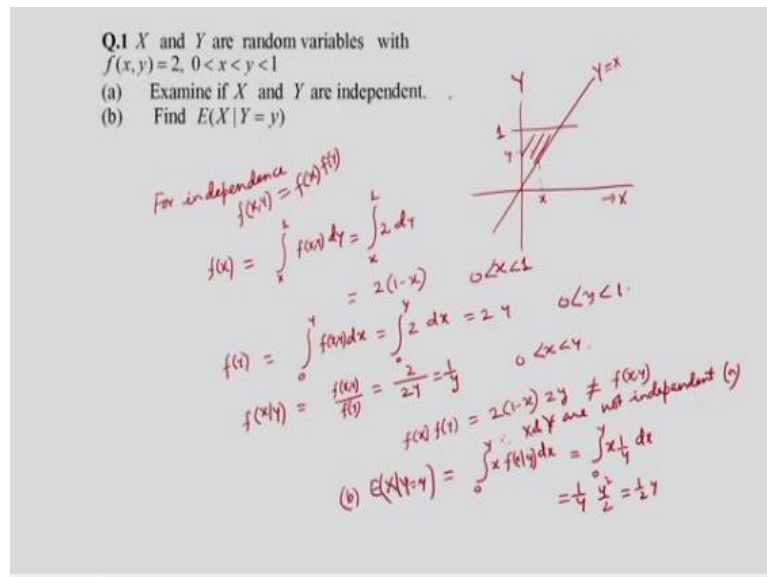


**Statistical Signal Processing**  
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**Lecture – 24**  
**Solution to Review Assignment 1**

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Hello students, welcome to this session on the solution to the review assignment 1, let us discuss the first question, let us solve question 1;  $X$  and  $Y$  are random variables with joint PDF,  $f_{xy}$  is equal to 2 for  $0 < x < y < 1$ . Examine if  $X$  and  $Y$  are independent, find the conditional expectation of  $X$ , given  $Y$  is equal to small  $y$ , this conditional expectation is very important for us.

Because this is the minimum mean square error estimator of  $X$  given  $Y$  is equal to small  $y$ , now the PDF is defined in this region, this is  $x$ , this is  $y$  and this is  $y$  is equal to  $x$  line, now  $0 < x < y$ , therefore  $y$  is greater than  $x$ , so it will be above  $y$  axis and it is bounded by 1 through that way this is the region, where this joint density function is defined. Now, to show independence, we have to find out this marginal density and  $f_{xy}$ , this joint density should be equal to product of  $f_x$  into  $f_y$ .

This is the condition for independence now, we will find out  $f_x$ , so  $f_x$  is equal to; now suppose this is a point  $x$ , this is the point  $x$ , so at that point, then  $f(x)$  (02:42) will be equal to; now we have to integrate joint density with respect to  $y$  and limit of integration will be from

this point to this point, so that way this will be integration, this would point is equal to  $x$  and this is 1 and  $f_{xy} dy$ .

So, this is; if we carry out the integration this is  $x$ , this is  $2 dy$ , so this will be 2 into; because integration of  $dy$  is  $y$  and if we put the limits, upper limit is 1, lower limit is  $x$ , therefore this will be 2 into  $1 - x$ , now  $x$  will lie between 0 and 1. Similarly,  $f_y$  we can find out;  $f_y$  is equal to integration now, we have to find out at this point  $y$ , suppose this is equal to  $y$ , therefore  $x$  will be varying from 0 to  $y$ .

