

Assignment 3 (ML for TS) - MVA

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1 Introduction

Objective. The goal is to implement (i) a signal processing pipeline with a change-point detection method and (ii) wavelets for graph signals.

Warning and advice.

- Use code from the tutorials as well as from other sources. Do not code yourself well-known procedures (e.g. cross validation or k-means), use an existing implementation.
- The associated notebook contains some hints and several helper functions.
- Be concise. Answers are not expected to be longer than a few sentences (omitting calculations).

Instructions.

- Fill in your names and emails at the top of the document.
- Hand in one report per pair of students.
- Rename your report and notebook as follows:
`FirstnameLastname1_FirstnameLastname1.pdf` and
`FirstnameLastname2_FirstnameLastname2.ipynb`.
For instance, `LaurentOudre_ValerioGuerrini.pdf`.
- Upload your report (PDF file) and notebook (IPYNB file) using the link given in the email.

2 Dual-tone multi-frequency signaling (DTMF)

Dual-tone multi-frequency signaling is a procedure to encode symbols using an audio signal. The possible symbols are 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, *, #, A, B, C, and D. A symbol is represented by a sum of cosine waves: for $t = 0, 1, \dots, T - 1$,

$$y_t = \cos(2\pi f_1 t / f_s) + \cos(2\pi f_2 t / f_s)$$

where each combination of (f_1, f_2) represents a symbol. The first frequency has four different levels (low frequencies), and the second frequency has four other levels (high frequencies); there are 16 possible combinations. In the notebook, you can find an example symbol sequence encoded with sound and corrupted by noise (white noise and a distorted sound).

Question 1

Design a procedure that takes a sound signal as input and outputs the sequence of symbols. To that end, you can use the provided training set. The signals have a varying number of symbols with a varying duration. There is a brief silence between each symbol.

Describe in 5 to 10 lines your methodology and the calibration procedure (give the hyperparameter values). Hint: use the time-frequency representation of the signals, apply a change-point detection algorithm to find the starts and ends of the symbols and silences, and then classify each segment.

Answer 1

Question 2

What are the two symbolic sequences encoded in the test set?

Answer 2

- Sequence 1:
- Sequence 2:

3 Wavelet transform for graph signals

Let G be a graph defined a set of n nodes V and a set of edges E . A specific node is denoted by v and a specific edge, by e . The eigenvalues and eigenvectors of the graph Laplacian L are $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$ and u_1, u_2, \dots, u_n respectively.

For a signal $f \in \mathbb{R}^n$, the Graph Wavelet Transform (GWT) of f is $W_f : \{1, \dots, M\} \times V \longrightarrow \mathbb{R}$:

$$W_f(m, v) := \sum_{l=1}^n \hat{g}_m(\lambda_l) \hat{f}_l u_l(v) \quad (1)$$

where $\hat{f} = [\hat{f}_1, \dots, \hat{f}_n]$ is the Fourier transform of f and \hat{g}_m are M kernel functions. The number M of scales is a user-defined parameter and is set to $M := 9$ in the following. Several designs are available for the \hat{g}_m ; here, we use the Spectrum Adapted Graph Wavelets (SAGW). Formally, each kernel \hat{g}_m is such that

$$\hat{g}_m(\lambda) := \hat{g}^U(\lambda - am) \quad (0 \leq \lambda \leq \lambda_n) \quad (2)$$

where $a := \lambda_n / (M + 1 - R)$,

$$\hat{g}^U(\lambda) := \frac{1}{2} \left[1 + \cos \left(2\pi \left(\frac{\lambda}{aR} + \frac{1}{2} \right) \right) \right] \mathbb{1}(-Ra \leq \lambda < 0) \quad (3)$$

and $R > 0$ is defined by the user.

Question 3

Plot the kernel functions \hat{g}_m for $R = 1$, $R = 3$ and $R = 5$ (take $\lambda_n = 12$) on Figure ???. What is the influence of R ?

