Detect behavioral changes in physiological signals

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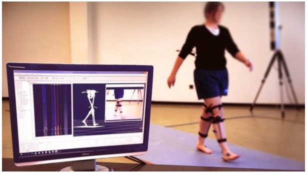
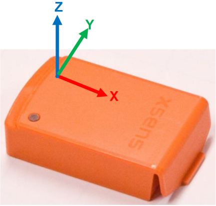
Monitoring and protocols

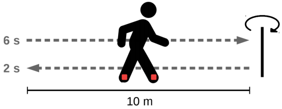
- In several studies, sensors are used to subjectively assess a subject's behavior: brain activity, heart rate, movement, breathing cycles, states of consciousness...
- In most cases, the aim is then to process the signals so as to extract biomarkers or relevant features that capture the phenomenon of interest
- However, as will be seen in the following examples, most of the times, the mathematical properties of the signals do not allow a direct calculation of the features

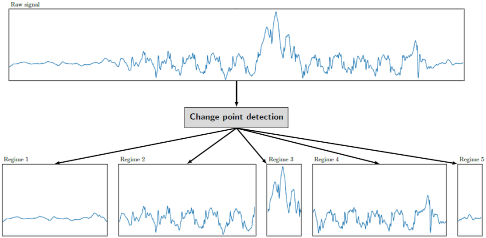
Usecase 1: Gait Analysis



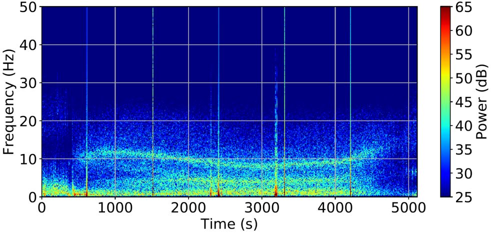
- Human activity can be recorded with inertial measurement units (IMUs)
- Complex protocols with several activities create non-stationary time series







Usecase 2: Anesthesia

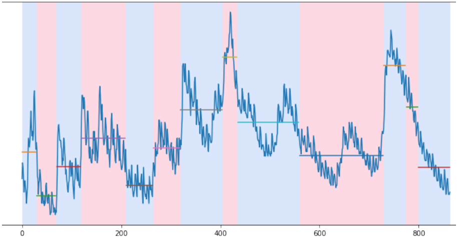


- EEG data recorded during general anesthesia
- Several phases appear: Awake , Loss of Consciousness (LoC), Anesthesia, Recovery of Consciousness (RoC), and emergence

Notion of stationarity

- Stationarity: statistical properties of the signal do not change over time
- Wide-sense stationarity is one of the most common assumption in signal processing
- In several contexts, some changes occur in the data over time: most real time series are not stationary
- Change-point detection consists in estimating as precisely as possible the times where these changes occur
- Two main usecases:
  - Usecase 1: Retrieve these breakpoints to detect when the changes occurred
  - Usecase 2: Use the breakpoint information to divide the time series into smaller stationary signals

Problem statement: Change-Point Detection

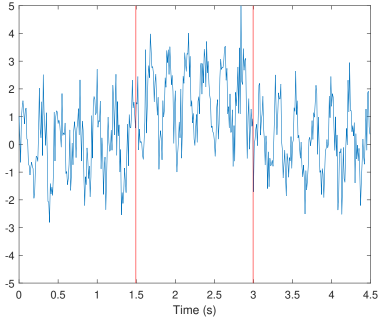


Change-Point Detection

Given a time series x**, retrieve the times** $(t_1, \dots, t_K)$ **where a significant change occurs**

- Necessitates to estimate both the change-points and the number of changes K
- Highly depends on the meaning given to *change*

Problem statement



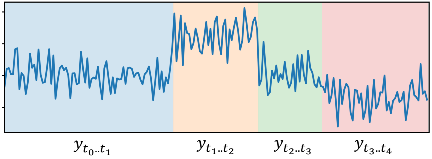
- Let assume that signal $x[n]$ undergoes abrupt changes at times

$$\mathcal{T}^* = (t_1^*, \ldots, t_{K^*}^*)$$

- Goal: retrieve the number of change-points K^* and their times $\mathcal{T}^*$
- Two assumptions: offline segmentation (but can easily be adapted to online setting) [Truong et al., 2020] and known number of changes K (will be discussed later)

