

3F3 - Ex. paper 2

Q1 $\{X_m\}_{m \geq 0}$ states $S = \{1, \dots, L\}$

Transition probabilities given by:

$$p(i_m | i_{m-1}, \dots, i_0) = P_{i_{m-1}, i_m}, \quad i_l \in S$$

a) Show $p(i_2 | i_1) = P_{i_1, i_2}$ $\leftarrow l \geq 1$

S.l.: In principle we don't know $p(i_2 | i_1)$

$$\begin{aligned} p(i_2 | i_1) &= \frac{p(i_2, i_1)}{p(i_1)} = \frac{1}{p(i_1)} \sum_{i_0=1}^L p(i_0, i_1, i_2) \\ &= \frac{1}{p(i_1)} \sum_{i_0 \in S} p(i_2 | i_1, i_0) \cdot p(i_1, i_0) \\ &= P_{i_1, i_2} \underbrace{\frac{1}{p(i_1)} \sum_{i_0 \in S} p(i_1, i_0)}_{= 1} \xrightarrow{P_{i_1, i_2}} p(i_1) \end{aligned}$$

b) Same reasoning:

$$p(i_m | i_{m-1}) = \frac{p(i_m, i_{m-1})}{p(i_{m-1})}$$

$$= \frac{1}{p(i_{m-1})} \sum_{i_0 \in S} p(i_0, i_{m-2}, i_{m-1}, i_m)$$

$$= \frac{1}{p(i_{m-1})} \sum_{i_0, \dots, i_{m-2} \in S} p(i_m | i_0, \dots, i_{m-1}) \cdot p(i_0, \dots, i_{m-1})$$

$$= P_{i_{m-1}, i_m} \cdot \frac{1}{p(i_{m-1})} \cdot \left(\sum_{i_0, \dots, i_{m-2}} p(i_0, \dots, i_{m-1}) \right)$$

Q2 Benoulli process with prob q
 (i.e. $p(X_m = 1) = q$, $p(X_m = -1) = 1 - q$)

a) Prob. as a pmf:

$$(*) \quad p(X_0, \dots, X_m) = \prod_{i=0}^m p(X_i = X_i) = q^{\#X_i=1} \cdot (1-q)^{\#X_i=-1}$$

because the prob. of each state is independent

• Transition probabilities (i.e. probability matrix)

$$p(X_m = 1 | X_{m-1} = 1) = p(X_m = 1 | X_{m-1} = 0) = q$$

$$p(X_m = -1 | X_{m-1} = 1) = p(X_m = -1 | X_{m-1} = 0) = (1 - q)$$

$$P = \begin{bmatrix} p(X_m = 1 | X_{m-1} = 1) & p(X_m = 1 | X_{m-1} = -1) \\ \dots & \dots \\ p(X_m = -1 | X_{m-1} = 1) & p(X_m = -1 | X_{m-1} = -1) \end{bmatrix} = \begin{bmatrix} q & 1-q \\ 1-q & q \end{bmatrix}$$

b) It can be argued from (*) that, since values at each time-step are and identically distributed independent, the process is unaffected by time shifts:

$$p(X_0 - X_m) = p(X_k - X_{k+m}) = \prod p(X_i = X'_i)$$

with X'_i either the value of X_i or X_{k+i} . Then it is strictly stationary.

However, we can also stick to the characterisation of WSS:

1. Common mean for all X_m : $\mathbb{E}(X_m) = (1)q + (-1) \cdot (1-q) = 2q - 1$
2. Finite variance: $\mathbb{E}(X_m^2) = 1^2 \cdot q + (-1)^2 \cdot (1-q) = 1$ due to independence
3. Lag-dependent autocovariance function: $\mathbb{E}(X_m X_{m+k}) = \underbrace{\mathbb{E}(X_m) \mathbb{E}(X_{m+k})}_{= (2q-1)^2}$

And the result holds regardless of lag k .

