

Statistical Signal Processing
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Lecture - 37
Linear Models of Random Signals 2

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Let us recall

- ❖ A general ARMA(p,q) model:

$$X(n) = \sum_{i=1}^p a_i X(n-i) + \sum_{j=0}^q b_j V(n-j)$$
- ❖ MA(q) model: $X(n) = \sum_{i=0}^q b_i V(n-i)$
- ❖ AR(p) model: $X(n) = \sum_{i=1}^p a_i X(n-i) + V(n)$
- ❖ ACF of an MA(q) process: nonlinearly related with parameters

$$R_X(m) = \begin{cases} \sum_{j=0}^{q-|m|} b_j b_{j+|m|} \sigma_V^2 & 0 \leq |m| \leq q \\ 0 & \text{otherwise} \end{cases}$$
- ❖ ACF of an AR(p) process: Yule Walker equations

$$R_X(m) = \sum_{i=1}^p a_i R_X(m-i) + \sigma_V^2 \delta(m), \forall m \in \mathbb{Z}$$
- ❖ AR(1) process $X(n) = a_1 X(n-1) + V(n)$, $|a_1| < 1$ is a Markov process

Hello students in this lecture i will discuss linear models of random signals 2. Let us recall a general ARMA p q model is given by X_n is equal to summation $a_i X$ of $n - i$ i going from 1 to p plus summation $b_j a$ of $n - j$ j going from 0 to q this is an ARMA p q model and we also discuss MA q model that is X_n is equal to summation $b_i V$ of $n - i$ i going from 0 to q AR p model autoregressive of order p that is X_n is equal to summation $a_i X$ of $n - i$ i going from 1 to p + V_n .

The ACF of an MA q process is non linearly related with parameters like this is the relationship R_x of m is equal to summation j is equal to 0 to $q - \text{mod of } m$ $b_j b$ of j plus $\text{mod of } m$ into σ_V^2 where $\text{mod of } m$ lies between 0 and q and otherwise R_x of m is 0. The ACF of an ERP process is given by the Yule Walker equations that is the set of linear equation R_x of m is equal to summation i is equal to 1 to p of a_i into R_x of $m - i$ + $\sigma_V^2 \delta(m)$ this is for all values of integer m .

Particularly we discussed about AR1 process X_n is equal to $a_1 X_{n-1} + V_n$ where $\text{mod of } a_1$ is less than 1 and this is required for stationarity of the signal and we have seen that this AR1 process is a Markov process.

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Example 3: AR(2) process given by

$$X(n) = a_1 X(n-1) + a_2 X(n-2) + V(n)$$

- ❖ The properties of the AR process can be studied with the help of the AR(2) model
- ❖ Linear filter transfer function is

$$H(z) = \frac{1}{1 - a_1 z^{-1} - a_2 z^{-2}}$$

- ❖ The PSD is given by

$$S_X(\omega) = \frac{\sigma_v^2}{|1 - a_1 e^{-j\omega} - a_2 e^{-2j\omega}|^2}$$

- ❖ The ACFs are given by the Yule Walker Equations

$$R_X[m] = a_1 R_X[m-1] + a_2 R_X[m-2] + \sigma_v^2 \delta[m], \quad m \in \mathbb{Z}$$

We will consider another example that is AR2 process given by X_n is equal to $a_1 X_{n-1} + a_2 X_{n-2} + V_n$ this is a very good example the properties of AR processes can be studied with the help of this model. Let us see firstly linear filter transfer function corresponding to this process this linear filter transfer function is given by $1 / (1 - a_1 z^{-1} - a_2 z^{-2})$. So, this is an all pole model it has two poles.

The PSD power spectral density of this process is given by $S_X(\omega)$ that is the power spectral density is equal to σ_v^2 divided by $|1 - a_1 e^{-j\omega} - a_2 e^{-2j\omega}|^2$. So, this is the power spectral density. The ACF's are given by the Yule Walker equations we can write down the Yule Walker equation that is $R_X[m]$ of m is equal to $a_1 R_X[m-1] + a_2 R_X[m-2] + \sigma_v^2 \delta[m]$ that is for all values of m integer.

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- ❖ For $\{X(n)\}$ to be stationary, the poles of $H(z)$ should lie inside the unit circle. Thus the roots of the characteristic equation

$z^2 - a_1 z - a_2 = 0$ should lie inside the unit circle.