Answer 3

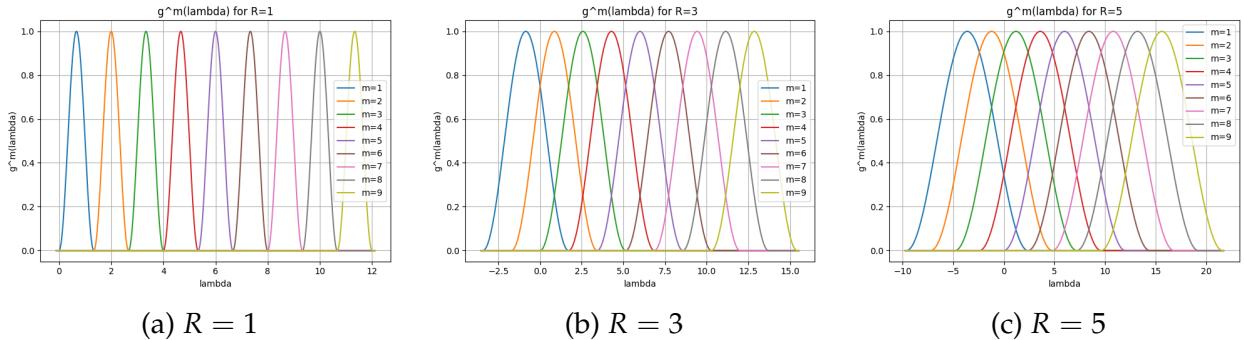


Figure 1: The SAGW kernels functions

We can see that as R increases, the support of the kernels grows (because $R < M + 1$), and the oscillation frequency decreases. Each kernel spans exactly π radians, forming a single "mountain". Also, the kernels get more and more overlapped as R increases.

We will study the Molene data set (the one we used in the last tutorial). The signal is the temperature.

Question 4

Construct the graph using the distance matrix and exponential smoothing (use the median heuristics for the bandwidth parameter).

- Remove all stations with missing values in the temperature.
- Choose the minimum threshold so that the network is connected and the average degree is at least 3.
- What is the time where the signal is the least smooth?
- What is the time where the signal is the smoothest?

Answer 4

The stations with missing values are ARZAL, BATZ, BEG_MEIL, BREST-GUIPAVAS, BRIGNOGAN, CAMARET, LANDIVISIAU, LANNAERO, LANVEOC, OUESSANT-STIFF, PLOUAY-SA, PLOUDALMEZEAU, PLOUGONVELIN, QUIMPER, RIEC SUR BELON, SIZUN, ST NAZAIRE-MONTOIR, VANNES-MEUCON.

The threshold is equal 0.8291457286432161. We computed the maximum threshold and not the minimum since for low values of epsilon the condition will be surely met.

The signal is least smooth at: 2014-01-21 03:00:00

The signal is the smoothest at: 2014-01-24 23:00:00

Question 5

(For the remainder, set $R = 3$ for all wavelet transforms.)

For each node v , the vector $[W_f(1, v), W_f(2, v), \dots, W_f(M, v)]$ can be used as a vector of features. We can for instance classify nodes into low/medium/high frequency:

- a node is considered low frequency if the scales $m \in \{1, 2, 3\}$ contain most of the energy,
- a node is considered medium frequency if the scales $m \in \{4, 5, 6\}$ contain most of the energy,
- a node is considered high frequency if the scales $m \in \{6, 7, 9\}$ contain most of the energy.

For both signals from the previous question (smoothest and least smooth) as well as the first available timestamp, apply this procedure and display on the map the result (one colour per class).