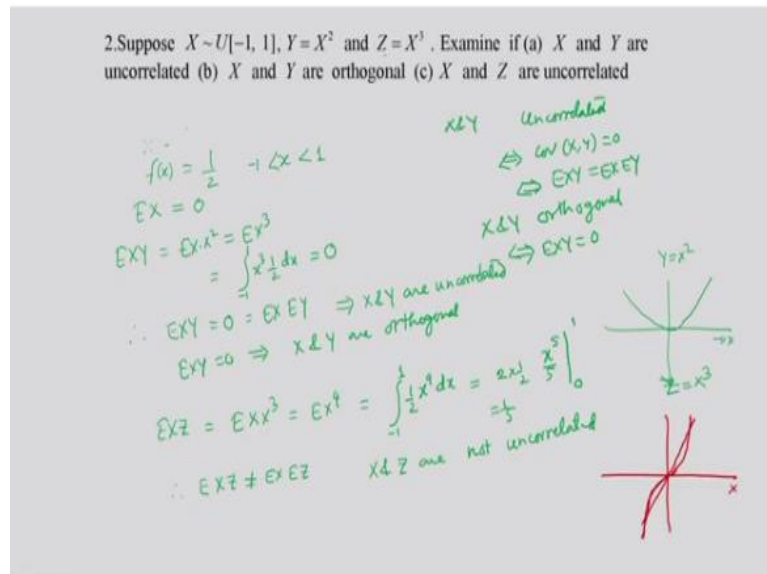
So, that way integration 0 to  $y$ ,  $f_{xy} dx$  that will be equal to 0 to  $y$  integration,  $f_{xy}$  is  $2 dx$ , so this will be simply  $2y$ ,  $y$  is lying between 0 and 1, therefore  $f$  of  $x$  given  $y$ , this is the conditional PDF will be equal to  $f$  of  $xy$  divided by  $f_y$  and that will be 2 by  $2y$  that is equal to  $1/y$ , this is for  $x$  lying between because once we have  $y$ ; given  $y$ ,  $x$  will lie between 0 and  $y$ , okay.

Now, we see that  $f$  of  $xy$  which is equal to 2 is not equal to  $f_x$  into  $f_y$  because  $f_x$  into  $f_y$  is equal to  $f_x$  we have find out, 2 into  $1 - x$  into 2 into  $y$  is not equal to  $f$  of  $xy$ , therefore  $X$  and  $Y$  are not independent, so this is the answer to part A. Now, part B we have to consider,  $E$  of  $X$  given  $Y$  is equal to small  $y$ , so part B;  $E$  of  $X$  given  $Y$  is equal to small  $y$ , so this is equal to; now we know the original PDF as a function of  $x$  we have to consider.

So, it is integration which respect to  $X$  because we are finding out the expectation of  $X$  given  $Y$  is equal to small  $y$ , so that way this will be  $x f$  of  $x$  given  $y dx$  and limit will be;  $x$  will be changing from 0 to  $y$ , so this is equal to integration 0 to  $y$   $x$ , now this is  $1/y dx$ ;  $1/y$  will come out, so this is  $x^2$  by 2 and the upper limit is  $y$ , therefore it will be  $y^2$  by 2 that is equal to  $1/2$  of  $y$ .

So, conditional expectation of  $X$  given  $Y$  is equal to small  $y$  is equal to  $1/2$  of  $y$ , so this is the conditional expectation, this conditional expectation we know that this is important for minimum mean square error estimation, so that way how to find out conditional expectation we have seen here.

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We will go to the next question; suppose,  $X$  is uniformly distributed between  $-1$  and  $1$ ,  $Y$  is equal to  $X$  square and  $Z$  is equal to  $X$  cube, examine if  $X$  and  $Y$  are orthogonal, if  $X$  and  $Z$  are uncorrelated, so these 3 questions we will solve. Now, we know that 2 random variables  $X$  and  $Y$  are uncorrelated, so that is covariance of uncorrelated  $X$  and  $Y$  uncorrelated imply that covariance of  $XY$  is equal to 0, which also implies that  $E$  of  $XY$  is equal to  $EX$  into  $EY$ .

And  $X$  and  $Y$  are orthogonal, so this is if and only if, this also we can write if and only if,  $E$  of  $XY$  is equal to 0. Now, coming to this question, so  $X$  is uniformly distributed between  $-1$  and  $1$ , so that means  $f_x$  will be equal to  $1$  by  $2$ ,  $X$  lies between  $-1$  and  $+1$ , so this is the distribution, therefore  $E$  of  $X$  will be equal to 0 because it is symmetrical distribution between  $-1$  and  $1$ , so you have  $X$  is equal to 0.

