Assignment 2 (ML for TS) - MVA

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1 Introduction

Objective. The goal is to better understand the properties of AR and MA processes and do signal denoising with sparse coding.

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 your report (one per pair of students) by Monday 2nd December 11:59 PM.
- Rename your report and notebook as follows:
 FirstnameLastname1_FirstnameLastname1.pdf and
 FirstnameLastname2_FirstnameLastname2.ipynb.
 For instance, LaurentOudre_CharlesTruong.pdf.
- Upload your report (PDF file) and notebook (IPYNB file) using this link: https://docs.google.com/forms/d/e/1FAIpQLSfCqMXSDU9jZJbYUMmeLCXbVeckZYNiDpPl4hRUwcJ2

2 General questions

A time series $\{y_t\}_t$ is a single realisation of a random process $\{Y_t\}_t$ defined on the probability space (Ω, \mathcal{F}, P) , i.e. $y_t = Y_t(w)$ for a given $w \in \Omega$. In classical statistics, several independent realizations are often needed to obtain a "good" estimate (meaning consistent) of the parameters of the process. However, thanks to a stationarity hypothesis and a "short-memory" hypothesis, it is still possible to make "good" estimates. The following question illustrates this fact.

Question 1

An estimator $\hat{\theta}_n$ is consistent if it converges in probability when the number n of samples grows to ∞ to the true value $\theta \in \mathbb{R}$ of a parameter, i.e. $\hat{\theta}_n \xrightarrow{\mathcal{D}} \theta$.

- Recall the rate of convergence of the sample mean for i.i.d. random variables with finite variance.
- Let $\{Y_t\}_{t\geq 1}$ a wide-sense stationary process such that $\sum_k |\gamma(k)| < +\infty$. Show that the sample mean $\bar{Y}_n = (Y_1 + \cdots + Y_n)/n$ is consistent and enjoys the same rate of convergence as the i.i.d. case. (Hint: bound $\mathbb{E}[(\bar{Y}_n \mu)^2]$ with the $\gamma(k)$ and recall that convergence in L_2 implies convergence in probability.)

Answer 1

Let X_1,\ldots,X_n be i.i.d. random variables with mean μ and variance σ^2 . The sample mean is $\bar{X}_n = \frac{(X_1+\cdots+X_n)}{n}$. Thanks to Bienaymé-Tchebychev inequality, we have that $\mathbb{P}(|\bar{X}_n-\mu|\geq \varepsilon)\leq \frac{Var(\bar{X}_n)}{\varepsilon}\leq \frac{\sigma^2}{n\varepsilon^2}$. The convergence rate is determined by the standard deviation of the sample mean, which is σ/\sqrt{n} .

$$\mathbb{E}[(\bar{Y}_n - \mu)^2] = \mathbb{E}[(\frac{1}{n} \sum_{i=1}^n (Y_i - \mu))^2]$$
 (1)

$$= \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n \mathbb{E}[(Y_i - \mu)(Y_j - \mu)]$$
 (2)

$$= \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\mathbb{E}(Y_i Y_j) - \mu^2)$$
 (3)

$$= \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n (\mathbb{E}(Y_i Y_j) - \mathbb{E}(Y_i) \mathbb{E}(Y_j))$$

$$\tag{4}$$

$$= \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma(i-j)$$
 (5)

$$= \frac{1}{n^2} \sum_{k=-(n-1)}^{n-1} (n-|k|)\gamma(k)$$
 (6)

$$\leq \frac{1}{n^2} \sum_{k=-(n-1)}^{n-1} n\gamma(k) \tag{7}$$

$$= \frac{1}{n} \sum_{k=-(n-1)}^{n-1} \gamma(k)$$
 (8)

$$\leq \frac{1}{n} \sum_{k=-\infty}^{\infty} \gamma(k) \xrightarrow{n \to \infty} 0 \tag{9}$$

We have proved that $\bar{Y}_n \xrightarrow{L^2} \mu$.

