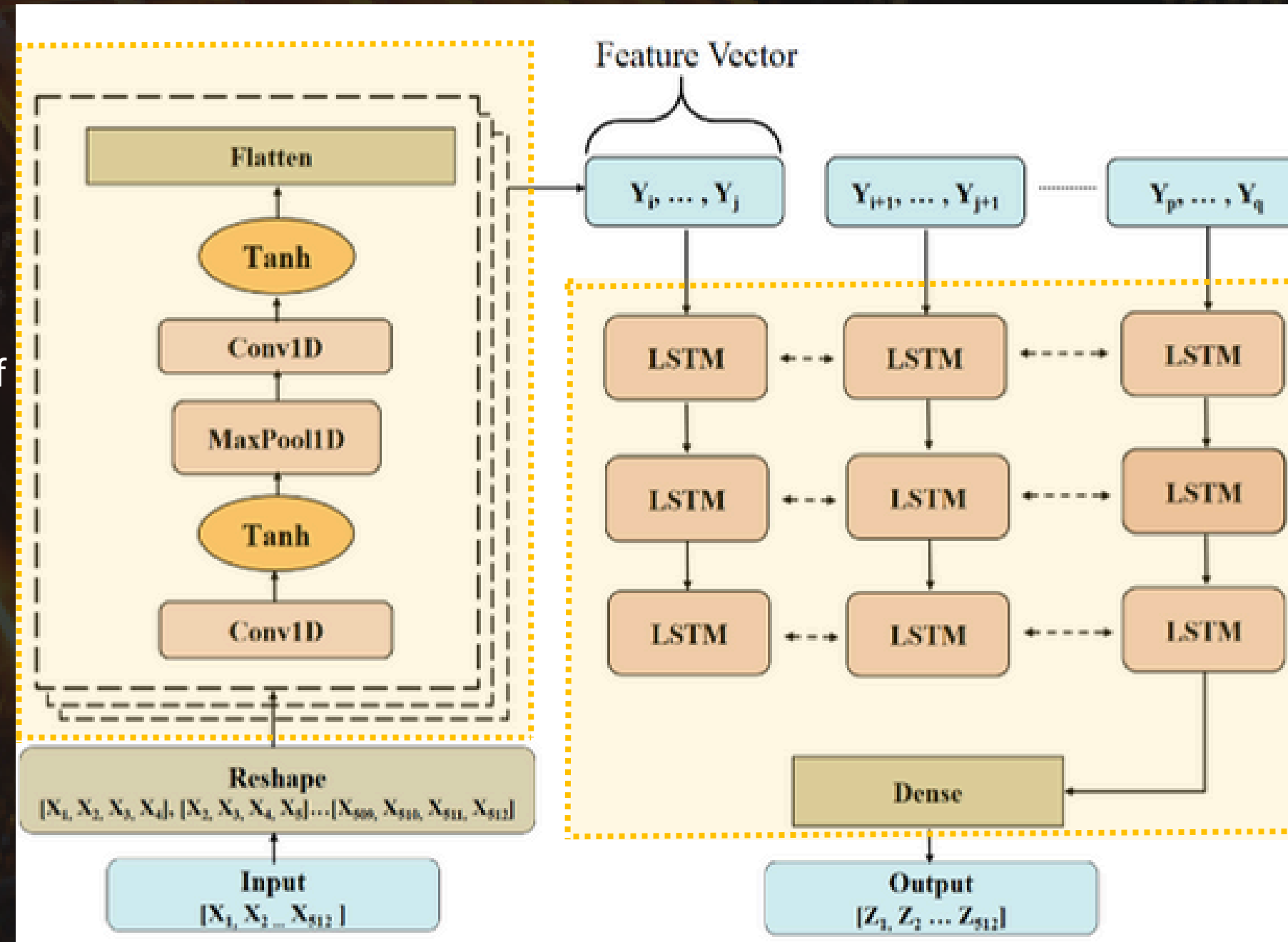
LSTM Cell

CNN-LSTM

Extraction of Binary Black Hole Gravitational Wave Signals from Detector Data Using Deep Learning