Q3 $S = \{1, \dots, L\}$, $\{X_n\}_{n \geq 0}$ taking values in S

$$p(X_0 = X_s) = \lambda_s \quad X_s \text{ any state } \in S$$

$$\sum_{s \in S} \lambda_s = 1$$

$P = \begin{bmatrix} \lambda_1 & \dots & \lambda_L \\ \vdots & \ddots & \vdots \\ \lambda_1 & \dots & \lambda_L \end{bmatrix}$ is the transition prob. matrix.

- Show that $\{X_n\}_{n \geq 0}$ is strictly stationary

From matrix P , $p(X_n = X_s | X_{n-1} = X_{s'}) = \lambda_s$ regardless of s' (the previous state)

$$\underline{\text{pmf}}: p(X_0, \dots, X_m) = p(x_0) \cdot p(x_1|x_0) \cdot \dots \cdot p(x_m|x_{m-1}) \cdot \lambda_{x_0} \cdot \lambda_{x_1} \cdot \dots \cdot \lambda_{x_m}$$

Strictly stationary: $p(x_0 - x_m) = p(x_k - x_{k+m})$ Just From the definition of a Markov chain

$$\cdot p(x_k, \dots, x_{k+m}) = p(x_k) \cdot p(x_{k+1}|x_k) \dots p(x_{m+k}|x_{m+k-1})$$

Transition probs. remain invariant:

$p(x_{m+k}|x_{m+k-1}) = \lambda_{x_{m+k}}$ whatever value $x_{m+k} \in S$ may take. But we don't know $p(x_k)$

Let's calculate $p(x_1)$ [the marginal of X_1]

$$p(x_1) = \sum_{x_0 \in S} p(x_0, x_1) = \sum_{x_0 \in S} p(x_0) \cdot p(x_1|x_0) = \lambda_{x_1} \cdot \left(\sum_{x_0=1}^S \lambda_{x_0} \right)^1$$

Advancing the same marginalisation $(k-1)$ steps, we conclude $p(x_k)$ and $p(x_0)$ are the same pmf, then $p(x_0 - x_m) = p(x_k - x_{m+k})$.

Q4

AR(1)

$$X_m = aX_{m-1} + W_m$$

from independence: $\mathbb{E}(W_m W_n) = 0$
whenever $m \neq n$

$$|a| < 1 \quad W_m \text{ iid. and } \mathbb{E}(W_m) = 0 \quad \mathbb{E}(W_m^2) = \sigma^2$$

a) Assume X_m has constant mean M , find μ .

$$\underbrace{\mathbb{E} X_m}_{\mu} = a \underbrace{\mathbb{E} X_{m-1}}_{\mu} + \underbrace{\mathbb{E} W_m}_{0}$$

$$\mu = a\mu$$

Since $|a| < 1$, the only value satisfying the Eq. is $\mu = 0$

b) Assuming $\text{Var}(X_m) = \sigma_X^2$, find σ_X

$$\text{Var}(X_m) = \text{Var}\{aX_{m-1} + W_m\}$$

$$\sigma_X^2 = \mathbb{E}\{(aX_{m-1} + W_m - \underbrace{\mathbb{E}\{aX_{m-1} + W_m\}}_0)^2\}$$

$$\sigma_X^2 = \mathbb{E}\left\{a^2 X_{m-1}^2 + 2a X_{m-1} \cdot W_m + W_m^2\right\}$$

$$\sigma_X^2 = a^2 \sigma_X^2 + 2a \mathbb{E}(X_{m-1} W_m) + \underbrace{\mathbb{E} W_m^2}_{\sigma^2}$$

$$X_{m-1} = aX_{m-2} + W_{m-1}$$

only contains realizations of W
in times $< m \Rightarrow$ All expected values
of products are zero $\Rightarrow \mathbb{E} X_{m-1} W_m = 0$

$$\boxed{\sigma_X^2 = \frac{\sigma^2}{1-a^2}}$$

Q5 Determine if the following processes are WSS.

a) $X_m = U$, U a random variable.

