Chapter 8: DFT for time series MATH5802M

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LSpectral density and autocovariance

8.1 Spectral density and autocovariance

Let $X_0, X_1, \ldots, X_{n-1}$ be a time series. Then 1. Recall $\widehat{X}_0 = \sqrt{n}\widetilde{X}$, where \widetilde{X} is the sample mean.

- 2. If $\tilde{X}=0$, we obtain

$$\operatorname{var}(X) \approx \int_0^1 I(f) \, \mathrm{d}f. \tag{1}$$

Then $\int_a^b I(f_j) df$ quantifies the variance contributed by the frequency range [a,b]

Link to autocovariance

3. If g_k is the lag-k sample autocovariance of X, then

$$I(f_j) = \sqrt{n} \ \widehat{g}_j.$$

If X is periodic, we have $g_{n-k}=g_k$ Therefore,

$$I(f_j) = g_0 + 2 \sum_{1 \leqslant k < \frac{n}{2}} g_k \cos(2\pi f_j k) + g_{\frac{n}{2}}(-1)^j$$
 if n even.

The spectral density I is an estimate for the power spectrum

$$\mathcal{I}(f) = \gamma_0 + 2 \sum_{k=1}^{\infty} \gamma_k \cos(2\pi fk).$$

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Spectral density of white noise

8.2 Spectral density of white noise

Let $X_t \sim \mathsf{N}(0,\sigma^2)$, i.i.d. Then \widehat{X}_j is (complex) normally distributed with $\mathbb{E}(\operatorname{Re}\widehat{X}_j) = \mathbb{E}(\operatorname{Im}\widehat{X}_j) = 0$.

For the variances and covariances, we get

$$\operatorname{var}(\operatorname{Re}\widehat{X}_j) = \left\{ \begin{array}{ll} \sigma^2 & \text{if } j \in \{0, \frac{n}{2}\} \\ \frac{\sigma^2}{2} & \text{if } j \not \in \{0, \frac{n}{2}\}, \end{array} \right.$$

$$\operatorname{var}(\operatorname{Im} \widehat{X}_j) = \left\{ \begin{array}{ll} 0 & \text{if } j \in \{0, \frac{n}{2}\} \\ \frac{\sigma^2}{2} & \text{if } j \not \in \{0, \frac{n}{2}\}, \end{array} \right.$$

$$\operatorname{\mathsf{cov}}(\operatorname{\mathsf{Re}}\widehat{X}_j,\operatorname{\mathsf{Im}}\widehat{X}_j)=0.$$

Also, $\widehat{X}_j, \widehat{X}_k$ are uncorrelated for $j \neq k$.

/(fj)	$\sigma^2 \chi_1^2$	$\frac{\sigma^2}{2}\chi_2^2$	$\sigma^2\chi_1^2$ only for even n
$\mathbb{E}\{I(f_j)\}$	σ^2	$\frac{\sigma^2}{2} + \frac{\sigma^2}{2} = \sigma^2$	σ^2
${\sf Im} \widehat{X}_j$	0	$N(0, \frac{\sigma^2}{2})$	0
$\operatorname{Re} \widehat{X}_j$	$N(0, \sigma^2)$	$N(0, \frac{\sigma^2}{2})$	$N(0, \sigma^2)$
j	0	$1 \leq j < \frac{n}{2}$	r N

On average, all frequencies contribute the same (hence the name "white noise").

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 \sqcup Spectral density of AR(p)

8.3 Spectral density of AR(p)

Let X be given by

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \dots + \alpha_p X_{t-p} + \varepsilon_t,$$

where $arepsilon_t \sim \mathcal{N}(0, \sigma^2)$ i.i.d. What is the DFT of X?

DFT of AR(p)

Recall

$$Y_t = X_{t-1} \Rightarrow \widehat{Y}_j = e^{-2\pi i f_j} \widehat{X}_j,$$

and if $Z_t = X_t + Y_t$ then

$$\widehat{Z}_j = a\widehat{X}_j + b\widehat{Y}_j.$$

Hence we obtain

$$\widehat{X}_j = \frac{\widehat{\varepsilon}_j}{1 - \sum_{k=1}^p \alpha_k e^{-2\pi i f_j \cdot k}}.$$

and

$$\mathbb{E}[I(f_j)] = \frac{\sigma^2}{|1 - \sum_{k=1}^p \alpha_k e^{-2\pi i f_j \cdot k}|^2}.$$

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 \sqcup Spectral density of AR(p)

AR(1),
$$X_t = \alpha X_{t-1} + \varepsilon_t$$

$$\mathbb{E}[I(f_j)] = \frac{\sigma^2}{1 - 2\alpha \cos(2\pi f_j) + \alpha^2}$$

 σ^2