- ✦ Roots are given by

$$p_1, p_2 = \frac{a_1 \pm \sqrt{a_1^2 + 4a_2}}{2}$$

so that $p_1 + p_2 = a_1$ and $p_1 p_2 = -a_2$.

each of p_1 and p_2 lies inside the unit circle, we get

$$|p_1 + p_2| < 2 \text{ and } |p_1 p_2| < 1 \Rightarrow |a_2| < 1 \text{ and } |a_1| < 2$$

- ❖ Particular cases:

(1) If p_1 and p_2 are complex then $a_1^2 + 4a_2 < 0 \Rightarrow a_2 < -\frac{a_1^2}{4}$

(2) If $p_1 = p_2$ then $a_1^2 + 4a_2 = 0 \Rightarrow a_2 = -\frac{a_1^2}{4}$

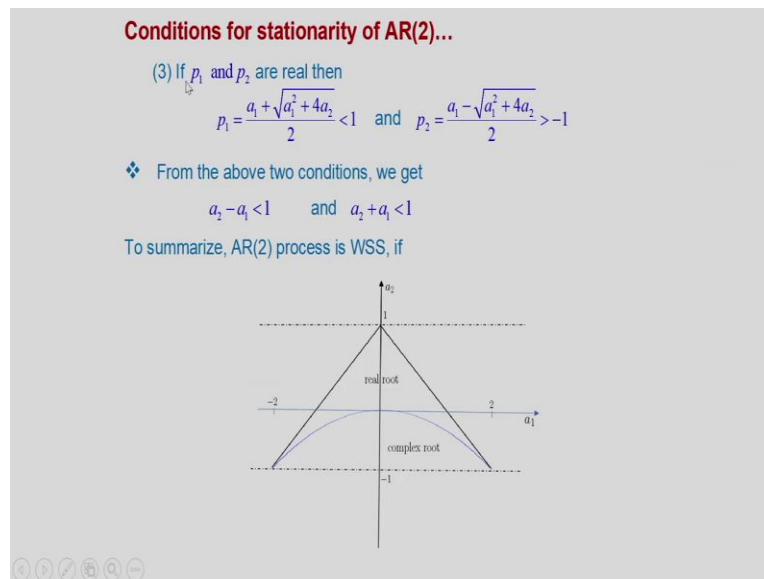
Now because AR2 process is an all pole model therefore for all values of a_1 and a_2 will not give stationarity. Let us consider the conditions for stationarity of AR2 process. For X_n to be stationary the poles of H_z to lie inside the unit circle that is the condition for stability that is the root of the characteristic equation because we can get the characteristic equation by putting the denominator is equal to 0 so that way denominator was we are H_z was $\Sigma V \text{ square } 1 - a_1 z$ to the power $-1 - a_2 z$ to the power -2 .

Now if i put this denominator is equal to 0 then we will get this equation. So, if we put this denominator is equal to 0 we will get this equation. Now the condition for stability of a Hz requires all the roots of this equation should lie inside the unit circle. Now roots are given right there will be two roots of this equation two roots p_1 and p_2 given by $\frac{-1 \pm \sqrt{1 - 4a^2}}{2}$. So, that if we consider the sum of the roots $p_1 + p_2$ is equal to -1 and product of the roots that is $p_1 p_2$ is equal to $-a^2$.

So we see that that a_1 and a_2 are related to the roots by this relationship ok. So, it is a_1 and p_2 lies inside the unit circle therefore we get this quantity because a_1 is nothing but mod of $p_1 + p_2$ therefore mod of $p_1 + p_2$ must be less than 2 and mod of p_1 into p_2 must be less than 1 and in turn these two conditions will imply that a_2 from here a_2 is less than 1 mod of a_2 is less than 1 and from this relationship we get that mod of a_1 is less than 2.

So that way a_1 will lie between -2 and 2 and a_2 will lie between -1 and 1 . Now let us consider the particular cases of the roots. So, p_1 and p_2 are complex then this part will be less than zero so $a_1^2 + 4a_2$ that must be less than 0 that will in turn imply that a_2 is less than $-a_1^2/4$. Now this region is a parabolic region and when roots are equal p_1 equal to p_2 then this term will be equal to 0 and in the case of a_2 equal to $-a_1^2/4$ we see the parabola.