1. Mean: $\mathbb{E} X_m = \mathbb{E}(U)$. it depends on whether U has a defined mean

2. Finite variance $\mathbb{E} X_m^2 = \mathbb{E} U^2$

3. Auto covariance $\mathbb{E} X_m X_{m+k} = \mathbb{E} U^2 \Rightarrow$ not lag-dependent

The process is WSS provided both $\mathbb{E}(U)$ and $\mathbb{E}(U^2)$ are finite.

b) $X_m = A \cos(mf_0) + B \sin(mf_0)$

A, B satisfy $\mathbb{E}(A) = 0$, $\mathbb{E}(B) = 0$, $\mathbb{E}(AB) = 0$
 $\mathbb{E}(A^2) = 1$ $\mathbb{E}(B^2) = 1$

1. $\mathbb{E}(X_m) = \underbrace{\mathbb{E}(A)}_0 \cdot \cos(mf_0) + \underbrace{\mathbb{E}(B)}_0 \cdot \sin(mf_0) = 0$ for all m
 (the sinusoids are deterministic)

2. $\mathbb{E}(X_m^2) = \mathbb{E}\{A^2 \cos^2(mf_0) + B^2 \sin^2(mf_0) - 2AB \cos(mf_0) \sin(mf_0)\}$
 $= \mathbb{E}(A^2) \cos^2(mf_0) + \mathbb{E}(B^2) \sin^2(mf_0) + 2\mathbb{E}(AB) \cancel{- etc}$
 $= 2 \cdot \{\cancel{\cos^2(mf_0) + \sin^2(mf_0)}^1\}$
 $= 2$ finite and same value for all n .

3. $\mathbb{E} X_m X_{m+k} = \mathbb{E}\{(A \cos(mf_0) + B \sin(mf_0))(A \cos((m+k)f_0) + B \sin((m+k)f_0))\}$
 $= \mathbb{E}\{A^2 \cos(mf_0) \cos((m+k)f_0) + B^2 \sin(mf_0) \sin((m+k)f_0) + AB \cdot \{\dots\}\}$
 $= 2 \cdot [\cos(mf_0) \cos((m+k)f_0) + \sin(mf_0) \sin((m+k)f_0)]$

From data book (standard trigonometric identity):

$$\sin x \sin y = \frac{1}{2} [\cos(x-y) - \cos(x+y)]$$

$$\cos x \cos y = \frac{1}{2} [\cos(x-y) + \cos(x+y)]$$

Replacing in $\mathbb{E} X_m X_{m+k}$

$$\begin{aligned}\mathbb{E} X_m X_{m+k} &= 2 \cdot \left\{ \underbrace{\frac{1}{2} [\cos(f_0 \cdot (-k)) + \cos(f_0 \cdot (2m+k))]}_{\cos(f_0 m) \cos(f_0(m+k))} \right. \\ &\quad \left. + \underbrace{\frac{1}{2} [\cos(f_0(-k)) + \cos f_0(2m+k)]}_{\sin(f_0 m) \sin((m+k)f_0)} \right\}\end{aligned}$$

$$= \cos(f_0 k)$$

(cosine is an even function:
 $\cos(-a) = \cos(a)$)

\Rightarrow WSS

Q5 c. $Y_m = X_m - X_{m-1}$

$$1. \mathbb{E} Y_m = \mathbb{E} X_m - \mathbb{E} X_{m-1} = 2 \mathbb{E} X_m = 2 \cdot (2q - 1)$$

$$\begin{aligned} 2. \mathbb{E} Y_m^2 &= \mathbb{E} \{X_m^2 + X_{m-1}^2 - 2 X_m X_{m-1}\} \\ &= \cancel{\mathbb{E} X_m^2} + \cancel{\mathbb{E} X_{m-1}^2} - 2(2q - 1)^2 = 2(1 - [2q - 1]^2) \\ &= 2 \cdot (4q^2 - 4q^2) \\ &= 8q(1 - q) \end{aligned}$$