Now, let us see what is  $E$  of  $XY$ ;  $E$  of  $XY$  and that is nothing but  $E$  of  $X$  into  $Y$  is equal to  $X$  square, so into  $X$  square, so that is equal to  $E$  of  $X$  cube, now you have  $X$  cube we can compute and this is integration from  $-1$  to  $1$   $X$  cube and then density is  $1$  by  $2$   $dx$  and this is again identically 0, so  $E$  of  $XY$  is equal to 0 and therefore, we see if  $X$  and  $Y$  are uncorrelated now, clearly  $E$  of  $XY$  is equal to 0 is equal to  $EX$ .

Because  $EX$  is also equal to 0 into  $E$  of  $Y$  because  $EX$  is equal to 0, already this is equal to 0, so therefore  $E$  of  $XY$  is equal to  $EX$  into  $EY$  implies that  $X$  and  $Y$  are uncorrelated and also  $E$  of  $XY$  is equal to 0, this implies that  $X$  and  $Y$  are orthogonal. Now, let us consider part C;  $E$  of  $XZ$  is equal to  $E$  of  $X$  into  $X$  cube that is equal to  $E$  of  $X$  to the power 4 and this will be now equal to minus 1 to 1,  $1/2$  that is the PDF  $x$  to the power 4  $dx$ .

So, here we see that  $Y$  is a function of  $X$  and  $Z$  is also function of  $X$  and  $Y$  are uncorrelated, whereas  $X$  and  $Z$  are correlated, so this is because of the nature of the function for example,  $Y$  is equal to  $X$  square, if I plot suppose, this is  $X$ ,  $Y$  is equal to  $X$  square, so this will be a parabola like this, so we cannot have a linear approximation of the parabola except that what is the mean suppose, mean we can find out that way we can approximate but we cannot get a line which approximate this parabola.

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3. A discrete-time random signal is given by

$$X(n) = A \cos(\omega_0 n + \theta) + W(n)$$

where  $\theta \sim U[-\pi, \pi]$ ,  $\theta$  and  $A$  are independent and  $W(n)$  is a zero-mean white-noise uncorrelated with  $\theta$  and  $A$

- Find the mean and the autocorrelation function of  $X(n)$
- Show that  $X(n)$  is wide-sense stationary.
- Find power spectral density of  $X(n)$ .

*Handwritten solution:*

$$X(n) = A \cos(\omega_0 n + \theta) + W(n)$$

(i)  $E[X(n)] = E[A \cos(\omega_0 n + \theta) + W(n)] = E[A \cos(\omega_0 n + \theta)] + E[W(n)]$

$$= EA \times E[\cos(\omega_0 n + \theta)] + 0$$

$$= EA \times 0 + 0 = 0$$

(ii)  $E[X(n)X(n-m)] = E[A \cos(\omega_0 n + \theta) A \cos(\omega_0 (n-m) + \theta) + W(n)W(n-m)]$

$$= EA^2 E[\cos(\omega_0 n + \theta) \cos(\omega_0 (n-m) + \theta)] + E[W(n)W(n-m)]$$

$$= EA^2 E[\cos(\omega_0 n + \theta) \cos(\omega_0 n - \omega_0 m + \theta)] + \sigma_w^2 \delta(m)$$

$$= EA^2 E[\cos(2\omega_0 n - \omega_0 m + 2\theta)] + \sigma_w^2 \delta(m)$$

$$= EA^2 \cos(\omega_0 m) + \sigma_w^2 \delta(m)$$

$\therefore X(n)$  is WSS.