Answer 5

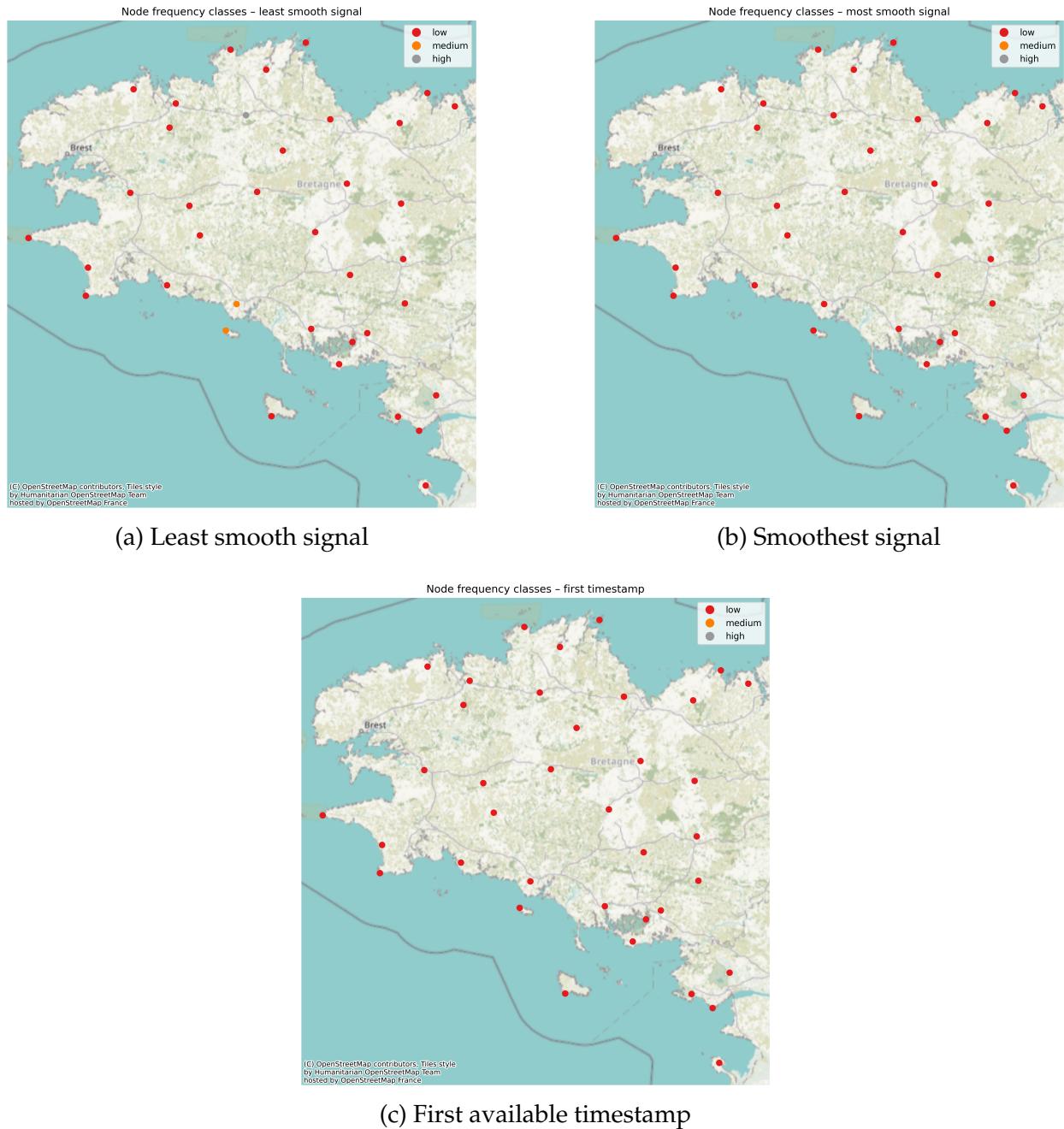


Figure 2: Classification of nodes into low/medium/high frequency

Question 6

Display the average temperature and for each timestamp, adapt the marker colour to the majority class present in the graph.

Answer 6

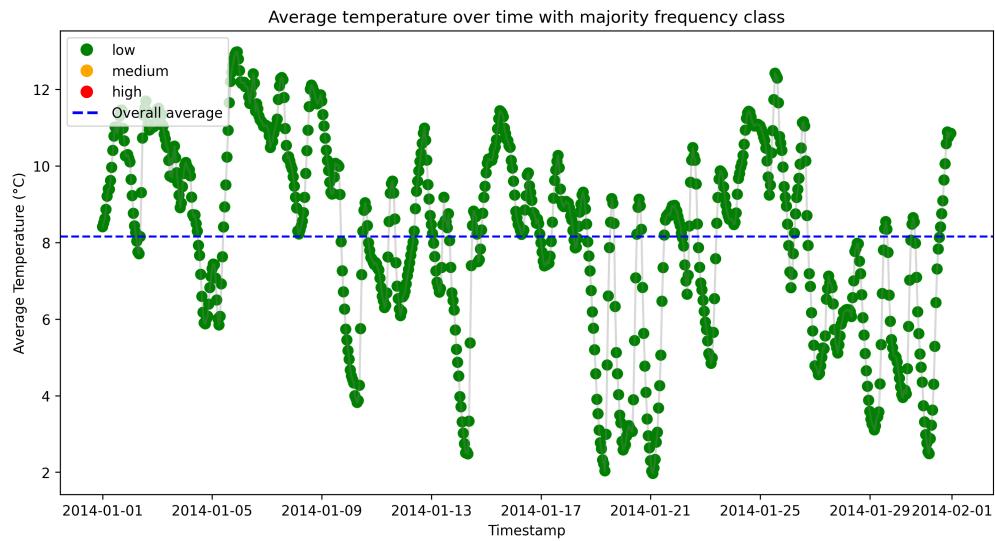


Figure 3: Average temperature. Markers' colours depend on the majority class.