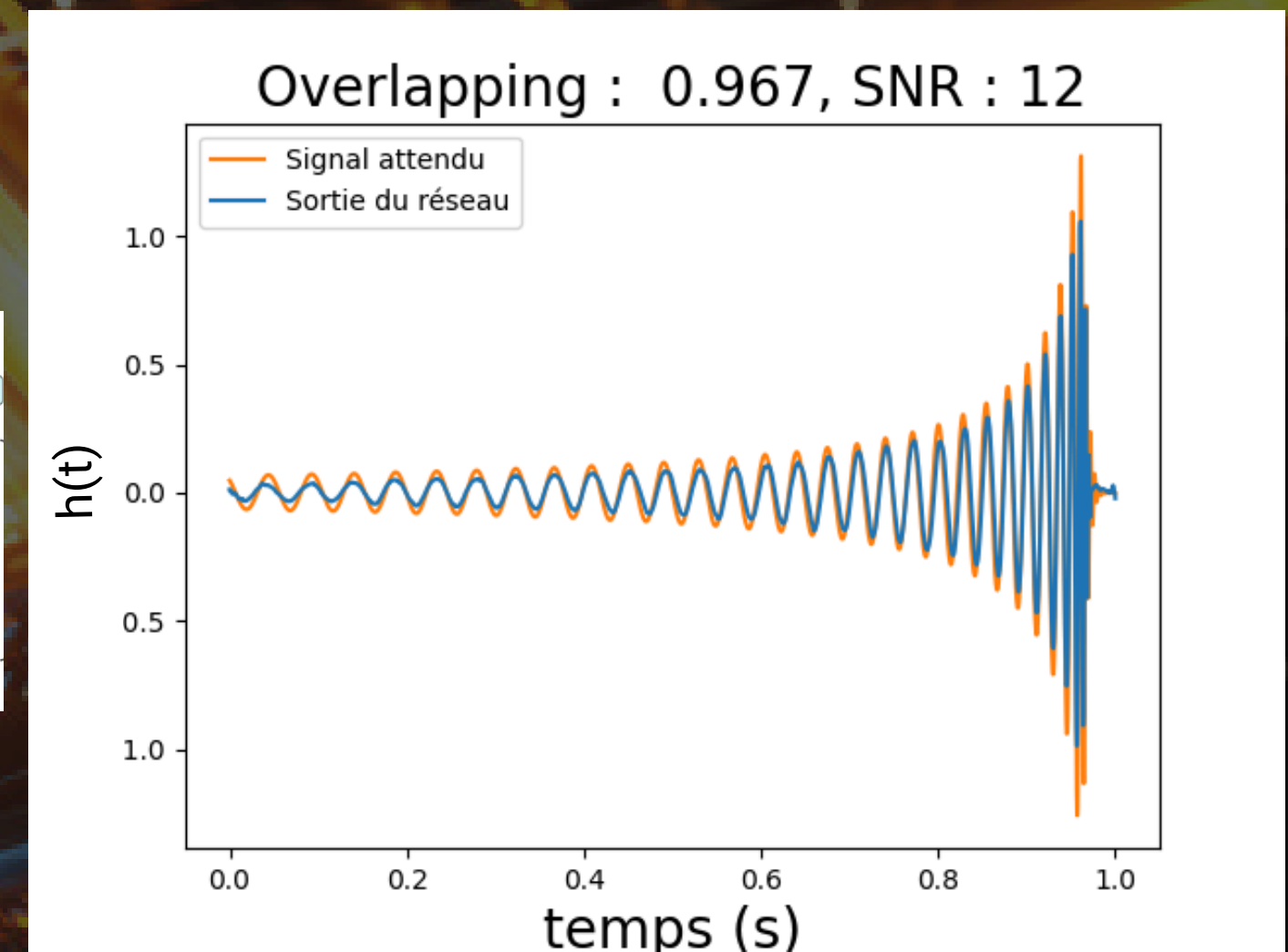
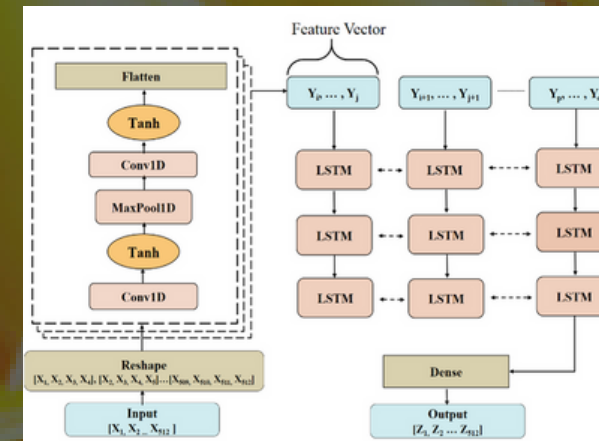
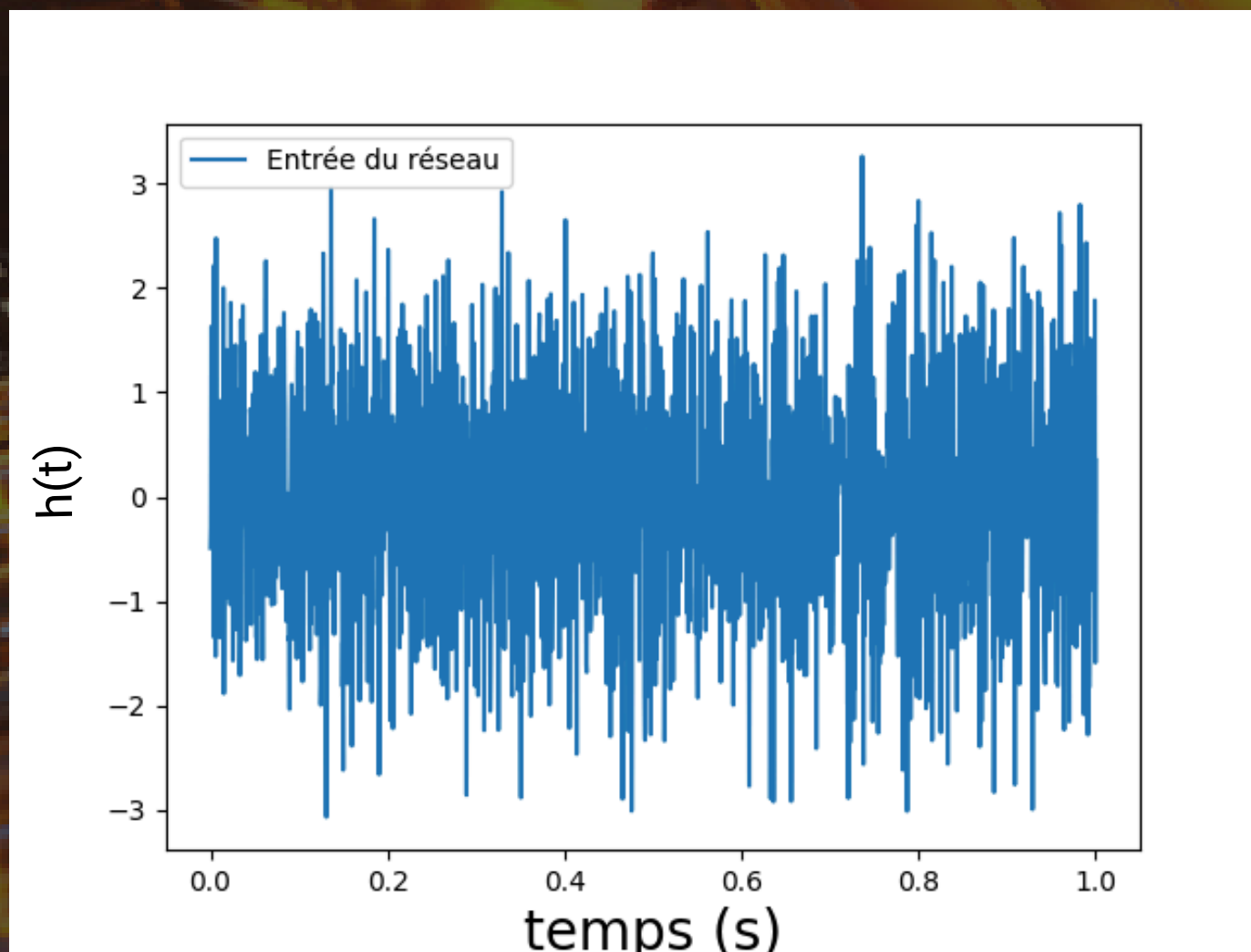
Chatterjee, Chayan and Wen, Linqing and Diakogiannis, Foivos and Vinsen, Kevin