*Power Spectral Density (PSD):*

$$S_X(\omega) = \frac{1}{2} [EA^2 \cos(\omega_0 m) + \sigma_w^2 \delta(m)]$$

$$= \frac{1}{2} [EA^2 \cos(\omega_0 m) + \sigma_w^2 \delta(m)]$$

Let us go to the third question; a discrete-time random signal is given by  $X_n$  is equal to  $A \cos(\omega_0 n + \theta) + W_n$ , where  $\theta$  is a uniform random variable distributed between minus  $\pi$  to  $\pi$  and  $\theta$  and  $A$  are independent, this  $A$  and  $\theta$  are independent and  $W_n$  is a zero

mean white noise uncorrelated with  $\theta$  and  $A$ , so  $W_n$  is uncorrelated with this random variable and this random variable.

Find the mean and the autocorrelation function of  $X_n$ , so that  $X_n$  is WSS, find the power spectral density of  $X_n$ , so in this case find the mean and autocorrelation of  $X_n$ , so let us solve the problem. We are given  $X_n$  is equal to  $A \cos(\omega_0 n + \theta) + W_n$  and  $A$  and  $\theta$  are independent and  $W_n$  is uncorrelated with  $\theta$  and  $A$  and now, you have  $X_n$ , so we will consider part 1.

$E$  of  $X_n$  will be equal to  $E$  of  $A \cos(\omega_0 n + \theta) + W_n$ , so expected value of the entire thing and this is some therefore expected value will be also some  $E$  of  $A \cos(\omega_0 n + \theta) + E$  of  $W_n$  and  $A$  and  $\theta$  are independent, so we can write  $E$  of  $A$  into  $\cos(\omega_0 n + \theta) + E$  of  $W_n$  and we are given that  $\theta$  is uniformly distributed between minus  $\pi$  and  $\pi$ .

Therefore,  $E$  of  $\cos(\omega_0 n + \theta)$   $\omega_0 n + \theta$ , so this term will be equal to 0, so that way this will be  $EA$  into 0 because this term we can determine  $E$  of  $\cos(\omega_0 n + \theta)$ , this is integration from minus  $\pi$  to  $\pi$   $\cos(\omega_0 n + \theta) d\theta$ , so this integration if we carry out this will be equal to 0, so and this part is also 0, so that way this will be 0, which is a constant.

So, mean is a constant, it does not depend on  $n$  and now, we will see the autocorrelation function  $E$  of  $X$  of  $n$  into  $X$  of  $n - m$ , so that is equal to  $E$  of  $A \cos(\omega_0 n + \theta)$  into  $A \cos(\omega_0 n - \omega_0 m + \theta)$ , so this is the at lag  $n - m$  and then  $E$  of  $W_n$  into  $W_{n-m}$  and plus; because this  $W_n$  and this signal are uncorrelated, therefore this joint expectation will be equal to 0 and all are zero mean that way this joint expectation will be equal to 0, so this will be 0.

Now, if I carry out this expectation, I will get this as this  $A$  and  $A$  will be  $A^2$ ,  $E$  of  $A^2$  into  $E$  of  $\cos(\omega_0 n + \theta)$  into  $\cos(\omega_0 n - \omega_0 m + \theta)$  and this one, plus this quantity is because it is the white noise within its variance 0 mean white noise, so that way will suppose, its variance is  $\sigma_W^2$ , so that way we can write it as  $\sigma_W^2$  into  $\delta_m$ , where  $\delta_m$  is equal to 1, for  $m$  is equal to 0 otherwise it will be 0.

Now, this part I can expand in terms of cosine formula;  $\cos A$  into  $\cos B$  is equal to  $1/2$  of  $\cos$  of  $A + B + \cos$  of  $A - B$ , so that way we will get this as  $E$  of  $A$  square into  $E$  of  $\cos$  of  $2$  will be also there;  $\cos$  of, if we add both twice  $\omega_0 n - \omega_0 m + 2\theta$ , this is the one corresponding to  $A + B$  and if we subtract we will get,  $\cos$  of this and this will get cancelled,  $\theta$  will get cancelled,  $\cos$  of  $\omega_0 m + \sigma_w^2 \delta m$ .