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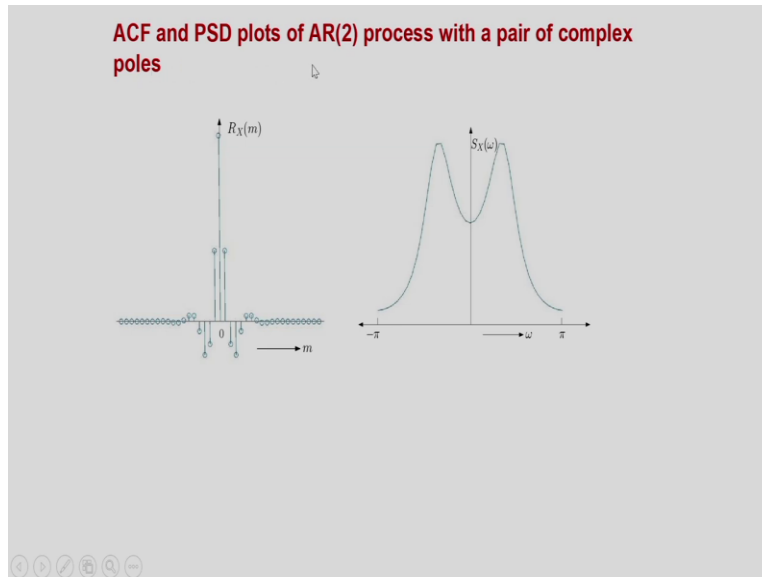


Now condition 3 if p_1 and p_2 are real then both roots p_1 and p_2 both their magnitude of both will be less than 1 now this is the larger root out of 2 this is the larger root therefore its value must be less than 1 and this is the smaller root because this minus sign, so this must be greater than -1 these are both real and from the stationarity conditions we get this. And from the above two conditions we will get that $a_2 - a_1 < 1$.

So if we simplify this condition $a_2 - a_1 < 1$ and $a_1 + a_2 < 1$ or $a_2 + a_1 < 1$ two conditions we get considering the real values of the poles. So, to summarize now AR2 processes WSS if suppose my a_1 and a_2 must be within this region. So, for real root it should be in this part for complex roots it should be inside this parabola. So, these are the conditions we get by analyzing the roots of the characteristic equation.

And in other words the AR 2 process is WSS a 1 and a 2 will lie within this triangular region then our roots will be stationary and if it lies inside this parabola then the roots will be complex and outside this parabola roots will be real.

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We can plot the ACF and PSD of AR2 process these are the plausibly simulated AR2 process and we see that this is a particular case for complex poles so the autocorrelation behaves like this both positive and negative values are there and power spectrum has a peak this is a negative side of the spectrum so there is a peak corresponding to this point. So, that way you suppose if we have a some dominant frequency component in a random process then we can get it by AR2 spectrum.

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State-space representation of AR(p) process

- ❖ AR(p) model: $X(n) = \sum_{i=1}^p a_i X(n-i) + V(n)$
- ❖ The p th order difference equation of the AR(p) model can be reduced to p first-order difference equations to give a state space representation of the random process.
- ❖ Suppose $\mathbf{Z}(n) = [Z_1(n) \ Z_2(n) \ \dots \ Z_p(n)]^T$ is a state vector where $Z_1(n) = x(n)$, $Z_2(n) = X(n-1)$, ..., $Z_p(n) = X(n-p+1)$ as states.
Clearly,
$$Z_2(n) = Z_1(n-1), Z_3(n) = Z_2(n-1), \dots, Z_p(n) = Z_{p-1}(n-1)$$
- ❖ We can also rewrite $X(n) = \sum_{i=1}^p a_i X(n-i) + V(n)$ as
$$Z_1(n) = a_1 Z_1(n-1) + a_2 Z_2(n-1) + \dots + a_p Z_p(n-1) + V(n)$$

We will introduce one important concept that is state space representation of AR(p) process that AR(p) model is $X(n)$ is equal to summation a_i into $X(n-i)$ i going from 1 to p + $V(n)$ the p th order difference equation this is the p th order difference equation of the AR(p) model can be reduced to p partial difference equations to give this space representation update random process. Now this is important thing because we have a p th order difference equation and corresponding to that we can get p first order difference equations.