 **CNN encoder**
Extract the main features of the noisy signal



 **Bi-LSTM decoder**
Reconstructs the denoised signal from the features

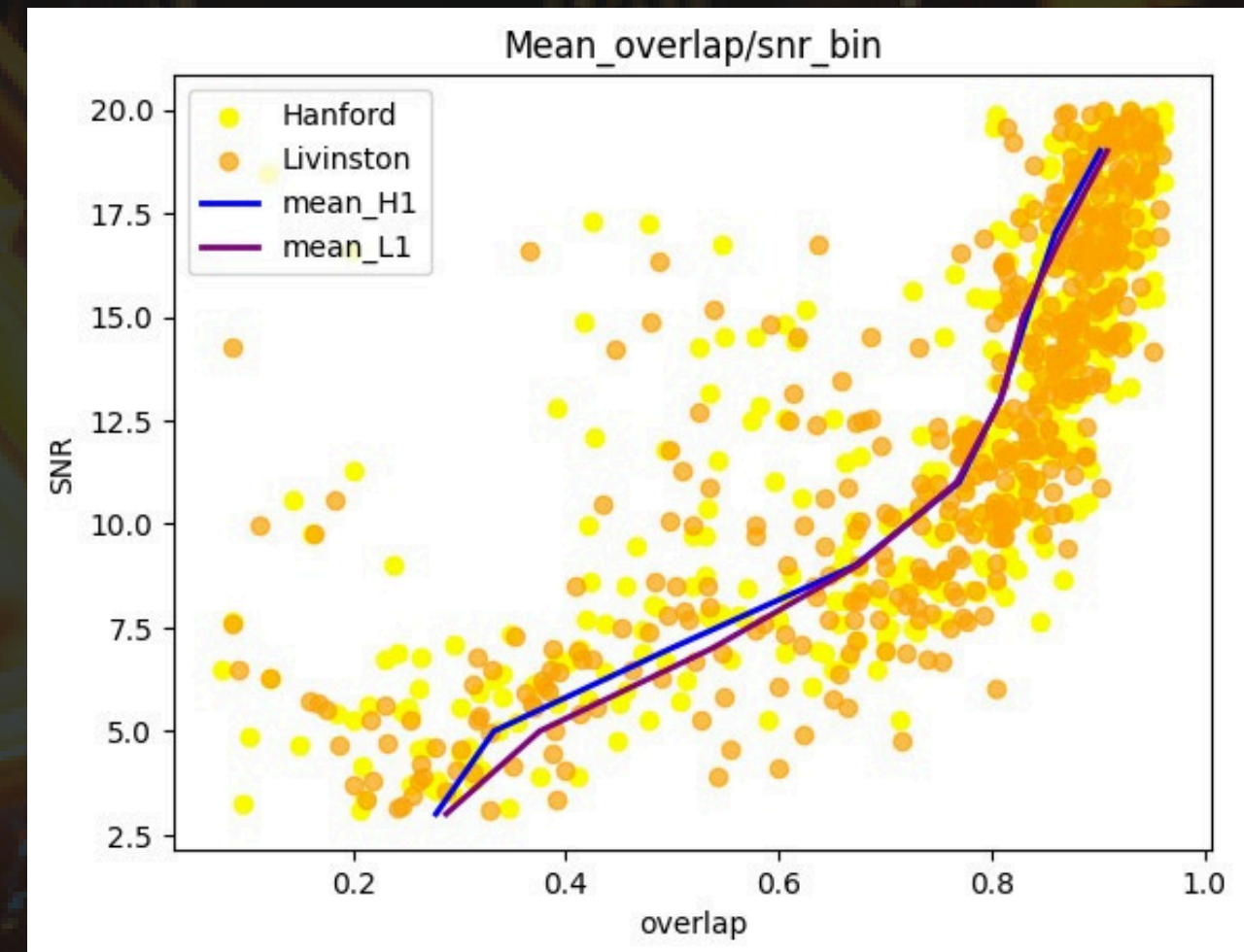
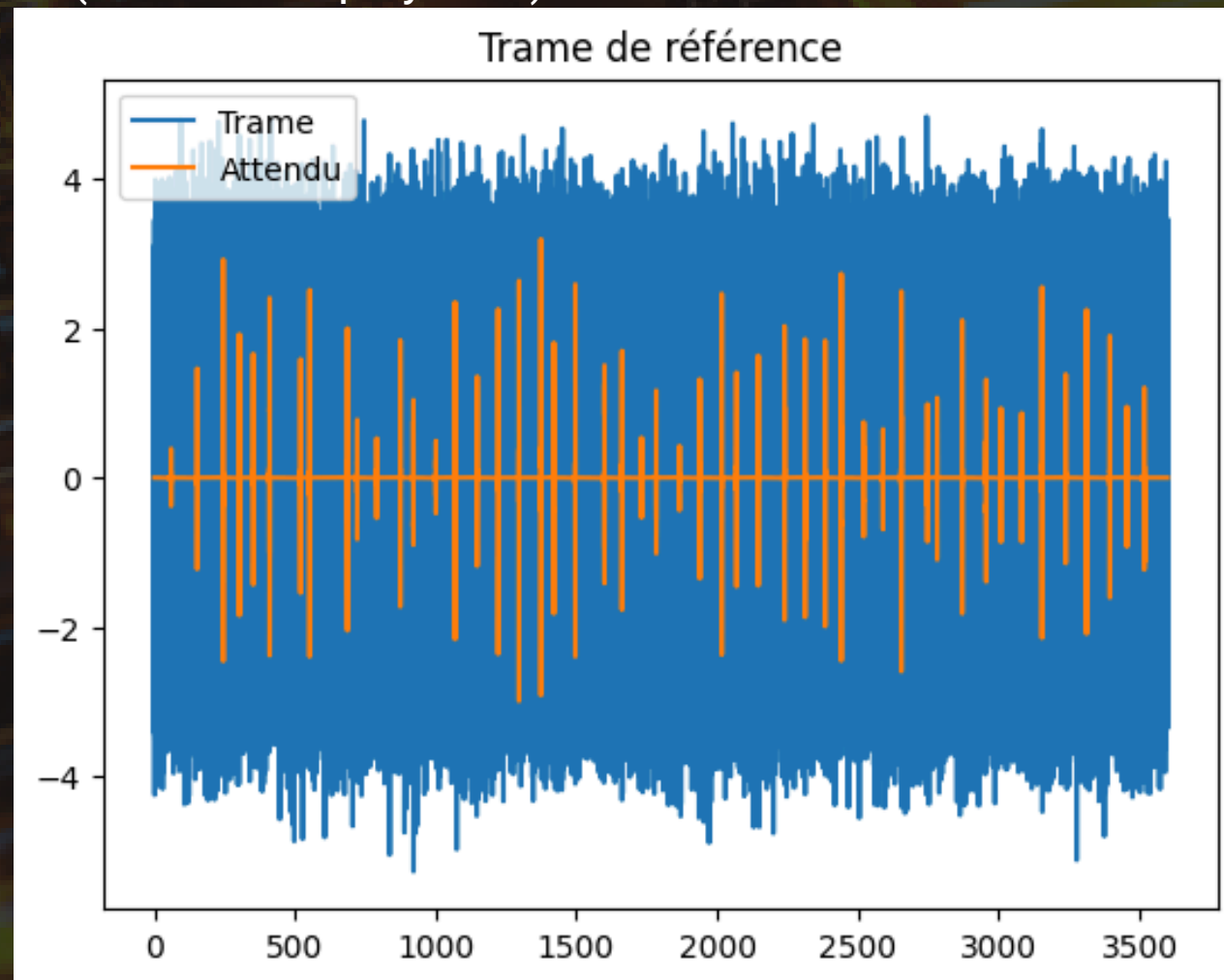
Principe