And this part again we can show that expected value of this part will be equal to 0 because if I integrate this function over minus  $\pi$  to  $\pi$ , then I will get exactly 0, so that way we will be left with  $E$  of  $A$  square by 2 into  $\cos$  of  $\omega_0 m + \sigma_w^2 \delta m$ , where  $\sigma_w^2$  is the variance of the white noise. Now, we see that this is a function of  $m$  only; this is a function of lag  $m$ .

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$$R_x(m) = \frac{E A^2}{2} \cos(\omega_0 m) + \sigma_w^2 \delta(m)$$

Taking DTFT

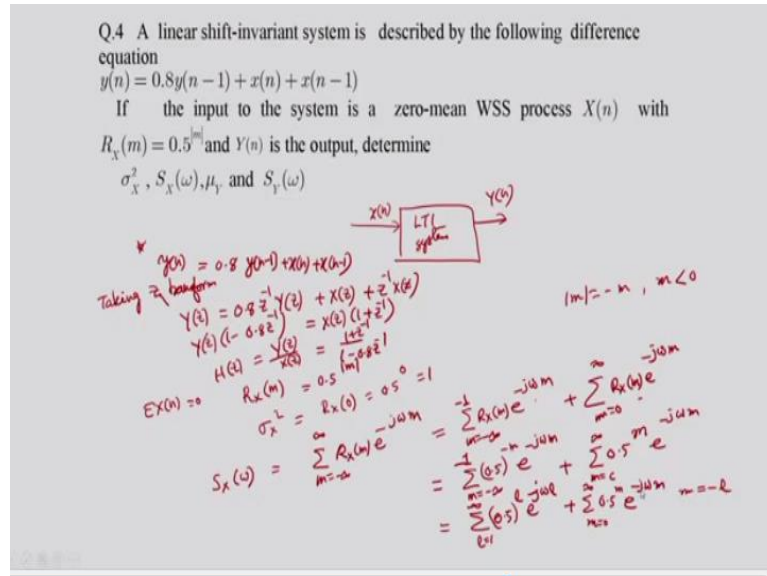
$$S_x(\omega) = \frac{E A^2}{2} \pi (\delta(\omega - \omega_0) + \delta(\omega + \omega_0)) + \sigma_w^2$$

Dirac delta function

And here we have seen that  $E$  of  $X_n$  is equal to 0 which is a constant, therefore  $X_n$  is WSS, now we have to find out the power spectral density we have  $R_x$  of  $m$  is equal to  $E$  of  $A$  square into  $\cos$  of  $\omega_0 m$  divided by 2 +  $\sigma_w^2 \delta m$ , we have the autocorrelation function like this, so by taking the DTFT now, we will get the PSD  $S_x$   $\omega$  that will be DTFT of this  $E$  of  $A$  square by 2 and this DTFT is given by  $\pi$  into  $\delta(\omega - \omega_0) + \delta(\omega + \omega_0) + \sigma_w^2 \delta(\omega)$ , where  $\delta$  is the Dirac delta function.

This is Dirac delta plus and DTFT of this term will be equal to simply  $\sigma_w^2$ , so this is the power spectrum of the signal  $X_n$ .

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$\sigma_X^2, S_X(\omega), \mu_Y$  and  $S_Y(\omega)$ 

Then we will have to find out  $S_x$  of  $\omega$ ,  $R_x$  of  $m$  is given that is equal to summation  $R_x$  of  $m$ ,  $e$  to the power  $-j \omega m$ ;  $m$  going from minus infinity to infinity. Now, my autocorrelation function is in terms of  $\text{mod}$  of  $m$ , therefore I will write separate out the summation, so first part will be summation  $R_x$  of  $m$ ,  $e$  to the power  $-j \omega m$ ,  $m$  going

from - infinity to - 1 + summation from m is equal to 0 to infinity  $R_x$  of m, e to the power - j omega m like this.