Moreover as the convergence in L_2 implies the convergence in probability, we have that $\bar{Y}_n \stackrel{P}{\to} \mu$.

3 AR and MA processes

Question 2 *Infinite order moving average MA*(∞)

Let $\{Y_t\}_{t\geq 0}$ be a random process defined bye

$$Y_t = \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \dots = \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k}$$
 (10)

where $(\psi_k)_{k\geq 0}\subset \mathbb{R}$ ($\psi=1$) are square summable, i.e. $\sum_k \psi_k^2 < \infty$ and $\{\varepsilon_t\}_t$ is a zero mean white noise of variance σ_ε^2 . (Here, the infinite sum of random variables is the limit in L_2 of the partial sums.)

- Derive $\mathbb{E}(Y_t)$ and $\mathbb{E}(Y_tY_{t-k})$. Is this process weakly stationary?
- Show that the power spectrum of $\{Y_t\}_t$ is $S(f) = \sigma_{\varepsilon}^2 |\phi(e^{-2\pi i f})|^2$ where $\phi(z) = \sum_j \psi_j z^j$. (Assume a sampling frequency of 1 Hz.)

The process $\{Y_t\}_t$ is a moving average of infinite order. Wold's theorem states that any weakly stationary process can be written as the sum of the deterministic process and a stochastic process which has the form (10).

Answer 2

$$\mathbb{E}(Y_t) = \sum_{k=0}^{\infty} \psi_k \mathbb{E}(\varepsilon_{t-k}) = 0$$

$$\mathbb{E}(Y_t Y_{t-k}) = \mathbb{E}\left[\left(\sum_{k=0}^{\infty} \psi_k \epsilon_{t-k}\right) \left(\sum_{k'=0}^{\infty} \psi_k' \epsilon_{t-k'}\right)\right]$$
(11)

$$= \sum_{k=0}^{\infty} \sum_{k'=0}^{\infty} \psi_k \psi_{k'} \mathbb{E}(\epsilon_{t-k} \epsilon_{t-k'})$$
(12)

$$=\sum_{k=0}^{\infty}\psi_k^2\sigma_{\epsilon}^2\tag{13}$$

(14)

This quantity exists, as $\sum_k \psi_k^2 < \infty$. Moreover, it only depends on |k - k'|, so the process **is weakly stationary**.

$$S(f) = \sum_{\tau = -\infty}^{\infty} e^{-2\pi f \tau} \tag{15}$$

$$= \sum_{\tau=-\infty}^{\infty} \left(\sum_{j=\tau}^{\infty} \psi_j \psi_{j-\tau} \right) \sigma_{\epsilon}^2 e^{-2i\pi f \tau} \tag{16}$$

$$= \sum_{\tau=-\infty}^{\infty} \left(\sum_{j=\tau}^{\infty} \psi_j \psi_{j-\tau}\right) \sigma_{\epsilon}^2 e^{-2i\pi f \tau} \tag{17}$$

$$= \sum_{j=-\infty}^{\infty} \psi_j \sum_{\tau=-\infty}^{j} \psi_{j-\tau} \sigma_{\epsilon}^2 e^{-2i\pi f \tau}$$
(18)

$$= \sum_{j=-\infty}^{\infty} \psi_j \sum_{\tau=0}^{\infty} \psi_{\tau} \sigma_{\epsilon}^2 e^{-2i\pi f(j-\tau)}$$
(19)

$$= \sum_{j,j'} \psi_j \psi_{j'} \sigma_{\epsilon}^2 e^{-2i\pi f(j-j')}$$
(20)

$$=\sum_{j,j'}\psi_j\psi_{j'}\sigma_{\epsilon}^2e^{-2i\pi fj}e^{-2i\pi fj'}$$
(21)

$$= \sigma_{\epsilon}^2 \sum_j \psi_j e^{-2i\pi f j} \sum_{j'} \psi_{j'} e^{2i\pi f j'}$$
(22)

$$= \sigma_{\epsilon}^2 |\sum_j \psi_j e^{-2i\pi f j}|^2 \tag{23}$$

$$= \sigma_{\epsilon}^2 |\phi(e^{-2\pi i f})|^2 \tag{24}$$

Which is the expected result.