Training efficiency

Testing on a long data frame

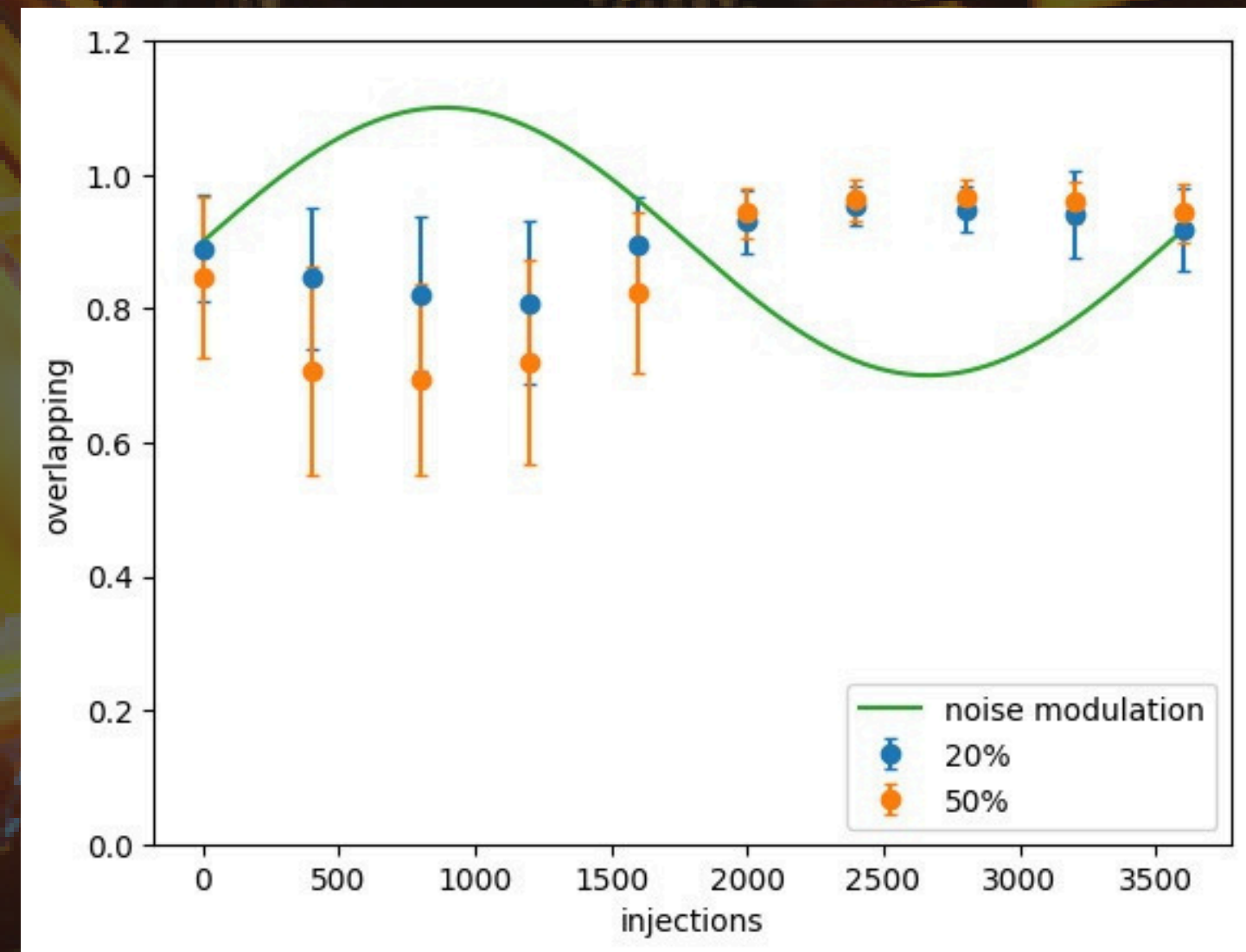
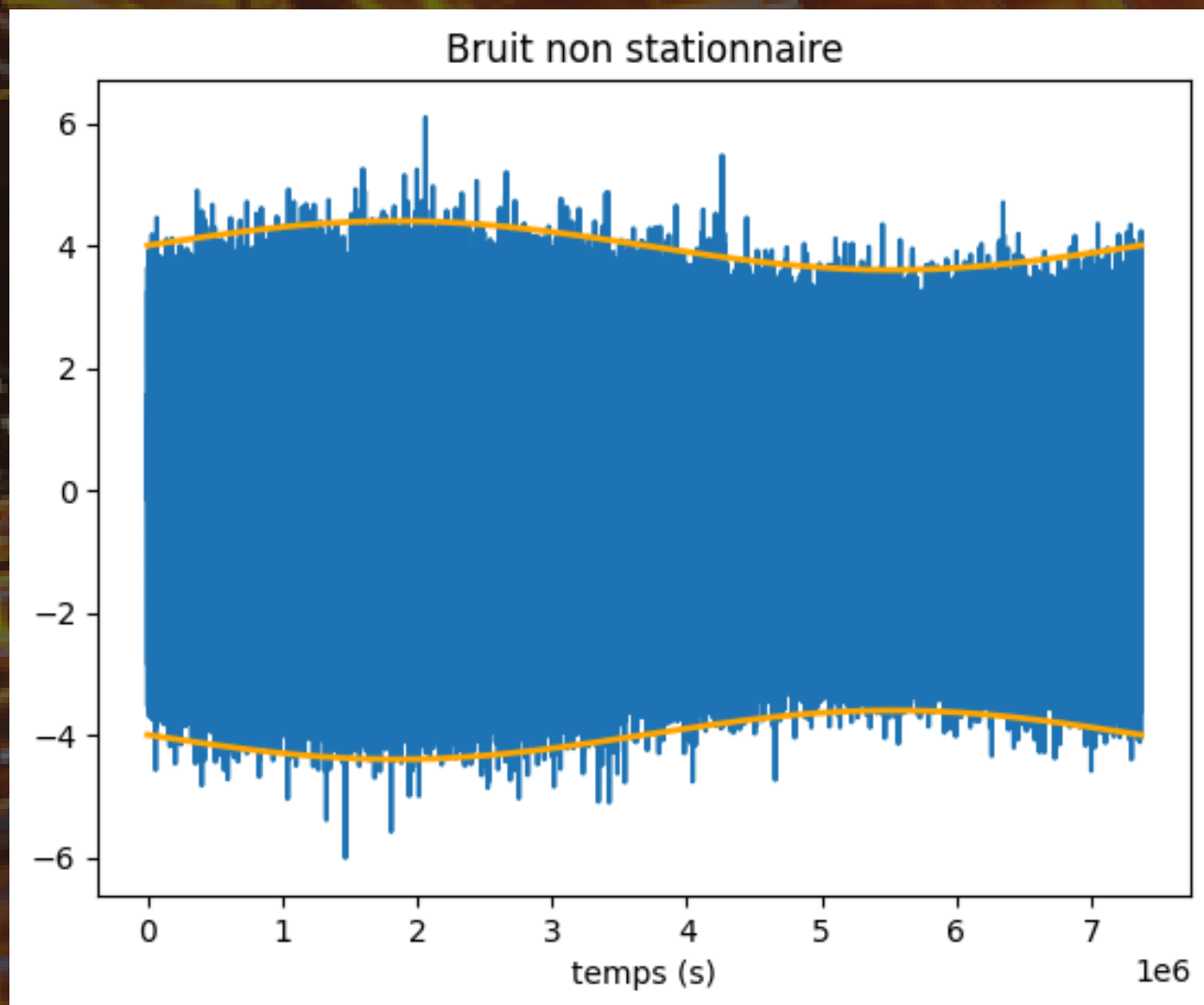
To test the effectiveness of the network training and show its strengths/weaknesses, we build a 10h reference frame with 500 signal injections (1st hour display here)