Both $\mathbb{E} Y_m$ and $\mathbb{E} Y_m^2$ are finite and equal for all m

$$\begin{aligned} 3. \mathbb{E} Y_m Y_{m+k} &= \mathbb{E} \{(X_m - X_{m-1})(X_{m+k} - X_{m+k-1})\} \\ &= \mathbb{E} \{X_m X_{m+k} - X_m X_{m+k-1} - X_{m-1} X_{m+k} + X_{m-1} X_{m+k-1}\} \end{aligned}$$

$$|k|=1 \Rightarrow \mathbb{E} Y_m Y_{m+k} = (2q - 1)^2 - 1$$

$$|k| \geq 2 \Rightarrow \mathbb{E} Y_m Y_{m+k} = 0$$

Then it depends on $|k|$ and not $(m, m+k)$

WSS ✓

$$\boxed{Q6} \quad AR(1): \quad X_m = \alpha X_m + W_m$$

$$|\alpha| < 1, \mathbb{E} W_m = 0, \mathbb{E} W_m^2 = \sigma^2, \mathbb{E} W_m W_{m+k} = 0 \quad m \neq k$$

$$a) \mathbb{E}(X_m X_{m+k})$$

Note that X_{m+k} can be expressed as a function of X_m and the "noises" W_{m+1}, \dots, W_{m+k} (for $k > 0$)

$$X_{m+k} = \alpha X_{m+k-1} + W_m$$

$$= \alpha \cdot [\alpha X_{m+k-2} + W_{m+k-1}] + W_m$$

$$= \alpha [\alpha [\alpha X_{m+k-3} + W_{m+k-2}] + W_{m+k-1}] + W_m$$

= ...

$$= \alpha^k X_m + \underbrace{\sum_{l=0}^{k-1} \alpha^l W_{m+k-l}}_{\text{contains terms from } W_{m+1} \text{ to } W_{m+k}}$$

contains terms from

W_{m+1} to W_{m+k}

$$\text{then } \mathbb{E} X_m X_{m+k} = \mathbb{E} \alpha^k X_m^2 + \mathbb{E} \left(X_m \cdot \sum_{l=0}^{k-1} \alpha^l W_{m+k-l} \right)$$

But $\mathbb{E} X_m W_{m+k-l} = 0$ for all l because X_m contains noises up to W_m whereas W_{m+k-l} ranges from $m+1$ to $m+k$

$$\mathbb{E} X_m X_{m+k} = \alpha^k \mathbb{E} X_m^2 = \alpha^k \left(\frac{\sigma^2}{1-\alpha^2} \right) \text{ from Q4.}$$

For negative lags the same reasoning can be applied:

$$\mathbb{E} X_m X_{m-k} = \mathbb{E} X_m X_{m+k}$$

($m = m-k$), concluding

$$R(-k) = R(k)$$

$$\boxed{\mathbb{E} X_m X_{m+k} = R_X(k) = \frac{\alpha^{|k|} \sigma^2}{1-\alpha^2}}$$

$$Q6.b] \quad S_x(f) = \sum_{k=-\infty}^{\infty} R_x(k) \exp(i 2\pi f k)$$

- if $R_x(k)$ is real and even:

$$S_x(f) = R_x(0) + 2 \sum_{k=1}^{\infty} R_x(k) \cos 2\pi f k$$

(real parts are equal and imaginary part is the additive inverse)

$$S_x(f) = \frac{\sigma^2}{1-a^2} \left[1 + 2 \left(-1 + \underbrace{\sum_{k=0}^{\infty} a^k \cos 2\pi f k}_{(*)} \right) \right]$$

(*) can be calculated as a special case of z-transform.
However, we'll simply use convergent series arguments.

$$\sum_{k=0}^{\infty} a^k \exp(-2\pi f k) = \left(\sum_{k=0}^{\infty} a^k \cos 2\pi f k \right) + i \left(\sum_{k=0}^{\infty} a^k \sin 2\pi f k \right)$$