Question 7

The previous graph G only uses spatial information. To take into account the temporal dynamic, we construct a larger graph H as follows: a node is now *a station at a particular time* and is connected to neighbouring stations (with respect to G) and to itself at the previous timestamp and the following timestamp. Notice that the new spatio-temporal graph H is the Cartesian product of the spatial graph G and the temporal graph G' (which is simply a line graph, without loop).

- Express the Laplacian of H using the Laplacian of G and G' (use Kronecker products).
- Express the eigenvalues and eigenvectors of the Laplacian of H using the eigenvalues and eigenvectors of the Laplacian of G and G' .
- Compute the wavelet transform of the temperature signal.
- Classify nodes into low/medium/high frequency and display the same figure as in the previous question.

Answer 7

Let's assume we have T time stamps and the size of the graph G is n . Let L_G be the laplacian of the initial graph, and let $L_{G'}$ be the laplacian of the graph of size T that is a line, so it contains 1's only in $(i, i+1)$ $1 \leq i < n$ and $(i, i-1)$ $1 < i \leq n$ (symmetrically). Let I_N and I_T be identity matrix. Then the new laplacian can be expressed as:

$$L_H = I_T \otimes L_G + \beta * L_{G'} \otimes I_N$$

Where β is the weight we want to add in the edges representing a link with itself in consecutive timestamps.

It is a well known fact that if v_i and w_j are the set of eigenvectors of L_G and $L_{G'}$ respectively, then $w_j \otimes v_i$ are the set of eigenvectors of L_H . If u_i and l_j are the eigenvalues of v_i and w_j respectively, then the eigenvalue of $w_j \otimes v_i$ is $u_i + \beta l_j$.

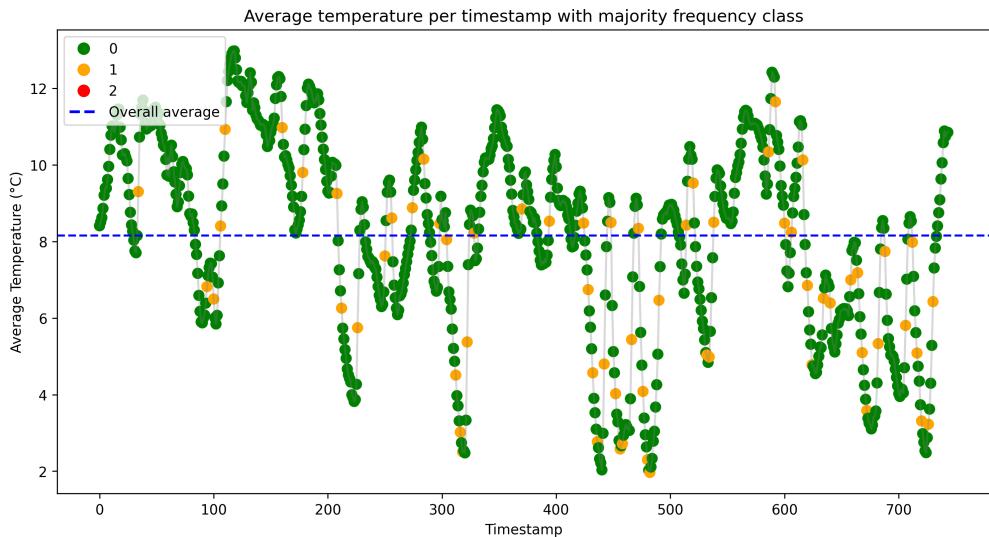


Figure 4: Average temperature. Markers' colours depend on the majority class.

In the figure, we can see that now we have the appearance of more middle frequencies, since before for every timestamp the majority class was low ones and now in a lot of timestamps we have middle frequencies as the dominant class. This is done since the new graph we have constructed takes into account temporal information as well, so the variation of the temperature in time is also reflected now, making it more complete. The values of the plot remain the same as it should be.