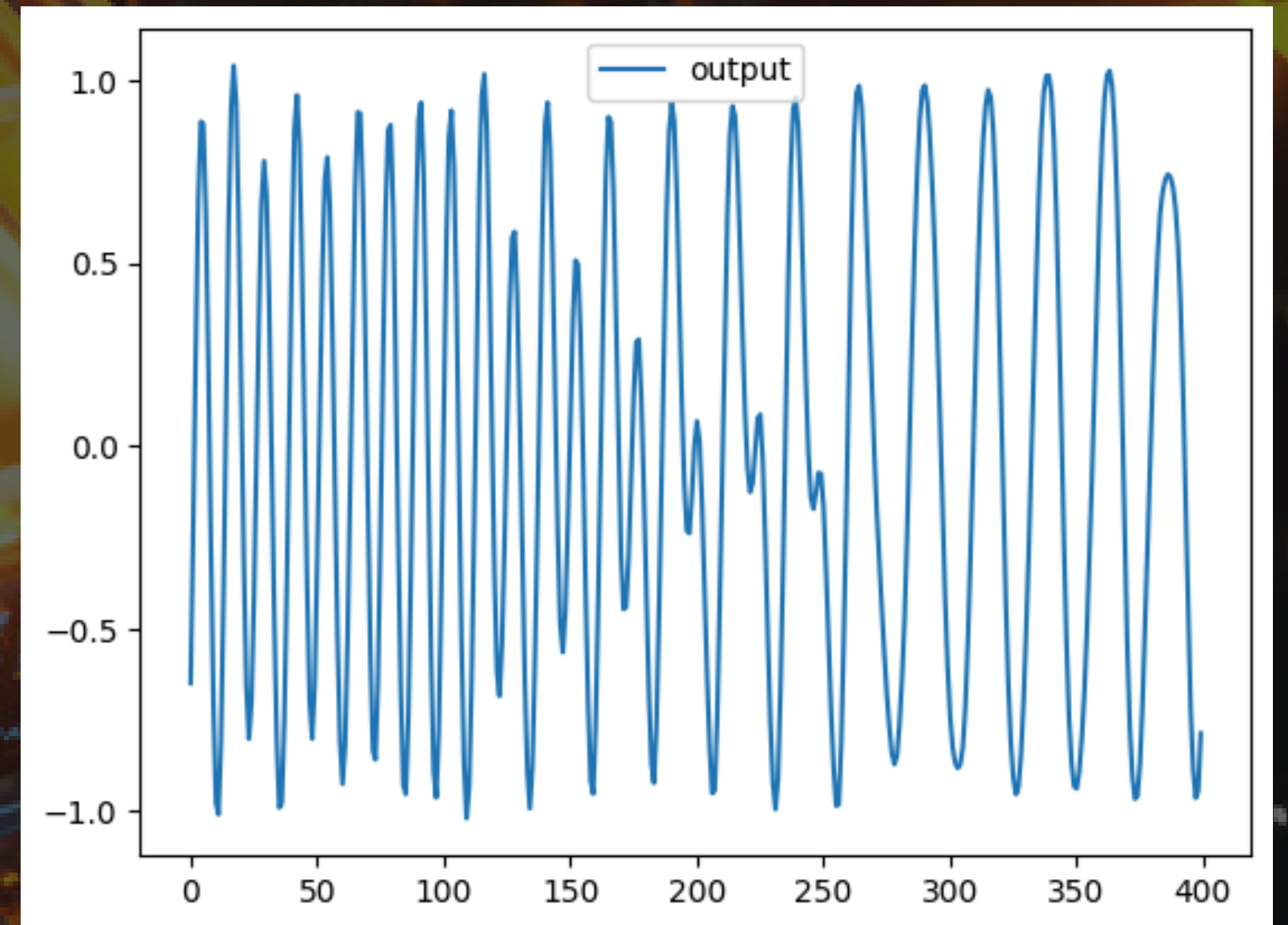
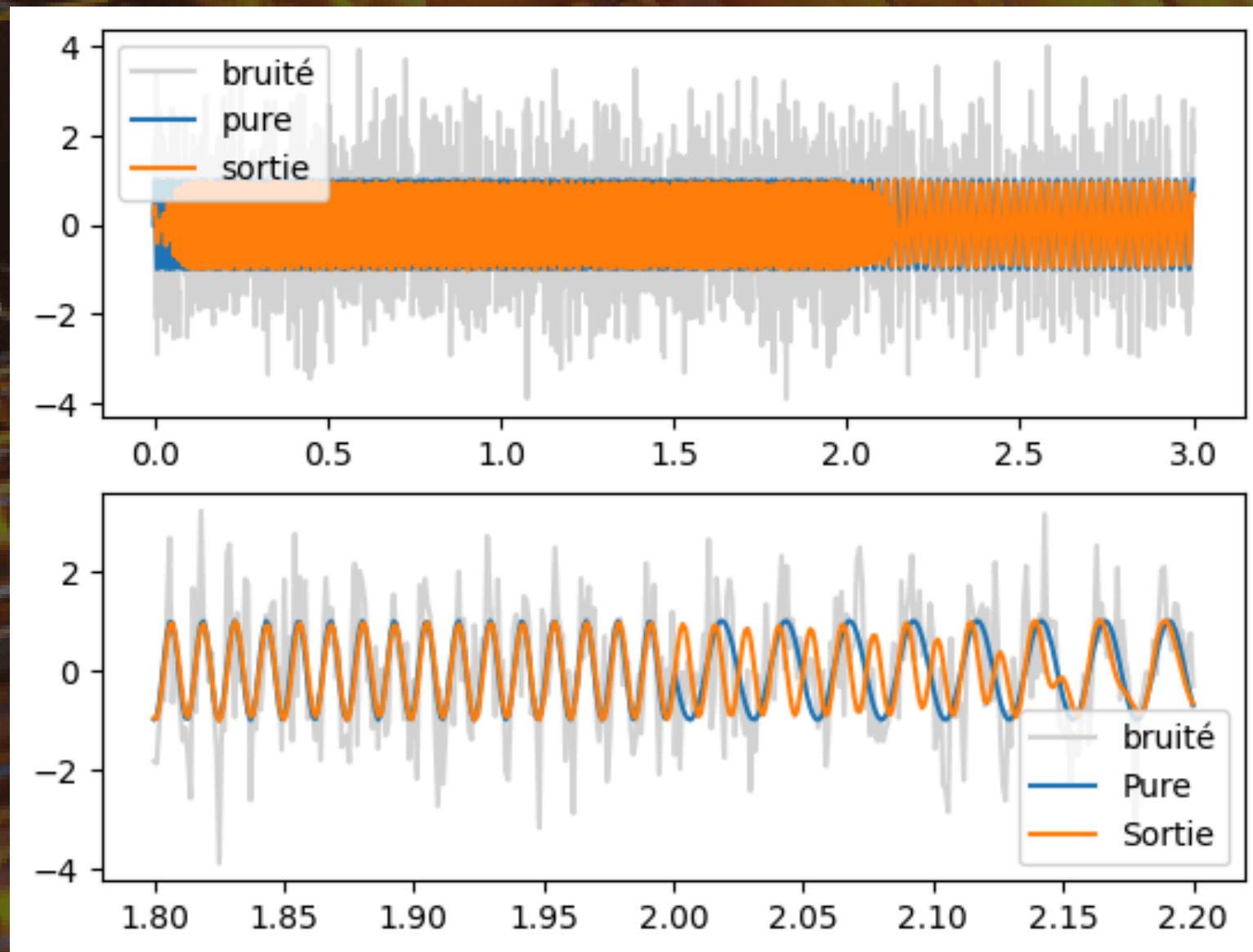
For each signal detected by the network, we plot its SNR as a function of its overlapping with the injection.