(*) is simply the real part of the series above.

$$(*) = \operatorname{Re} \left\{ \sum_{k=0}^{\infty} r^k \right\} = \operatorname{Re} \left\{ \frac{1}{1-r} \right\} = \operatorname{Re} \left[\frac{1}{1 - a \cos 2\pi f - i \sin 2\pi f} \right]$$

$$= \operatorname{Re} \left[\frac{1 - a \cos 2\pi f + i \sin 2\pi f}{(1 - a \cos 2\pi f)^2 + a^2 \sin^2 2\pi f} \right] = \frac{1 - a \cos 2\pi f}{1 - 2a \cos 2\pi f + a^2}$$

$$\begin{aligned} S_x(f) &= \frac{\sigma^2}{1-a^2} \left[-1 + 2 \frac{1 - a \cos 2\pi f}{1 - 2a \cos 2\pi f + a^2} \right] \\ &= \frac{\sigma^2 \left[(-1) + 2a \cos 2\pi f - a^2 + 2 - 2a \cos 2\pi f \right]}{[1 - 2a \cos 2\pi f + a^2][1 - a^2]} \end{aligned}$$

$$= \frac{\sigma^2}{1 - 2a \cos 2\pi f + a^2}$$

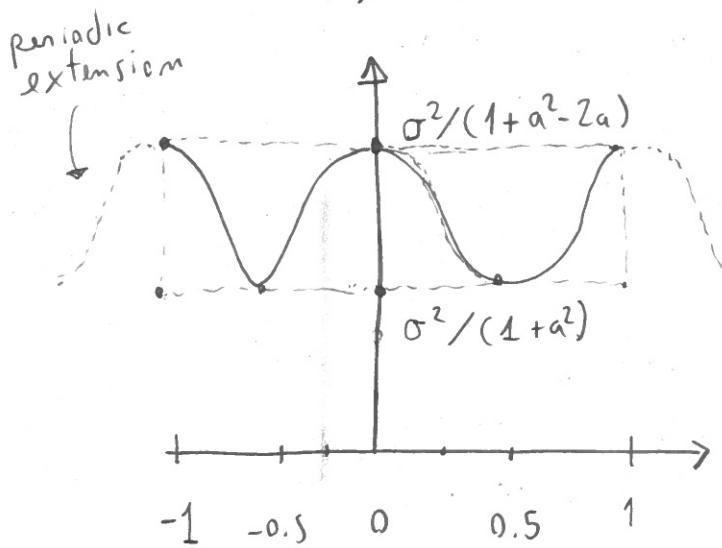
Q6.C $R_x(0) = \frac{\sigma^2}{1-a^2} = 5.26$

$$R_x(1) = \frac{\sigma^2}{1-a^2} \cdot a = 4.74$$

$$a = R_x(1)/R_x(0) \sim 0.9$$

$$\sigma^2 \sim 5.26 \cdot (1 - 0.9^2) = 0.999 \sim 1$$

$$S_x(f)$$



$$S_x(f)$$

$$= \frac{\sigma^2}{1+a^2-2a} \quad f=0$$

$$= \frac{\sigma^2}{1+a^2} \quad f=1/4$$

$$= \frac{\sigma^2}{1+a^2+2a} \quad f=1/2$$

$$= \frac{\sigma^2}{1+a^2} \quad f=3/4$$

$$= \frac{\sigma^2}{1+a^2-2a} \quad f=1$$

$$Q7 \quad X_0 \sim N(\mu, \sigma_0^2)$$

$$X_K \sim N(aX_{K-1}, \sigma^2)$$

equivalently

$$X_0 \sim N(\mu, \sigma_0^2)$$

$$W_K \sim N(0, \sigma^2)$$

$$X_K = aX_{K-1} + W_K$$

find mean and covariance of the random vector $X_0 - X_K$

Sol 1

$$p_X(X_0, X_1 - X_K) = p(X_0) \cdot p(X_1 | X_0) \cdots p(X_K | X_{K-1}) \quad (*)$$