Problem statement

$$(\hat{t}_1, \ldots, \hat{t}_K) = \underset{(t_1,\ldots,t_K)}{\operatorname{argmin}} \sum_{k=0}^{K} c(x[t_k : t_{k+1}])$$

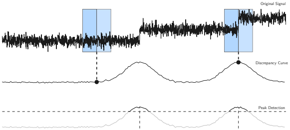


Cost function $c(.)$

- Measures the homogeneity of the segments
- Choosing $c(.)$ conditions the type of change-points that we want to detect
- Often based on a probabilistic model for the data

Problem solving

- Optimal resolution with dynamic programming
- Approximate resolution (sliding windows...)



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Cost function

$$(\hat{t}_1, \ldots, \hat{t}_K) = \underset{(t_1, \ldots, t_K)}{\text{argmin}} \sum_{k=0}^{K} c(x[t_k : t_{k+1}])$$

Convention : $t_0 = 0$, $t_{K+1} = N$

- Function $c(.)$ is characteristic of the notion of *homogeneity*
- The most common cost functions are linked to parametric probabilistic models: in this case change-points are defined as changes in the parameters of a probability density function [Basseville et al., 1993]
- Non parametric cost functions can also be introduced when no model is available

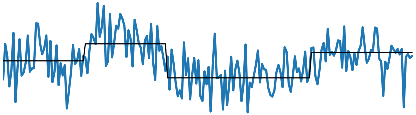
Change in mean

The most popular is indubitably the L2 norm [Page, 1955]

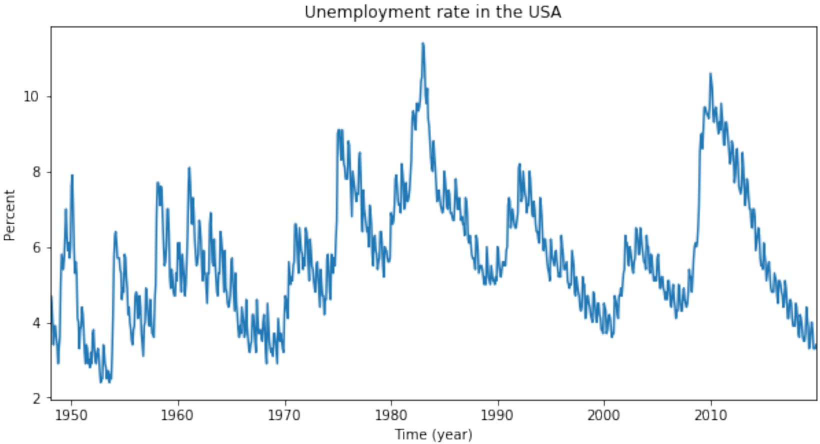
$$c_{L_2}(x[a:b]) = \sum_{n=a+1}^{b} \|x[n] - \mu_{a:b}\|_2^2$$

where $\mu_{a:b}$ is the empirical mean of the segment $x[a:b]$.

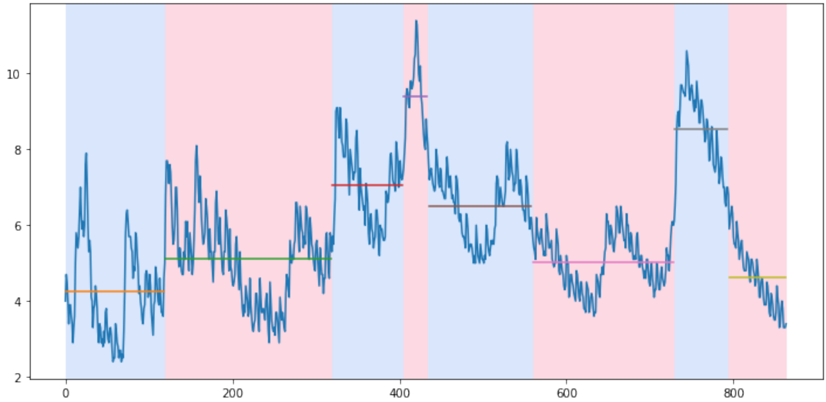
- Particular case of c_{ML} with Gaussian model with fixed variance
- Allows to detect changes in mean