We look at the average overlapping for different SNR values to get an idea of the effectiveness of the training.

Frame modulation



Two-frequency problem



Tanimoto distance

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}}$$

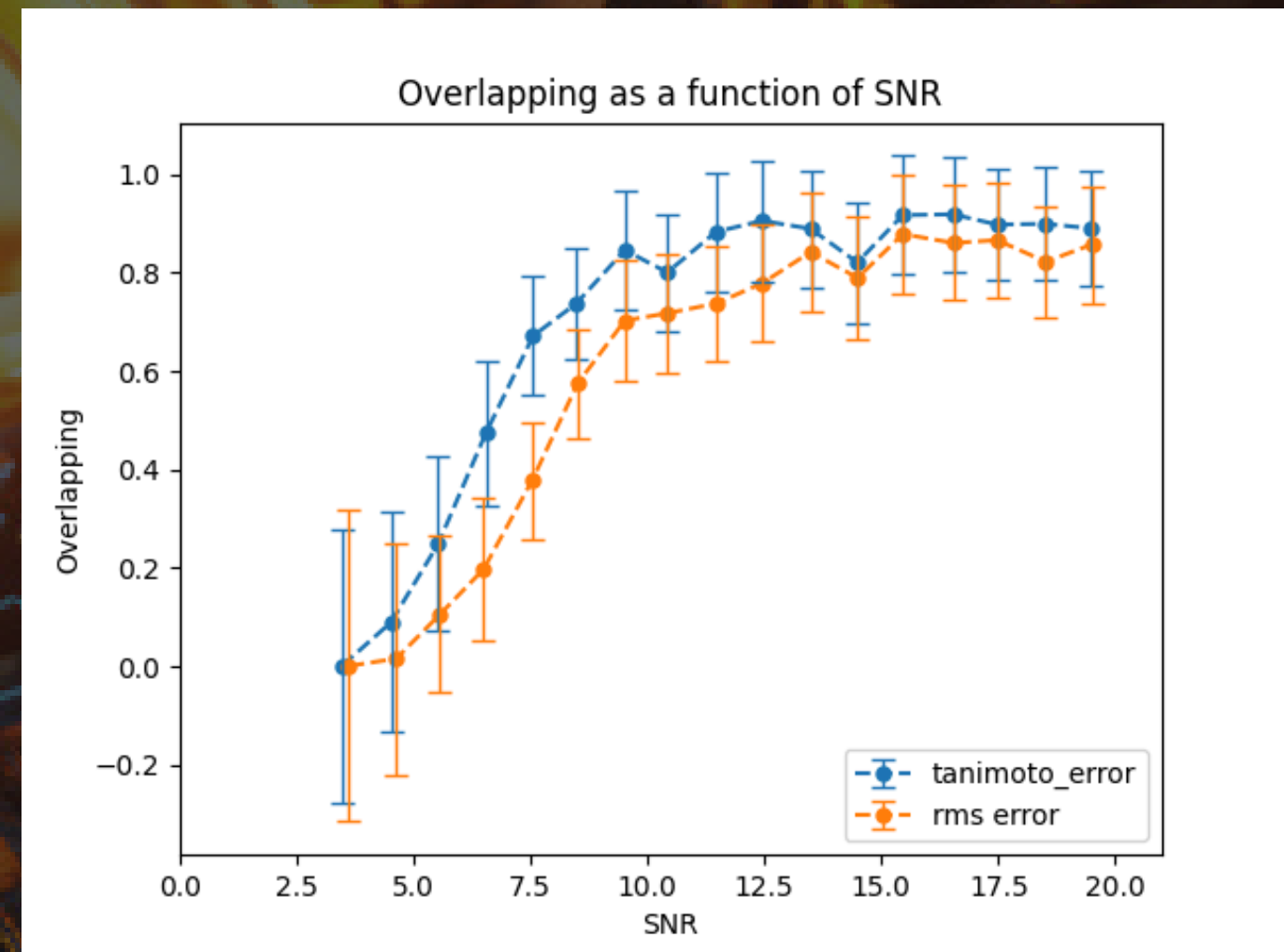
$\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$ are predicted values