Is it clear?

$$p(X_0, X_1 - X_K) = \underbrace{p(X_K | X_0 - X_{K-1})}_{= p(X_K | X_{K-1})} \cdot \underbrace{p(X_0 - X_{K-1})}_{= p(X_{K-1} | X_0 - X_{K-2}) \cdot p(X_0 - X_{K-2})}$$

$$p(X_0, X_1 - X_K) = N(X_K | aX_{K-1}, \sigma^2) \cdot N(X_{K-1} | aX_{K-2}, \sigma^2) \cdot (\dots)$$

- Although valid, the representation provided by the pdf $(*)$ is not easily amenable for a characterization in terms of mean and covariance.

- Instead, note that X_0 and $W_1 - W_K$ are independent

$$\begin{aligned} \text{Then } p_{XW}(X_0, W_1 - W_K) &= p(X_0) \prod_{l=1}^K p(W_l) \\ &= N(X_0 | \mu, \sigma_0^2) \prod_{l=1}^K N(W_l | 0, \sigma^2) \end{aligned}$$

It's easy to see that $X_0 - X_K$ is a linear transformation of $X_0, W_1 - W_K$

$$A \left\{ \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a & 1 & 0 & \cdots & 0 \\ a^2 & a & 1 & 0 & \cdots \\ \vdots & \vdots & \vdots & \ddots & a \\ a^K & \cdots & a & \cdots & a \end{bmatrix} \begin{bmatrix} X_0 \\ W_1 \\ \vdots \\ W_K \end{bmatrix} \right\} = \begin{bmatrix} X_0 \\ aX_0 + W_1 \\ \vdots \\ a^K X_0 + \sum_{l=0}^{K-1} a^l W_{K-l} \end{bmatrix}$$

Using change of variables:

$$A \begin{bmatrix} x_0 \\ w_1 \\ \vdots \\ w_K \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_K \end{bmatrix} \Rightarrow \begin{bmatrix} x_0 \\ w_1 \\ \vdots \\ w_K \end{bmatrix} = A^{-1} \begin{bmatrix} x_0 \\ \vdots \\ x_K \end{bmatrix} = \begin{bmatrix} (A^{-1})x_0 \\ A^{-1}x_1 \\ \vdots \\ A^{-1}x_K \end{bmatrix}$$

$H(x) = A^{-1}x$ is the inverse function we need in the change of variables formula.

$$p(x_0 - x_k) = p_{\text{rw}}(A_0^{-1}x, A_1^{-1}x, \dots, A_K^{-1}x) \cdot |A^{-1}|$$

$$|A^{-1}| = |A|^{-1}$$

$|L| = \text{prod. of the diagonal terms}$

if L is triangular

$$= \frac{N(A_0^{-1}x | \mu, \sigma^2)}{|A|} \cdot \prod_{l=1}^K N(A_l^{-1}x | 0, \sigma^2)$$

$$= \frac{1}{\sqrt{2\pi^{k+1} \sqrt{\sigma^2}^k \sqrt{\sigma_0^2} |A|}} \exp \left\{ -\frac{1}{2} \frac{(A_0^{-1}x - \mu)^2}{\sigma_0^2} \right\} \cdot \prod_{l=1}^K \exp \left\{ -\frac{1}{2} \frac{(A_l^{-1}x)^2}{\sigma^2} \right\}$$