Example

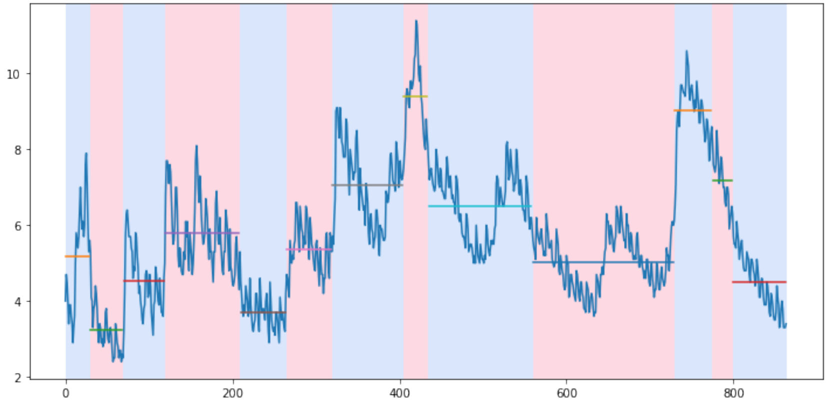

Unemployment rate in the USA
Percent
2
4
6
8
10
1950
1960
1970
1980
1990
2000
2010
Time (year)

Example: Change-Point Detection with c_{L_2}



$$K = 7$$

Example: Change-Point Detection with c_{L_2}



$$K = 12$$

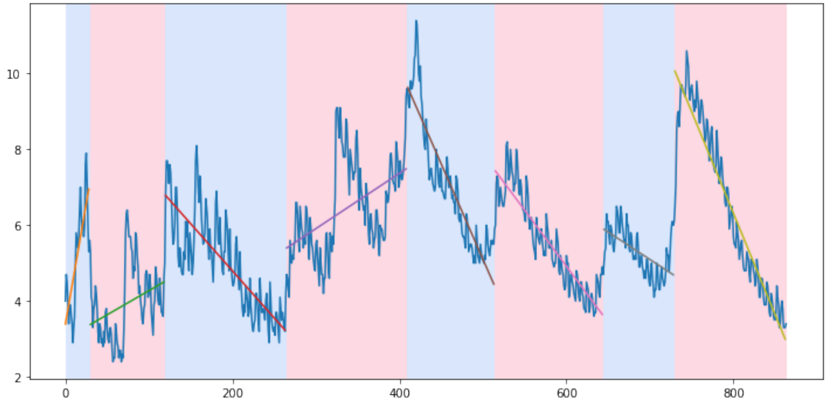
Change in slope and intercept

Change in slope and intercept can be handled in the general context of piecewise linear regression

$$c_{linear}(x[a:b]) = \min_{\boldsymbol{\alpha}} \sum_{n=a+1}^{b} \left\| x[n] - \sum_{i=1}^{M} \alpha_i \beta_i[n] \right\|_2^2$$

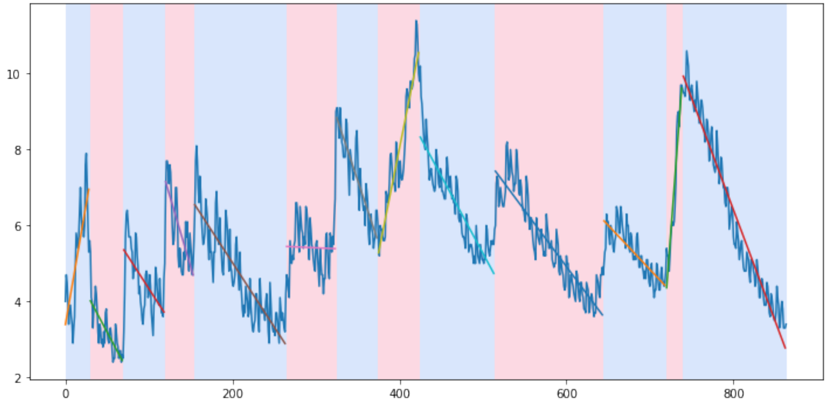
- Functions $\beta_1[n], \ldots, \beta_M[n]$ are covariate functions and we seek for changes in the regression parameters
- Allows to detect changes in trend, seasonality, etc... [Bai et al., 1998]
- For slope and intercept, we choose $\beta_1[n] = 1$ and $\beta_2[n] = n$