So, this now I know that this is equal to  $R_x$  of m is equal to 0.5 to the power mod of m and when m is negative, mod of m is equal to - m for m less than 0, so therefore this sum will be equal to 0.5 to the power - m e to the power - j omega m; m going from minus infinity to minus 1 this is 0.5 to the power m into e to the power - j omega m; m going from 0 to infinity okay.

Now this I can write suppose, if I write m is equal to suppose, minus 1, then this will be summation from 1 is equal to 1 to infinity 0.5 to the power 1 e to the power + j omega 1, so this we are writing 1 is equal to minus m, so that way this limit will be now interchange like this and this will remain same, summation m is equal to 0 to infinity 0.5 to the power m, e to the power - j omega m, okay.

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$$\begin{aligned}
 S_x(\omega) &= \sum_{l=1}^{\infty} 0.5^l e^{j\omega l} + \sum_{m=0}^{\infty} 0.5^m e^{-j\omega m} \\
 &= \frac{0.5 e^{j\omega}}{1 - 0.5 e^{j\omega}} + \frac{1}{1 - 0.5 e^{-j\omega}} \\
 &= \frac{0.5 e^{j\omega} (1 - 0.5 e^{-j\omega}) + (1 - 0.5 e^{j\omega})}{(1 - 0.5 e^{j\omega})(1 - 0.5 e^{-j\omega})} \\
 S_y(\omega) &= |H(\omega)|^2 S_x(\omega) \\
 &= \left| \frac{1 + e^{j\omega}}{1 - 0.5 e^{j\omega}} \right|^2 S_x(\omega) = \text{PSD of the output signal } y(n)
 \end{aligned}$$

So, we can find out  $S_x$  omega in this manner, so  $S_x$  omega is equal to summation 0.5 to the power 1 e to the power j omega 1; 1 going from 1 to infinity plus summation 0.5 to the power m, e to the power - j omega m; m going from 0 to infinity, now this is a geometric series with common ratio here 0.5 into e to the power j omega, here also common ratio 0.5 into e to the power - j omega.

So that way this is a; this is also infinite geometric series, this is also infinite geometric series, so that way we can find out this is equal to first term will be 0.5 into e to the power j omega



and common ratio will be 1 minus, common ratio is 0.5; 0.5 into e to the power j omega. Similarly, this part will be also equal to summation, so that way a first term here will be m is equal to 0, this is 1 divided by 1 - 0.5 into e to the power -j omega.

So, this now we can simplify this expression and we will get the final result, so we can carry out 1 - 0.5 into e to the power j omega into 1 - 0.5 into e to the power -j omega and here 0.5 into e to the power j omega multiplied by 1 - 0.5 into e to power -j omega + 1 into 1 - 0.5 into e to the power j omega, we can simplify this expression and we can get the  $S_x(\omega)$ , so that way we can find out the  $S_x(\omega)$ .

And then we have to find out  $S_y(\omega)$ , so  $S_y(\omega)$  will be simply because we know  $S_z$ ;  $S_y(\omega)$  will be simply mod of  $H(\omega)$  whole square into  $S_x(\omega)$ , so mod of  $H(\omega)$  we have; we can find out because here  $H_z$  is given, so if we put z is equal to e to the power j omega, then we can find out  $H$  of omega, so that way we can find out mod of  $H(\omega)$  square into  $S_x(\omega)$ .

And hence find out the  $S_y(\omega)$ , so this will be 1 + e to the power j omega divided by 1 minus, this one will be equal to 1 - 0.8 e to the power -j omega and this we have to take the mod into  $S_x(\omega)$ , so this will give me the PSD of the output signal. So, we can further simplify, you can carry out the simplification and this will be the PSD of the output signal  $Y_n$ .

