

# Time Series Exercise Sheet 11

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## Exercise 11.1

Consider two LTI filters  $L_1$  and  $L_2$ , and let  $\alpha \in \mathbb{C}$  then the filter

$$L = \alpha L_1 + L_2 \quad (1)$$

is also an LTI filter.

## Solution 11.1

Let  $\{X_t\}$ ,  $\{Y_t\}$  be sequences, and  $\beta \in \mathbb{C}$ , then

$$\begin{aligned} L[\beta\{X_t\} + \{Y_t\}] &= \alpha L_1[\beta\{X_t\} + \{Y_t\}] + L_2[\beta\{X_t\} + \{Y_t\}] \\ &= \alpha\beta L_1[\{X_t\}] + \alpha L_1[\{Y_t\}] + \beta L_2[\{X_t\}] + L_2[\{Y_t\}] \quad (\text{linearity of LTI filters}) \\ &= \beta L[\{X_t\}] + L[\{Y_t\}]. \end{aligned}$$

Now for time invariance,

$$\begin{aligned} L[B[\{X_t\}]] &= \alpha L_1[B[\{X_t\}]] + L_2[B[\{X_t\}]] \\ &= B[\alpha L_1[\{X_t\}]] + B[L_2[\{X_t\}]] \quad (\text{linearity of LTI filters}) \\ &= B[L[\{X_t\}]]. \end{aligned}$$

## Exercise 11.2

Consider two LTI filters  $L_1$  and  $L_2$ . The filter  $L = L_1 L_2$ , i.e. so that

$$L[\{X_t\}] = L_1[L_2[\{X_t\}]] \quad (2)$$

is also an LTI filter.

## Solution 11.2

Let  $\{X_t\}$ ,  $\{Y_t\}$  be sequences, and  $\alpha \in \mathbb{C}$ , then

$$\begin{aligned} L[\alpha\{X_t\} + \{Y_t\}] &= L_1[L_2[\alpha\{X_t\} + \{Y_t\}]] \\ &= L_1[\alpha L_2[\{X_t\}] + L_2[\{Y_t\}]] \\ &= \alpha L_1[L_2[\{X_t\}]] + L_1[L_2[\{Y_t\}]] \\ &= \alpha L[\{X_t\}] + L[\{Y_t\}]. \end{aligned}$$

Now for time invariance

$$\begin{aligned} L[B[\{X_t\}]] &= L_1[L_2[B[\{X_t\}]]] \\ &= L_1[B[L_2[\{X_t\}]]] \\ &= B[L_1[L_2[\{X_t\}]]]. \end{aligned}$$

### Exercise 11.3

A digital filter  $L$  is an LTI filter if and only if we can write the filter output as a convolution:

$$L[\{X_t\}]_u = \Delta \sum_{m \in \mathcal{T}} h_{u-m} X_m \quad (3)$$

for any  $u \in \mathcal{T}$ .

### Solution 11.3

( $\Rightarrow$ ) Assume that  $L$  is a linear time invariant filter, then notice that for any  $t \in \mathcal{T}$

$$X_t = \sum_{m \in \mathcal{T}} \delta_{t,m} X_m.$$

Therefore

$$\begin{aligned} L[\{X_t\}]_u &= L \left[ \sum_{m \in \mathcal{T}} \{\delta_{t,m}\} X_m \right]_u \\ &= \sum_{m \in \mathcal{T}} X_m L[\{\delta_{t,m}\}]_u \\ &= \sum_{m \in \mathcal{T}} X_m B^{-u/\Delta} [L[\{\delta_{t,m}\}]]_0 \\ &= \sum_{m \in \mathcal{T}} X_m L[\{\delta_{t,m-u}\}]_0 \quad (\text{time invariance}) \\ &= \Delta \sum_{m \in \mathcal{T}} X_m h_{u-m}. \end{aligned}$$

( $\Leftarrow$ ) Now assume that there exists some sequence  $h$  such that

$$L[\{X_t\}]_u = \Delta \sum_{m \in \mathcal{T}} h_{u-m} X_m.$$

Then we have for  $\alpha \in \mathbb{C}$ , and for any  $u \in \mathcal{T}$

$$\begin{aligned} L[\alpha \{X_t\} + \{Y_t\}]_u &= \Delta \sum_{m \in \mathcal{T}} h_{u-m} (\alpha X_m + Y_m) \\ &= \alpha \Delta \sum_{m \in \mathcal{T}} h_{u-m} X_m + \Delta \sum_{m \in \mathcal{T}} h_{u-m} Y_m \\ &= \alpha L[\{X_t\}]_u + L[\{Y_t\}]_u. \end{aligned}$$

Finally,

$$\begin{aligned} L[B[\{X_t\}]]_u &= \Delta \sum_{m \in \mathcal{T}} h_{u-m} X_{m-\Delta} \\ &= \Delta \sum_{m' \in \mathcal{T}} h_{u-\Delta-m'} X_{m'} \quad (m' = m - \Delta) \\ &= L[\{X_t\}]_{u-\Delta} \\ &= B[L[\{X_t\}]]_u. \end{aligned}$$

Thus we have  $L$  is an LTI filter.