Example: Change-Point Detection with c_{linear}



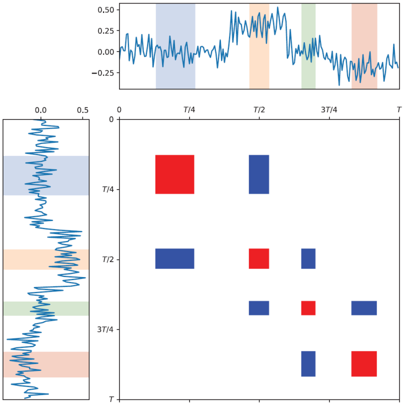
$K = 7$

Example: Change-Point Detection with c_{linear}



$K = 12$

Supervised change-point detection



- Supervised approach based on metric learning [Truong et al., 2019]
- Use a few annotated examples to learn an adequate cost function
- Samples belonging to adjacent regimes form a set of constraints that can be used for metric learning
- Allows to relax the need for an off-the-shelf cost function

- C. Truong and L. Oudre. Supervised change-point detection with dimension reduction, applied to physiological signals. In NeurIPS Workshop on Learning from Time Series for Health, 2022.
- C. Truong, L. Oudre and N. Vayatis. Supervised kernel change point detection with partial annotations. In Proceedings of the International Conference on Acoustics, Speech, and Signal Processing (ICASSP), pages 3147-3151, Brighton, UK, 2019.

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Search method

$$(\hat{t}_1, \ldots, \hat{t}_K) = \underset{(t_1, \ldots, t_K)}{\operatorname{argmin}} \sum_{k=0}^{K} c(x[t_k : t_{k+1}])$$

Convention : $t_0 = 0$, $t_{K+1} = N$

- Several methods can be used to solve this problem with a fixed K
- Optimal resolution with dynamic programming: find the true solution of the problem (but costly : Complexity of $\mathcal{O}(N^2)$)
- Approximated resolution with windows: test for one unique change-point on a window (necessitates some extra parameters and less precise)

The `ruptures` package

ruptures

https://centre-borelli.github.io/ruptures-docs/

- Package in Python implementing most of the offline approaches for change-point detection
- Many cost functions, resolution algorithms and parametrizations
- More than 7 Million downloads!

C. Truong, L. Oudre, N. Vayatis. Selective review of offline change point detection methods. Signal Processing, 167:107299, 2020

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Finding the number of change points

- In all previously described algorithms, the number of change-point K was supposed to be known
- In practice, this parameter is difficult to set: as such, the total cost $\mathcal{V}(\mathcal{T}, \mathrm{x})$ will always decrease when K increases...
- Three solutions
  - Use heuristics by testing several values of K
  - Use a penalized formulation of the CPD problem to seek for a compromise between reconstruction error and complexity
  - Use supervised approaches from annotated signals [Truong et al., 2018]

- C. Truong and L. Oudre. Supervised change-point detection with dimension reduction, applied to physiological signals. In NeurIPS Workshop on Learning from Time Series for Health, 2022.
- C. Truong, L. Oudre and N. Vayatis. Penalty Learning for Changepoint Detection. In Proceedings of the European Signal Processing Conference (EUSIPCO), pages 1614-1618, Kos Island, Greece, 2017.

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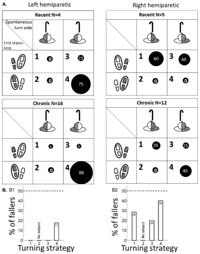
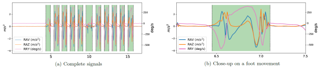
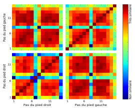
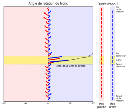
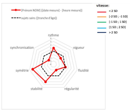
Use for biomedical research

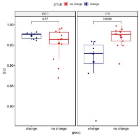












- Study of U-turn for post-stroke patients [Barrois-Müller et al., 2017]
- Step analysis for multiple sclerosis patients [Vienne-Jumeau et al., 2020]
- Comparison of gait exercises through pattern matching techniques [Vienne-Jumeau et al., 2019]

Thank you for your attention