And those will represent this state space equations. Suppose we define $Z(n)$ is equal to there are p th order differentiation therefore Δ^p States suppose $Z(n)$ is equal to z_1 and $z_2(n)$ up to $z_p(n)$ vector this is a vector comprising of these elements. Now each of this element will be called a state. Now let us define they Z_1 end to be $X(n)$ $Z_2(n)$ to be $X(n-1)$ and similarly $Z_p(n)$ to be $X(n-p+1)$. So, these p states are defined like this.

Now clearly how these states are related $Z_2(n)$ is equal to z_1 of $n-1$ $Z_3(n)$ is equal to Z_2 of $n-1$ like that $Z_p(n)$ is equal to Z_{p-1} of $n-1$ so now we have a difference equation relationship between state variables. We can also rewrite $X(n)$ is equal to summation $a_i X(n-i)$ i going from 1 to p + $V(n)$ as now we will start substitute these state variables corresponding to each of the terms we get $Z_1(n)$ is equal to a_1 into Z_1 of $n-1$ + a_2 into Z_2 of $n-1$ + up to Z_p into Z_p of $n-1$ + $V(n)$.

So this equation now $Z_1(n)$ is this similarly $Z_2(n)$ is Z_1 of $n - 1$ $Z_3(n)$ is equal to Z_2 of $n - 1$ etcetera this can be rearranged.

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State-space representation of AR(p) process...

❖ Rearranging the equations. We get

$$Z_1(n) = a_1 Z_1(n-1) + a_2 Z_2(n-1) + \dots + a_p Z_p(n-1) + V(n)$$

$$Z_2(n) = Z_1(n-1)$$

$$Z_3(n) = Z_2(n-1)$$

$$\vdots$$

$$Z_p(n) = Z_{p-1}(n-1)$$

$$\mathbf{Z}(n) = \mathbf{A}\mathbf{Z}(n-1) + \mathbf{B}V(n)$$

where $\mathbf{A} = \begin{bmatrix} a_1 & a_2 & \dots & a_p \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$ and $\mathbf{B} = [1 \ 0 \dots 0]^T$

❖ We can write $X(n)$ in terms of $\mathbf{Z}(n)$ as

$$X(n) = \mathbf{C}\mathbf{Z}(n)$$

where $\mathbf{C} = [1 \ 0 \dots 0]$

Rearranging the equations we get a $Z_1(n)$ is equal to a_1 into $Z_1(n-1)$ + a_2 into $Z_2(n-1)$ plus up to Z_p into $Z_p(n-1)$ + V_n so this is the representation first step. Similarly $Z_2(n)$ is equal to Z_1 of $n - 1$ $Z_3(n)$ is equal to Z_2 of $n - 1$ etc and finally get $Z_p(n)$ is equal to $Z_{p-1}(n-1)$, so that we can now write Z_n this is a Z_n state vector $\mathbf{Z}(n)$ which comprises of element $Z_1(n)$ $Z_2(n)$ up to $Z_p(n)$ that is the $\mathbf{Z}(n)$ vector it is a column vector is equal to \mathbf{A} matrix times $\mathbf{Z}(n-1)$ vector + \mathbf{B} matrix time V_n , V_n is a scalar only.

So, where \mathbf{A} is given by this matrix now it is p by p matrix first row is a_1 a_2 up to a_p second row is first element is 0 then 1 and rest of the elements are 0 and similarly last row is 0 0 last element is 1 so this is the \mathbf{A} matrix, these equations we are writing in terms of \mathbf{A} matrix equation. And similarly \mathbf{B} matrix is given by 1 0 0 rest of the elements are 0 transpose, transpose of this row vector so that we will get a column vector here.

We can also write $X(n)$ in terms of $\mathbf{Z}(n)$ suppose if we have to write $X(n)$ in terms of $\mathbf{Z}(n)$ then we can write $X(n)$ is equal to actually $Z_1(n)$ so that way if we write \mathbf{C} is equal to 1 0 0 up to 0 all the remaining elements are 0 if we consider \mathbf{C} to be this matrix this is a row vector actually then $X(n)$

will be C times Z_n so that way we can get suppose X_n , X_n is equal to C times C is now $1 \ 0 \ 0$ like that 0 into Z_n vector and Z_n vector is z_1 and like that up to Z of p_n .