y_1, y_2, \dots, y_n are observed values

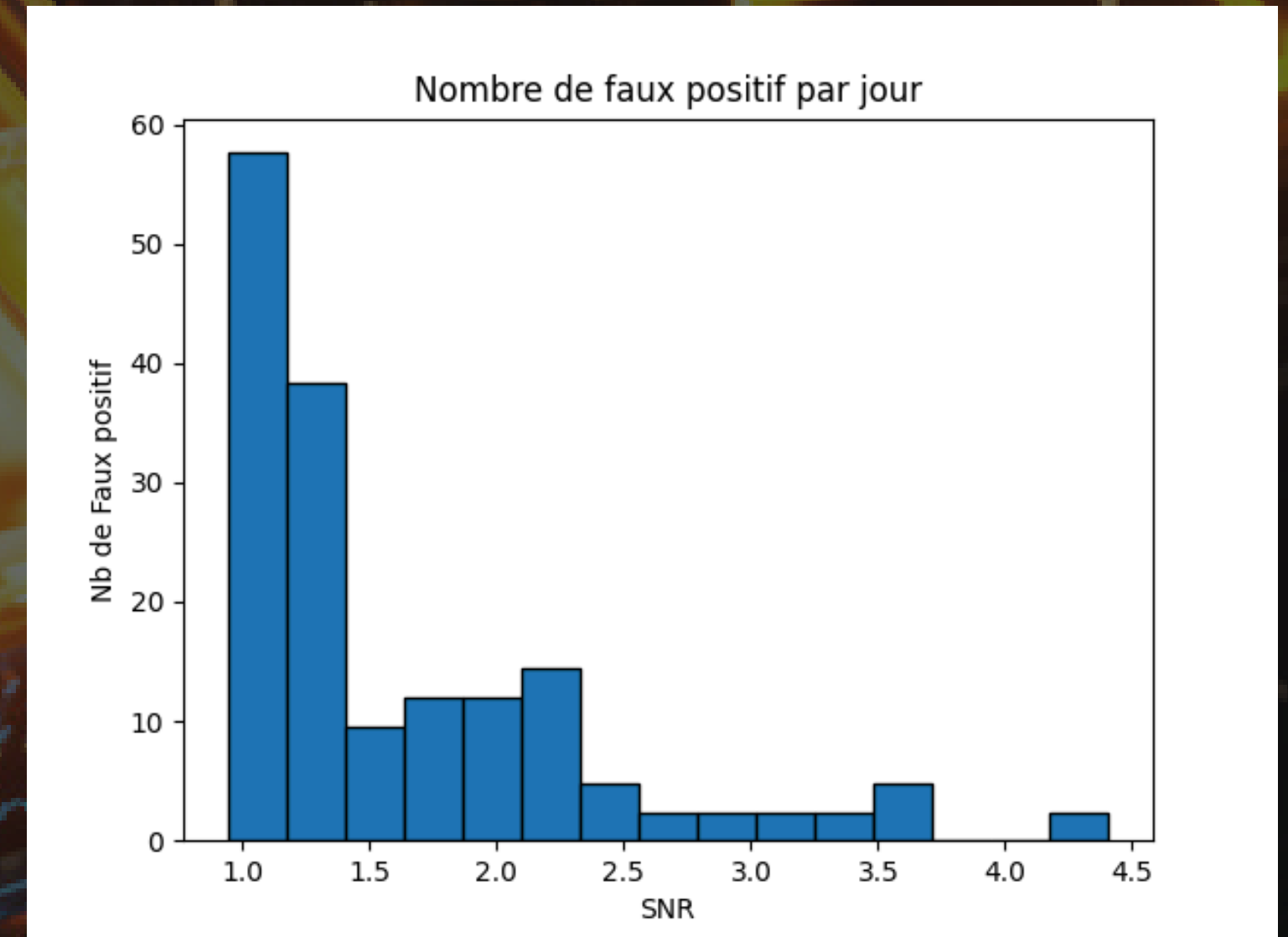
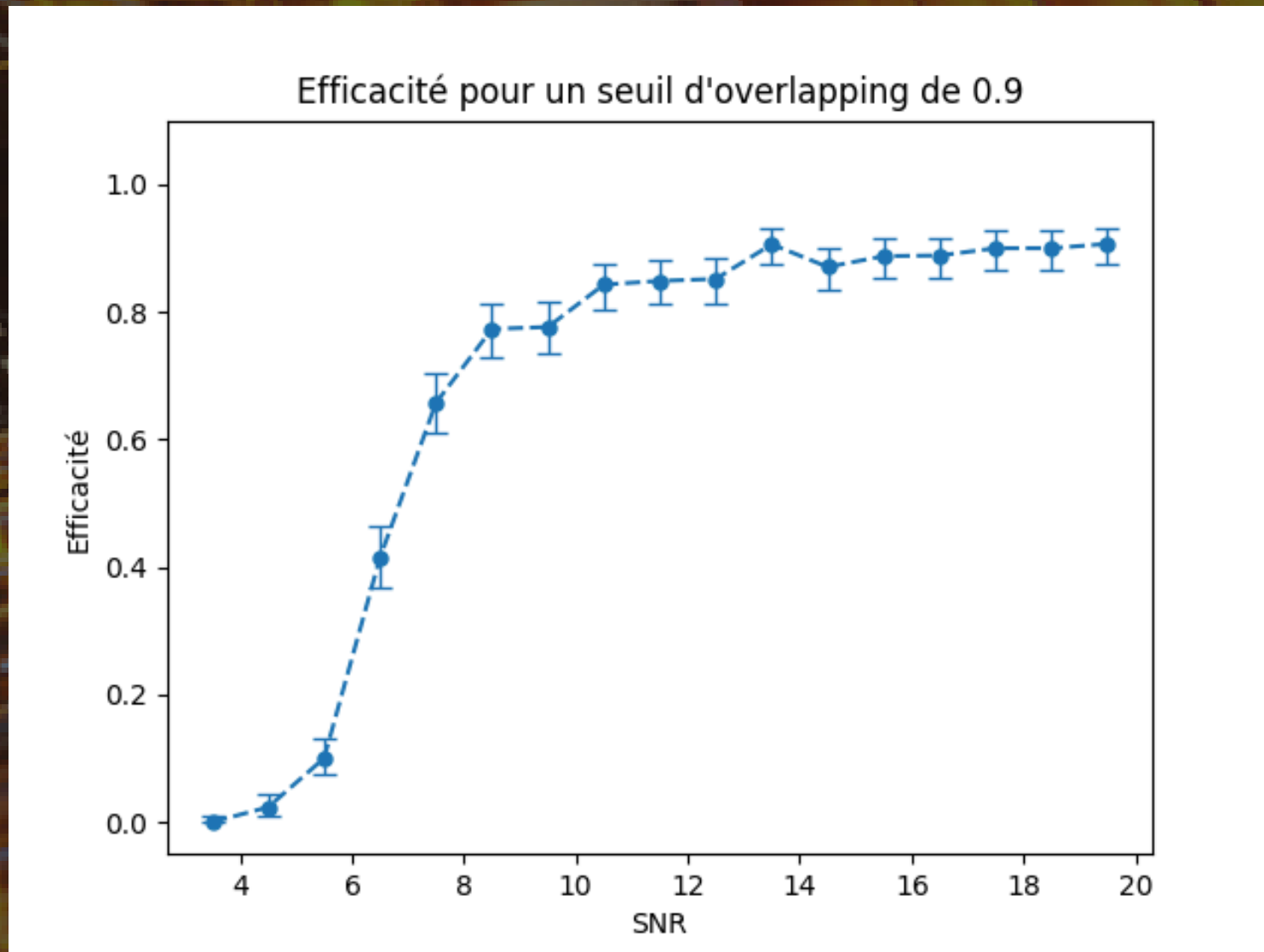
$$L_{z,x} = \frac{(\mathbf{x}_i - \mathbf{z}_i)^2}{n} - r_{w,z,x}^d$$