### Exercise 11.4

Consider a stationary mean-zero time series  $\{X_t\}$ , with spectral representation

$$X_t = \int_{-1/2\Delta}^{1/2\Delta} e^{2\pi ift} dZ(f). \quad (4)$$

Assume that we observe this time series at the points  $T = \{\Delta, \dots, \Delta n\}$ , and we define the tapered discrete Fourier transform by

$$J_h(f) = \sum_{t \in T} h_t X_t e^{-2\pi ift} \quad (5)$$

where  $\|h_t\|_2^2 = 1$  (we assume the mean is known to be zero, so do no mean correction). Show that

$$J_h(f) = \frac{1}{\Delta} \int_{-1/2\Delta}^{1/2\Delta} H(f - f') dZ(f'). \quad (6)$$

### Solution 11.4

We see from the definition that

$$\begin{aligned} J_h(f) &= \sum_{t \in T} h_t X_t e^{-2\pi ift} \\ &= \sum_{t \in T} h_t \int_{-1/2\Delta}^{1/2\Delta} e^{2\pi if't} dZ(f') e^{-2\pi ift} \\ &= \frac{1}{\Delta} \int_{-1/2\Delta}^{1/2\Delta} \Delta \sum_{t \in T} h_t e^{2\pi i(f' - f)t} dZ(f') \\ &= \frac{1}{\Delta} \int_{-1/2\Delta}^{1/2\Delta} H(f - f') dZ(f'). \end{aligned}$$

### Exercise 11.5

If  $\{X_t\}$  is a stationary series, define  $\{Y_t\} = (I - B)[\{X_t\}]$ . Is  $Y_t$  stationary? If so, what is the spectral density function of  $\{Y_t\}$  in terms of the spectral density function of  $\{X_t\}$ ?

### Solution 11.5

Note that  $(I - B)$  is an LTI filter with impulse response in  $\ell_1$ , so from Theorem 9.11  $\{Y_t\}$  is stationary. Now we may use Theorem 9.12 to compute the spectral density function. In particular, the transfer function of this filter is given by

$$H(f) = 1 - e^{-2\pi if\Delta}, \quad (7)$$

and so

$$\begin{aligned} S_Y(f) &= |1 - e^{-2\pi if\Delta}|^2 S_X(f) \\ &= 2(1 - \cos(2\pi f\Delta)) S_X(f) \\ &= 4 \sin^2(\pi f\Delta) S_X(f). \end{aligned}$$

### Exercise 11.6

For this question we fix  $\Delta = 1$ . In lecture 3, we claimed that AR(p) processes were time reversible. In other words, If  $\{X_t\}$  is an AR(p) process, then if  $\{Y_t\}$  is such that for all  $t \in \mathbb{Z}$ ,  $Y_t = X_{-t}$ , then  $Y_t$  is an AR(p) process with the same parameters as  $X_t$ . Specifically, if  $X_t$  had an AR representation

$$X_t = \sum_{j=1}^p \phi_j X_{t-j} + \epsilon_t \quad (8)$$

then

$$Y_t = \sum_{j=1}^p \phi_j Y_{t-j} + \tilde{\nu}_t \quad (9)$$

where  $\tilde{\nu}_t$  has the same distribution as  $\epsilon_t$ . Prove this result.

### Solution 11.6

Let  $\phi_0 = -1$ , and define

$$\tilde{\nu}_t = \sum_{j=0}^p \phi_j Y_{t-j}.$$

All that remains is to show that  $\tilde{\nu}_t$  is Gaussian white noise with mean zero and variance  $\sigma_\epsilon^2$ . Clearly it is Gaussian as it is a linear combination of Gaussians. Furthermore,  $\mathbb{E}[X_t] = 0$ , so  $\mathbb{E}[\tilde{\nu}_t] = 0$  by linearity.

Now, we see that for all  $\tau \in \mathbb{Z}$

$$\begin{aligned} \gamma_\tau^{(Y)} &= \mathbb{E}[Y_t Y_{t+\tau}] \\ &= \mathbb{E}[X_{-t} X_{-\tau}] \\ &= \gamma_{-\tau}^{(X)} \\ &= \gamma_\tau^{(X)}. \end{aligned}$$

Therefore  $S_Y(f) = S_X(f)$  for all  $f \in \mathbb{R}$ . Finally, we see that  $\{\tilde{\nu}_t\}$  results from applying an LTI filter to  $\{Y_t\}$ . In particular, from Lemma 9.13 and Theorem 9.12, we have

$$\begin{aligned} S_{\tilde{\nu}}(f) &= |\Phi(e^{-2\pi i f \Delta})|^2 S_Y(f) \\ &= |\Phi(e^{-2\pi i f \Delta})|^2 S_X(f) \\ &= \Delta \sigma_\epsilon^2 \left| \frac{\Phi(e^{-2\pi i f \Delta})}{\Phi(e^{-2\pi i f \Delta})} \right|^2 \\ &= \Delta \sigma_\epsilon^2 \end{aligned}$$

where the penultimate line follows from Theorem 9.14. Therefore, we know that  $\tilde{\nu}$  is white noise with variance  $\sigma_\epsilon^2$ .