So, if we multiply these two matrices we will get X_n is equal to $Z_1 n$ that is exactly what we have shown earlier $Z_1 n$ is equal to X_n that way or we can write X_n also that observed at all so in terms of state variable that is C times Z_n this model is known as the state variable model and this equation Z_n is equal to A into $Z_{n-1} + B$ into V_n this is known as the state equation and X_n is equal to C times Z_n that is known as the observation equation.

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Example State-space representation of AR(2) process

- ❖ AR(2) model: $X(n) = a_1 X(n-1) + a_2 X(n-2) + V(n)$
- ❖ Two states.
- ❖ The state space representation is given by

$$Z(n) = AZ(n-1) + BV(n)$$

$$X(n) = CZ(n)$$

where $A = \begin{bmatrix} a_1 & a_2 \\ 0 & 1 \end{bmatrix}$, $B = [1 \ 0]^T$ and $C = [1 \ 0]$

We shall consider one example that is AR2 model X_n is equal to $a_1 X$ of $n-1$ + a_2 into X of $n-2$ + V_n this is the AR2 model how to get this state space representation. There will be two states one is X_n and another one is X of $n-1$ this representation is given by now there will be two state vector Z_n is equal to A into $Z_{n-1} + V$ into V_n where X_n that is the observed data is equal to C times Z_n then what is A matrix where A is equal to $a_1 \ a_2 \ 0 \ 1$ this is a 2 by 2 matrix B is $1 \ 0$ transpose and C is $1 \ 0$ this is a row matrix.

So that way get this state space representation corresponding to this difference equation. So, this is a second order differential equation that we have converted into a matrix first order difference equation though the number of states is 2 here we can define the state variable representation in

different manners there are different ways to represent state variables but this is the model we will be using.

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ARMA(p,q) Model

- ❖ Under most practical situations, the WSS process may be considered as an output of a filter that has both zeros and poles
- ❖ Filter transfer function is given by

$$H(z) = \frac{\sum_{i=0}^q b_i z^{-i}}{1 - \sum_{i=1}^p a_i z^{-i}}$$
- ❖ The model is given by

$$X(n) = \sum_{i=1}^p a_i X(n-i) + \sum_{j=0}^q b_j V(n-j)$$
- ❖ The a_i parameters determine the stability of $H(z)$ and hence the wide-sense stationarity of $X(n)$.

Let us consider the ARMA p q model I am not in most practical situations the WSS process may be considered as an output of a filter that has both zeros and poles. So, ma model and AR model are particular cases in ma model we have only zeros in AR models we have poles but most generally we will have both poles and zeros. The filter transfer function corresponding to ARMA p q model is given by $H(z)$ is equal to this is the relationship ratio of summation b_i is e to the power - i i going from 0 to keep q divided by 1 - summation I going from 1 to p of a_i into z to the power - i.

This is the transfer function corresponding to a ARMA p q model. The model is given by X_n is equal to summation i going from 1 to p of $a_i X$ of $n - i$ + summation j going from 0 to q of $b_j V$ of $n - j$ this is the difference equation model for the ARMA p q model that filter $H(z)$ has both poles and zeros and stability is determined by poles only therefore the a_i parameters determine the stability of a $H(z)$ and hence the wide sense stationarity of X_n . So, X_n will be WSS under certain conditions on a_i 's.

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PSD and ACFs of ARMA(p,q) process

❖ The PSD of is given by

$$S_x(\omega) = \frac{\left| \sum_{i=0}^q b_i e^{-j\omega i} \right|^2}{\left| 1 - \sum_{i=1}^p a_i e^{-j\omega i} \right|^2}$$

❖ The ACFs are given by

$$\begin{aligned} R_x(m) &= E[X(n)X(n+m)] = \sum_{i=1}^p a_i E[X(n+m-i)X(n)] + \sum_{i=1}^q b_i E[V(n+m-i)X(n)] \\ &= \sum_{i=1}^p a_i R_x(m-i) + \sum_{i=1}^q b_i E[V(n+m-i)X(n)] \end{aligned}$$

Note that $X(n)$ is a function past $V(n)$ s and uncorrelated with future $V(n)$ s.