- \mathbf{x} : Expected signal
- \mathbf{z} : Network output
- \mathbf{w} : Weight
- \mathbf{d} : Hardness parameter

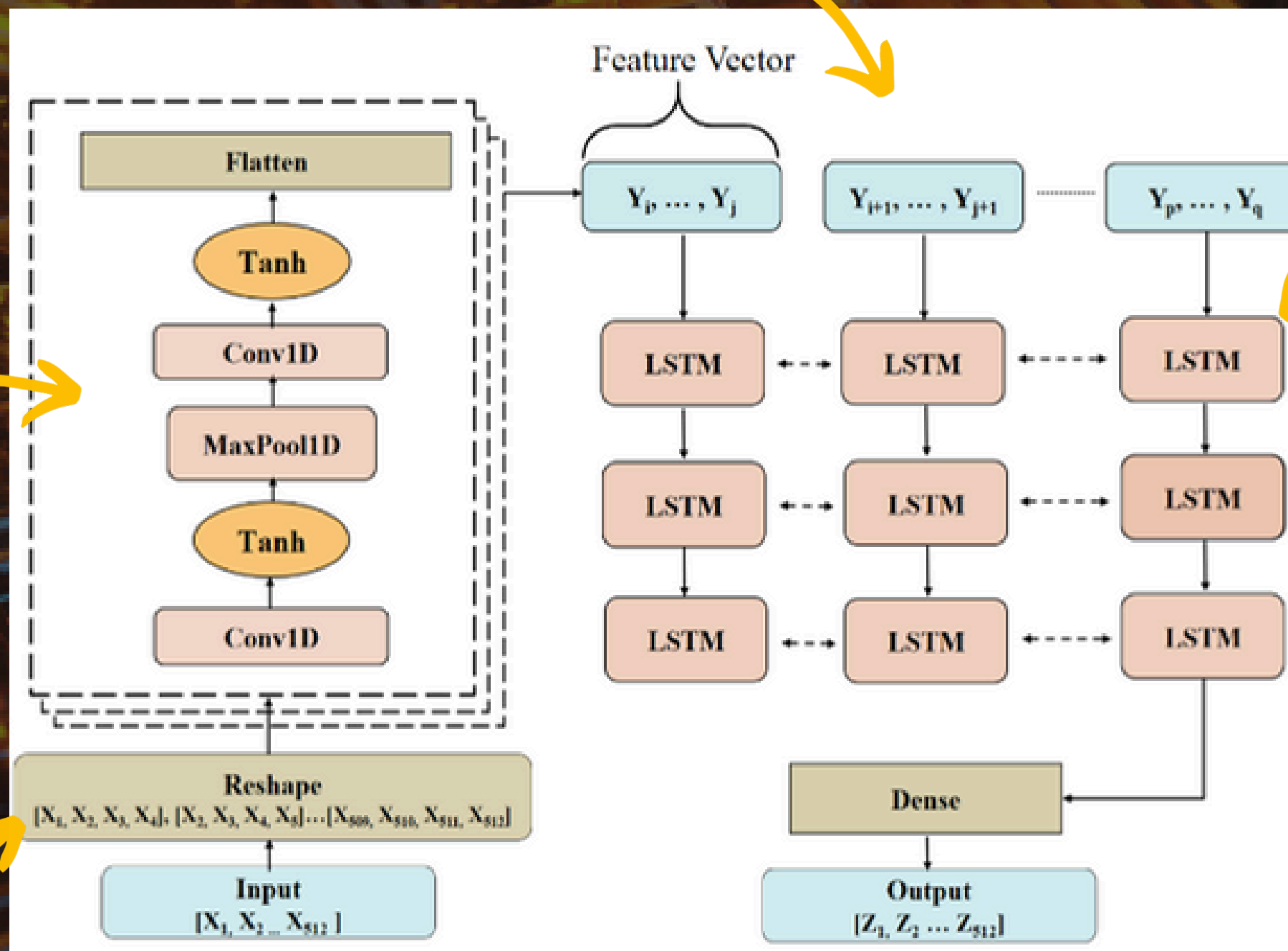
$$r_{w,z,x}^d = \frac{\sum_i^n w_i \cdot \mathbf{z}_i \cdot \mathbf{x}_i}{2^d \sum_i^n w_i \cdot (\mathbf{z}_i^2 + \mathbf{x}_i^2) - (2^{d+1} - 1) \sum_i^n w_i \cdot \mathbf{z}_i \cdot \mathbf{x}_i}$$



holesjoliplot



Hyperparameters



- Batch size
- Numbers of epochs
- Percentage of signal
- Learning rate
- Weights in tanimoto
- SNR during training



Thank You