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Q.5 An ARMA(1,1) system is given by the following difference equation  

$$Y(n) = 0.5Y(n-1) + V(n) - 0.8V(n-1)$$
  
 where  $V(n)$  is a 0-mean white noise with variance 1.  
 Determine  $\mu_y$ ,  $\sigma_y^2$  and  $R_y(l)$

*Solution:*

$$Y(n) = 0.5Y(n-1) + V(n) - 0.8V(n-1)$$

$$EY(n) = 0.5EY(n-1) + EV(n) - 0.8EV(n-1)$$

$$\mu_y = 0.5\mu_y + 0 - 0.8 \times 0 \Rightarrow \mu_y = 0$$

$$\sigma_y^2 = R_y(0) = E(Y(n)^2) = E((0.5Y(n-1) + V(n) - 0.8V(n-1))^2)$$

$$= E(0.25Y(n-1)^2 + EV(n)^2 + E(0.64V(n-1)^2) + 2E(0.5Y(n-1)V(n)) - 2E(0.5Y(n-1)V(n-1)) - 2E(0.8Y(n-1)V(n-1))$$

$$= 0.25\sigma_y^2 + 1 + 0.64 \times 1 + 0 + 0 - 0.8EY(n-1)V(n-1)$$

$$= 0.25\sigma_y^2 + 1 + 0.64 - 0.8 \times 0$$

$$= 0.25\sigma_y^2 + 1.64$$

$$\therefore \sigma_y^2 = R_y(0) = \frac{1.64}{1-0.25} = \frac{1.64}{0.75} = \frac{164}{75} \times 10^{-2}$$

We will go to the next question; An ARMA 1, 1 system is given by the following difference equation, this is a linear difference equation;  $Y_n$  is equal to  $0.5 Y_{n-1} + V_n - 0.8 V_{n-1}$ , where  $V_n$  is a 0 mean white noise with variance 1, determine  $\mu_y$   $\sigma_y^2$  and  $R_y$  of 1. So, here solution  $Y_n$  is equal to  $0.5 Y_{n-1} + V_n - 0.8 V_{n-1}$ , therefore  $E$  of  $Y_n$  will be equal to  $0.5$  into  $E$  of  $Y_{n-1} + E$  of  $V_n - 0.8 E$  of  $V_{n-1}$ .

Now,  $Y_n$  is WSS, so this will be  $\mu_y$  is equal to  $0.5 \mu_y$ , this is also  $\mu_y$  because of stationarity and  $E$  of  $V_n$  is equal to 0 -  $0.8$  into this is also equal to 0, so that way we will have  $\mu_y$  is equal to  $0.5 \mu_y$ , implies that  $\mu_y$  is equal to 0, then we have to find out  $\sigma_y^2$ ;  $\sigma_y^2$  this is same as  $R_y$  of 0 because it is 0 mean,  $\mu_y$  is 0, so therefore  $\sigma_y^2$  is simply  $R_y$  of 0.

That is equal to  $E$  of  $y^2_n$ , so this will be equal to  $E$  of  $0.5 Y_{n-1} + V_n - 0.8 V_{n-1}$  whole square, so that is equal to  $E$  of  $0.25$  into  $y^2_{n-1} + E$  of  $V^2_n +$  then  $E$  of  $0.8$  square is  $0.64 V^2_{n-1}$  and then cross terms will come, so plus twice, now first one will be  $E$  of  $0.5 Y_{n-1}$  into  $V_n$  + next term will be  $-2$  into  $E$  of  $V_n$  into  $0.8 V_{n-1}$  and last one will be  $-2$  into  $E$  of  $0.5 Y_{n-1}$  into  $V_{n-1}$ ,  $0.8 V_{n-1}$ .

So, first term will be, so  $0.25 E$  of  $Y^2_{n-1}$  is  $\sigma_y^2$  and this one will be  $\sigma_V^2$  that is equal to 1, this one will be  $0.64$ , again  $E$  of  $V^2_{n-1}$  is also equal to 1, then this is  $Y_{n-1}$ , signal at instant  $n-1$  and noise at  $V_n$ , instant  $n$ , they are uncorrelated, so this term will become 0; plus 0 and similarly,  $V_n$  and  $V_{n-1}$ , these 2 noises are uncorrelated, so this is also equal to 0, only we are left with this term;  $0.5$  into  $2 E$  of  $Y_{n-1}$  into  $0.8$  will also come,  $2$  into  $0.5$  is 1.