$\therefore E[V(n+m-i)X(n)] = 0$ if
 $n+m-i > n$ or $m > i$

$\therefore R_x(m) = \sum_{i=1}^p a_i R_x(m-i), \quad m \geq q+1$ (Yule Walker equations)

PSD and ACF's of ARMA p q process the PSD is given by $S_x(\omega)$ $S_x(\omega)$ is equal to this is the mod of the numerator term squared divided by mod of the denominator term square $S_x(\omega)$ is given by this ratio that is equal to summation i going from 0 to q $b_i e^{-j\omega i}$ whole mod square divided by $1 - \sum_{i=1}^p a_i e^{-j\omega i}$ whole mod square so this is the value for $S_x(\omega)$.

This is the expression for $S_x(\omega)$ and here in harm applicable model we consider from j is equal to 0 to q therefore there is a $b_0 V$ of n and this b_0 absorbs the variance of V_n so that way V_n will be considered as unit variance so that it is variance will be taken care off by b_0 so this b_0 here there will be an expression suppose there will be $b_0 V_0$ will be there and this $V_0, b_0 V_0$ n will be there and this V_0 n is now unit variance.

Because variance of the white noise process really taken care of by b_0 so that is why we do not have any σ_b^2 term here. The ACF of the ARMA p q process is given by this expression x, R_x of m by definition it is equal to e of X n into X of n + m now we will be writing X of n + m in terms of the difference equation model. So, that way we will have this summation i going from 1 to p X of n + m - i that way X of n + m will be written + b_i will be there.

The ACF's of X_n are given by this expression R_x of m equal to E of X n into X of n + m now we can write X of n + m this we can write as X of n + m is equal to summation $a_i X$ of n + m - i, i

going from 1 to $p + \text{summation } b_i$ $n + m - i$, i going from 0 to q we are expanding X of $n + m$ then this autocorrelation function will be given by summation i going from 1 to p a_i into E of X of $n + m - i$ into $X_n + \text{summation } i$ going from 0 to q of b_i into your V of $n + m - i$ into X_n .

So, this is the autocorrelation function of X_n at lag $m - i$ so that way we can write summation i is equal to 1 to p a_i into R_x of $m - i$ this X_n and X of $n + m - i$ so there are differences $m - i$ here and plus summation b_i into E of V of $n + m - i$ into X_n i going from 0 to q . So, this is the expression for autocorrelation function of X_n R_x of m is equal to this and we see that there are these b_i terms are contributing to this expression.

But we know that X_n is a function of past V_n 's and uncorrelated so that where action is uncorrelated with future V_n 's. So, suppose X_n and any future V_n 's for example V_{n+1} V_{n+2} etcetera uncorrelated because X_n is generated due to the earlier V_n 's so that way we can write E of V of $n + m - i$ into X_n is equal to 0 if suppose this quantity is greater than n and $n + m - q$ is greater than n okay so this term is greater than this so in the case we get m is greater if m is greater than q then this term will be equal to 0.

Therefore for m greater than equal to $q + 1$ we will get this equation R_x of m is equal to summation a_i into R_x of $m - i$, i going from 1 to p . So, this is part values of lag greater than equal to $q + 1$. So, this is the set of Yule Walker equation.

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Example 4: ARMA(1,1) process

❖ The model is given by

$$X(n) = a_1 X(n-1) + b_0 V(n) + b_1 V(n-1)$$

❖ For $X(n)$ to be WSS $|a_1| < 1$

❖ The PSD is given by

$$S_X(\omega) = \frac{|b_0 + b_1 e^{-j\omega}|^2 \sigma_V^2}{|1 - a_1 e^{-j\omega}|^2}, \quad -\pi \leq \omega \leq \pi$$

We can consider one example suppose ARMA 1, 1 process the model is given by X_n into a 1 X of $n - 1$ that is the AR part + b_0 into V_n + b_1 into V_{n-1} . Now here the condition for what is in stationarity will be determined by the a_1 parameters like AR1 process. So, mod of a_1 should be less than 1 for a White sense stationarity of X_n and the PSD will be again given by and this expression but here σ_V^2 we have already taken σ_V^2 is equal to 1.

So, that way this σ_b^2 will be equal to 1, so that way we have S_X of Ω is equal to $b_0 + b_1 e^{-j\Omega}$ whole mod square divided by $1 - a_1 e^{-j\Omega}$ whole mod square and for Ω lying between $-\pi$ and π , this is the expression for power spectral density.