Rearranging

$$= \text{const.} \cdot \exp \left\{ -\frac{1}{2} \left[A^{-1}x - \begin{bmatrix} \mu \\ 0 \\ \vdots \\ 0 \end{bmatrix} \right]^T \Sigma^{-1} \left[A^{-1}x - \begin{bmatrix} \mu \\ 0 \\ \vdots \\ 0 \end{bmatrix} \right] \right\}$$

$$= \text{const.} \cdot \exp \left\{ -\frac{1}{2} \left[x - A \begin{bmatrix} \mu \\ 0 \\ \vdots \\ 0 \end{bmatrix} \right]^T A^{-T} \Sigma^{-1} A^{-1} \left[x - A \begin{bmatrix} \mu \\ 0 \\ \vdots \\ 0 \end{bmatrix} \right] \right\}$$

$$\Sigma_x = \begin{bmatrix} M \\ aM \\ a^2M \\ \vdots \\ a^K M \end{bmatrix}$$

$$\Sigma_x = A \Sigma A^T$$

$$\Sigma = \begin{bmatrix} \sigma_0^2 & & & \\ & \ddots & & \\ & & 0 & \\ & & & \ddots & \sigma^2 \end{bmatrix}$$

The jacobian of a linear transformation is the matrix itself.
Calculate the partial derivatives yourself.

Q8

MA process

$$X_m = \sum_{i=1}^q b_i W_{m-i} + W_m$$

MA (q)

 $\{W_m\}_{m \in \mathbb{Z}}$

$\mathbb{E} W_m = 0$

white

$\mathbb{E} W_m^2 = \sigma^2$

$\mathbb{E} W_m W_n = 0$

if $m \neq n$ a) X_m as the output of a

LTI filter with infinite response

$h_K = 1 \quad k = 0$

$h_k = b_k \quad k \in \{1, \dots, q\}$

$h_k = 0 \quad k \notin \{0, 1, \dots, q\}$

b) $\stackrel{\text{wss}}{=} \mathbb{E}\{X_m\} = \mathbb{E} \sum_{i=1}^q b_i W_{m-i} + \mathbb{E} W_m = 0 \quad \checkmark$

2. $\mathbb{E}\{X_m^2\} = \mathbb{E}\left(\sum_{i=1}^q b_i W_{m-i} + W_m\right)^2 = \sigma^2 \left[1 + \sum_{i=1}^q b_i^2\right] \text{ finite}$

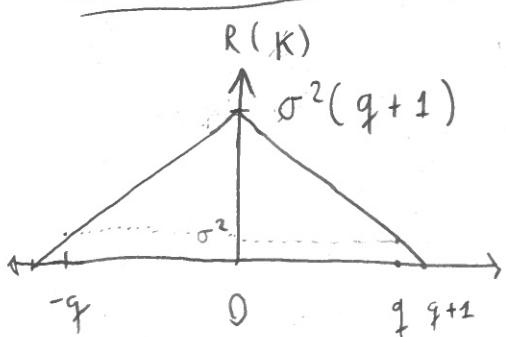
Because All cross-products satisfy $\mathbb{E}(\cdot \cdot \cdot) = 0 \quad \checkmark$

3. $\mathbb{E} X_m X_{m+k} = \sigma^2 \left[\sum_{l=0}^{q-k} b_l b_{l+k} \right] \quad (b_0 = 1)$

$R(k) = \sigma^2 \sum_{i=-\infty}^{\infty} h_i h_{i+k} \quad \checkmark$

It is wss \checkmark

c)



$R(k) = \sigma^2 (q+1 - |k|)$

\downarrow In that case all terms $b_l b_{l+k}$ are just 1

$$\sum_{i=0}^{q-1} b_i b_{i+k} = 1$$

$$\begin{aligned}
 \text{(d)} \quad S_X(f) &= \sum_{k=-2}^2 R(k) e^{-i2\pi f k} \\
 &= R(0) + 2R(1) \cos 2\pi f + 2R(2) \cos 4\pi f \\
 &= \sigma^2 \left[3 + 4 \cos 2\pi f + 2 \cos 4\pi f \right]
 \end{aligned}$$

for any b_1, b_2 :

$$\begin{aligned}
 &= \sigma^2 \left[(1 + b_1^2 + b_2^2) + 2 \left\{ (b_0 b_1 + b_2 b_1) \cos 2\pi f \right. \right. \\
 &\quad \left. \left. + b_0 b_2 \cos 4\pi f \right\} \right]
 \end{aligned}$$