Question 3 *AR*(2) *process*

Let $\{Y_t\}_{t>1}$ be an AR(2) process, i.e.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \varepsilon_t \tag{25}$$

with $\phi_1, \phi_2 \in \mathbb{R}$. The associated characteristic polynomial is $\phi(z) := 1 - \phi_1 z - \phi_2 z^2$. Assume that ϕ has two distinct roots (possibly complex) r_1 and r_2 such that $|r_i| > 1$. Properties on the roots of this polynomial drive the behavior of this process.

- Express the autocovariance coefficients $\gamma(\tau)$ using the roots r_1 and r_2 .
- Figure 1 shows the correlograms of two different AR(2) processes. Can you tell which one has complex roots and which one has real roots?
- Express the power spectrum S(f) (assume the sampling frequency is 1 Hz) using $\phi(\cdot)$.
- Choose ϕ_1 and ϕ_2 such that the characteristic polynomial has two complex conjugate roots of norm r=1.05 and phase $\theta=2\pi/6$. Simulate the process $\{Y_t\}_t$ (with n=2000) and display the signal and the periodogram (use a smooth estimator) on Figure 2. What do you observe?

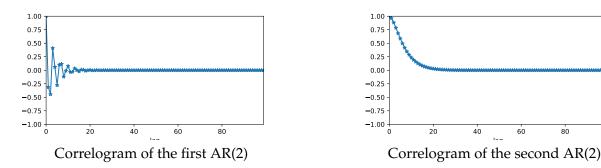


Figure 1: Two AR(2) processes

Answer 3

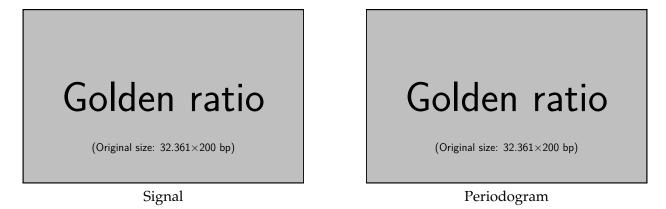


Figure 2: AR(2) process

4 Sparse coding

The modulated discrete cosine transform (MDCT) is a signal transformation often used in sound processing applications (for instance, to encode an MP3 file). A MDCT atom $\phi_{L,k}$ is defined for a length 2L and a frequency localisation k (k = 0, ..., L - 1) by

$$\forall u = 0, \dots, 2L - 1, \quad \phi_{L,k}[u] = w_L[u] \sqrt{\frac{2}{L}} \cos\left[\frac{\pi}{L} \left(u + \frac{L+1}{2}\right) (k + \frac{1}{2})\right]$$
 (26)

where w_L is a modulating window given by

$$w_L[u] = \sin\left[\frac{\pi}{2L}\left(u + \frac{1}{2}\right)\right]. \tag{27}$$

Question 4 Sparse coding with OMP

For the signal provided in the notebook, learn a sparse representation with MDCT atoms. The dictionary is defined as the concatenation of all shifted MDCDT atoms for scales L in [32,64,128,256,512,1024].

- For the sparse coding, implement the Orthogonal Matching Pursuit (OMP). (Use convolutions to compute the correlation coefficients.)
- Display the norm of the successive residuals and the reconstructed signal with 10 atoms.

Answer 4

Golden ratio (Original size: 32.361×200 bp)

Norms of the successive residuals

Golden ratio

(Original size: 32.361×200 bp)

Reconstruction with 10 atoms

Figure 3: Question 4