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ACF of ARMA(1,1) process

❖ The ACF is given by

$$\begin{aligned} R_X(m) &= E[X(n+m)X(n)] \\ &= a_1 R_X(m-1) + b_0 EV(n+m)X(n) + b_1 EV(n+m-1)X(n) \end{aligned}$$

Therefore,

$$R_X(0) = a_1 R_X(-1) + b_0^2 = a_1 R_X(1) + b_0^2$$

$$R_X(1) = a_1 R_X(0) + b_1 b_0$$

$$R_X(m) = a_1 R_X(m-1), \quad m \geq 2$$

Solving we get

$$R_X(0) = \frac{b_0^2 + a_1 b_1 b_0}{1 - a_1^2}$$

ACF of ARMA 1, 1 process the ACF autocorrelation function is given by $R_X(m)$ that is $E[X(n+m)X(n)]$ and using the previous relation we can write this is equal to $a_1 R_X(m-1) + b_0 EV(n+m)X(n) + b_1 EV(n+m-1)X(n)$. Now $R_X(0)$ from this equation this part we can write $R_X(0)$ is equal to $a_1 R_X(-1)$ plus b_0^2 so this part b_0^2 again when m is equal to 0 suppose when m is equal to zero then this will be V_n into X_n and this will contribute b_0^2 into V_n squares.

So that way we will get here b_0^2 similarly $R_X(1)$ will be equal to $a_1 R_X(0) + b_1 b_0$ that way we will get $R_X(1)$ and these two equations $R_X(0)$ is given by this $R_X(1)$ is given by this they can be solved to find out $R_X(0)$ and $R_X(1)$. For m greater than equal to 2 now we will have the Yule Walker equation that is $R_X(m) = a_1 R_X(m-1)$. So, that way we can get the remaining autocorrelation functions like $R_X(2)$ we can get $R_X(3)$ etc we can obtain.

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Fitting of ARMA(p,q) model

- ❖ Given the autocorrelation functions, we can find the model parameters of an ARMA(p,q) process.
- ❖ The autocorrelation functions are estimated from data
- ❖ ARMA(p,q) is a more economical model. Only AR(p) or MA(q) model may require a large number of model parameters to represent the random data adequately. This concept in model building is known as *the parsimony of parameters*.

How to fit an ARMA p, q model, so given the autocorrelation functions we can find the model parameters of an ARMA p q process so because of the relationship between the autocorrelation functions and the model parameters we can find out the model parameters. The autocorrelation functions are estimated from data generally autocorrelation functions will be estimated from the data and those autocorrelation functions are used to estimate the model parameters.

ARMA p, q is more economical model economical means it is less number of parameters only AR p or MA q model may require a large number of model parameters. Suppose it were given data if i try to model by MA q model then this merely require very large value of q. so, only AR p or MA q model may require a large number of model parameters to represent the random data adequately that was given random data if we try to fit on the AP p and MA q model they may require large values of p and q.

Therefore if we use a ARMA p q model then a p and q need not be very large. This concept of model building is known as the parsimony of parameters. We should be parsimonious in selecting the parameters so that p and q should be as small as possible.

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ARMA(p, q) Model building Steps

- (1) Identify the parameters p and q .
- (2) Estimate the model parameters a_s and b_s .
- (3) Check the modeling error.
- (4) If it is white noise then stop.
Else select new values for p and q and repeat the steps 2-4.

We will broadly describe ARMA p, q model building steps, first step is identify the model order parameters p and q . After p and q are identified estimate the model parameters a_i 's and b_i 's check for the modeling error, if suppose we will find out the difference between actual sample value and the value predicted by the model. If it is white noise then stop so model building is over else select a new values of p and q and repeat these steps 2 to 4.

So that way we can build ARMA p, q model though this is a quite involving process in a nutshell these steps can be described as this.

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Models for nonstationary random processes

Most of the practical data are non-stationary. Operations like differencing, logarithm etc., may make data stationary. Two such models for nonstationary data are:

- ❖ **Autoregressive integrated moving average (ARIMA) model:** Here the differenced data $X(n) - X(n-1)$ can be modelled as an ARMA model.
- ❖ **Seasonal ARMA (SARMA) model:** Here the signal contains a seasonal fluctuation term. The signal after differencing by a step equal to the seasonal period, $X(n) - X(n-p)$ becomes stationary and ARMA model can be fitted to the resulting data.