And then  $0.8$ , so this will be  $0.8$  into  $E$  of  $Y_{n-1}$  into  $V_{n-1}$ , now this term we can write as  $E$  of  $Y_{n-1}$  into  $V_{n-1}$  will be equal to  $E$  of; now  $Y_{n-1}$  is equal to  $0.5 Y_{n-2} + V_{n-1} - 0.8 V_{n-2}$  into  $V_{n-1}$  because this  $V_{n-1}$  now, this and this are uncorrelated, similarly this and this are uncorrelated, we are left with only  $V$  of  $n-1$  into  $V$  of  $n-1$  that is  $V^2_{n-1}$ , so that way this quantity will be simply  $E$  of  $V^2_{n-1}$ .

So, therefore what we will have is  $0.25 \sigma_y^2 + 1 + 0.64 - 0.8$  into  $E$  of  $V^2_{n-1}$  that is equal to 1, so that way we will get this, so this term will be  $0.25 \sigma_y^2$  and if I carry out this, this will be 1.12, okay. So, therefore we can find out  $\sigma_y^2$  that is

equal to  $R_y$  of 0 that is equal to; I can take this to the left hand side and then carry out the algebra, so that we will get this is equal to 1.12 divided by  $1 - 0.25$ .

So, this will be equal to 4 by 3 into 1.12 okay, we can find out the value similarly, now we want to find out  $R_y$  of 1.

**(Refer Slide Time: 40:47)**

The image shows a handwritten derivation for  $R_y(1)$  on a light gray background. The steps are as follows:

$$\begin{aligned}
 R_y(1) &= E(Y_n Y_{n-1}) \\
 &= E\left(0.5 Y_{n-1} + V_n - 0.8 V_{n-1}\right) Y_{n-1} \\
 &= 0.5 E Y_{n-1}^2 + E V_n Y_{n-1} - 0.8 E V_{n-1} Y_{n-1} \\
 &= 0.5 \sigma_Y^2 + 0 - 0.8 \times 1 \\
 &= 0.5 \times \frac{4}{3} \times 1.12 - 0.8
 \end{aligned}$$

There is a bracket under the term  $E V_{n-1} Y_{n-1}$  with the label  $\sigma_V^2 = 1$  written below it.

So,  $R_y$  of 1 is equal to  $E$  of  $Y_n$  into  $Y_{n-1}$ , okay so, this is equal to we can write in the same manner,  $Y_n$  is equal to  $0.5 Y_{n-1} + V_n - 0.8 V_{n-1}$  into  $Y_{n-1}$ , so that way this will be  $0.5$  into  $E$  of  $Y$  square  $n - 1$  +  $E$  of  $V_n$  into  $Y_{n-1}$  -  $0.8$  into  $E$  of  $V$  of  $n - 1$  into  $Y_{n-1}$ . Now, this is equal to  $0.5$  into  $\sigma_y$  square that we know well,  $E$  of  $V_n$  into  $Y_{n-1}$  this is the white noise path signal, they are uncorrelated so, this is equal to 0.

And this is minus  $0.8$  into; now  $E$  of  $V_{n-1}$  into  $Y_{n-1}$ , so in the same way like the previous problem we can show that this is equal to; this will be equal to  $\sigma_V$  square that is equal to 1, this we can show, so that way minus  $0.8$  into 1. So, we have  $(())$  (42:36)  $\sigma_y$  square, so we can put the value of  $\sigma_y$  square here that is  $\sigma_y$  square was 4 by 3 into 1.12 -  $0.8$  and we can compute this to find out  $R_{y1}$ , thank you.