So, far we have discussed how to model WSS random process but most of the practical that there are non stationary operations like differencing logarithm etcetera may be are found to make data stationary. There are different ways to make data stationary to such models for non stationary data. First one is ARIMA model autoregressive integrated moving average model. Here the difference data $X_n - X_{n-1}$ can be modeled as a ARMA model after differencing this data will be fitted into an ARMA model.

That model includes integration therefore after differencing it is becoming ARMA model. Seasonal ARMA that is SARMS, SARMA model here signal contains a seasonal fluctuation terms for example weather data the signal after differencing by step equal to the seasonal period that is p becomes stationary and ARMA model can be fitted to the resulting data. So, $X_n - X_{n-p}$ so this difference data can be fitted to an ARMA model that is it SARMA, seasonal ARMA model. So, these are some of the ways to deal with non stationarity but we will not discuss this in details.

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Summary

- ❖ AR(2) process is a typical example of the AR(p) process.
- ❖ The state-space representation for the AR(p) is given by

$$Z(n) = AZ(n-1) + BV(n)$$

$$\text{where } A = \begin{bmatrix} a_1 & a_2 & \dots & a_p \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 \end{bmatrix} \text{ and } B = [1 \ 0 \dots 0]^T$$

$$X(n) = CZ(n)$$

$$\text{where } C = [1 \ 0 \dots 0]$$

- ❖ Thus AR(p) process is vector Markov process.

Let us summarize an AR 2 process is a typical example of ARp process so we discussed how to analyze this AR2 process stationarity of the process. AR2 process is a typical example of the ARp process we discussed how to analyze the AR2 process in terms of stationarity autocorrelation function power spectral density etc. This state space representation for an ARp

process is given by the Z_n is equal to $AZ_{n-1} + B V_n$ where A is p by p matrix given by this, this is the AR parameters a_1, a_2 up to a_p and rest of the rows will contain 0 except 1, 1.

So there will be one in one place and even in place it will be 0 so this is the A matrix similarly B matrix we can find out B is equal to $1 \ 0 \ 0$ up to 0 transpose so this way we can write Z_n is equal to $AZ_{n-1} + B V_n$ this is the state equation. Similarly we have the observation equation so this data X_n can be written as C times Z_n where C is the row matrix thus ARp process is a vector Markov process. So, because this is a first order in terms of the state variable vectors so this is a first order in terms of vector it is a first order AR process and therefore it is a vector Markov process.

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Summary

ARMA(p,q) process

❖ Difference equation model: $X(n) = \sum_{i=1}^p a_i X(n-i) + \sum_{j=0}^q b_j V(n-j)$

❖ ACF

$$R_x(m) = E[X(n)X(n+m)] = \sum_{i=1}^p a_i R_x(m-i) + \sum_{j=0}^q b_j E[V(n+m-j)X(n)]$$

For $m \geq q+1$

$$R_x(m) = \sum_{i=1}^p a_i R_x(m-i), \quad (\text{Yule Walker equations})$$

❖ PSD $S_x(\omega) = \frac{\left| \sum_{j=0}^q b_j e^{-j\omega} \right|^2}{\left| 1 - \sum_{i=1}^p a_i e^{-j\omega} \right|^2}$

❖ The parsimony of parameters play an important role in ARMA(p,q)

model fitting.

We discussed about ARMA p, q process the difference equation model is given by X_n is equal to summation $a_i X_{n-i}$, i going from 1 to p plus summation $b_j V_{n-j}$, j going from 0 to q this is the ARMA p, q model difference equation. Autocorrelation function is given by R_x of m is equal to this is the expression summation $a_i R_x$ of $m-i$, i going from 1 to p + summation $b_i EV$ of $n+m-i$ into X_n i going from 0 to q and for m greater than equal to $q+1$ this autocorrelation expression will result into Yule Walker equations given by R_x of m is equal to summation $a_i R_x$ of $m-i$, i going from 1 to p .

And power spectral density is simply given by this expression $S_x(\omega)$ is equal to summation $b_i e^{-j\omega i}$ whole mod square divided by $1 - \text{summation } a_i e^{-j\omega i}$, i going from 1 to p whole mod square this is the expression for power spectral density for ARMA p, q process and we also discussed very briefly about model building and the parsimony of parameters play an important role in ARMA p, q model fitting, thank you.