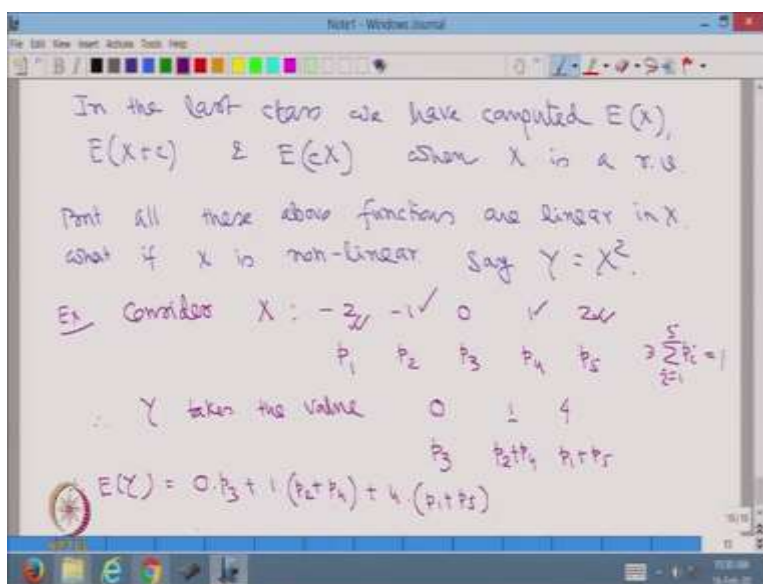
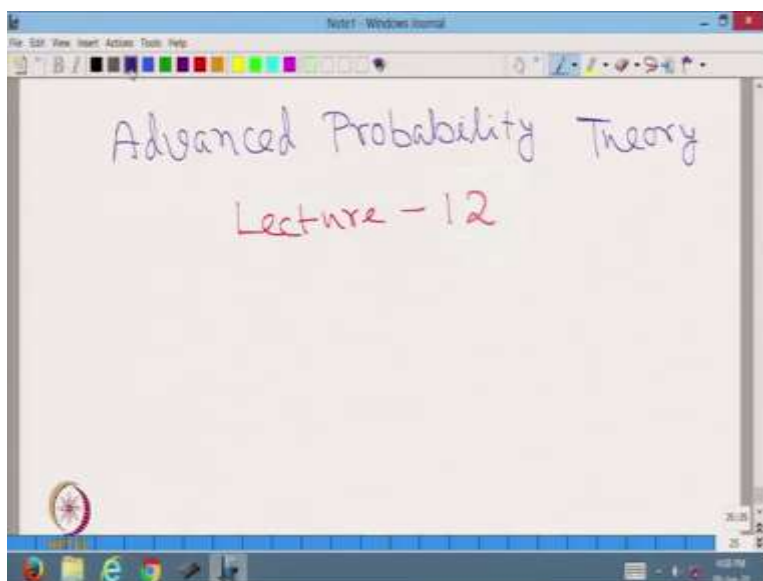


Advanced Probability Theory
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Lecture 12

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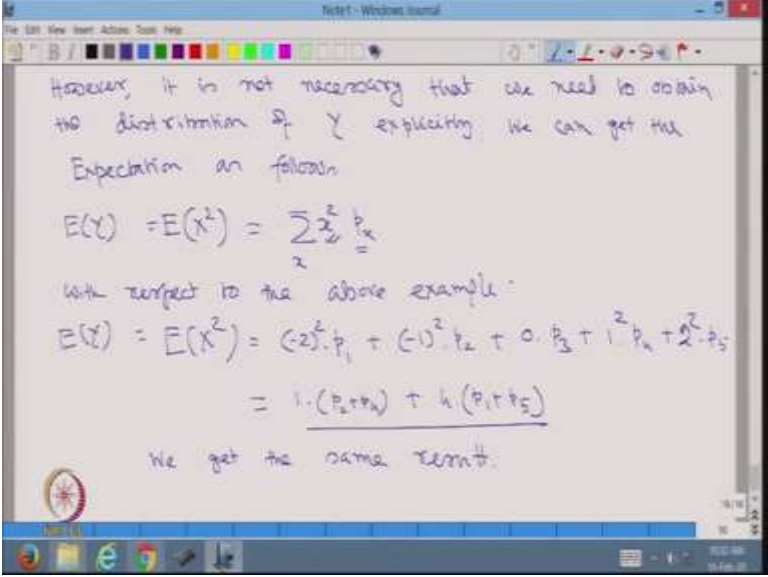
Welcome, students to the MOOCS lecture series on Advanced Probability Theory, this is lecture number 12. In the last class, we have computed expectation of X , expectation of X

plus c and expectation of cX when X is a random variable. But all these above functions are linear in X . What if x is non-linear?

Say, Y is equal to X square. Example, consider X which takes the value minus 2, minus 1, 0, 1 and 2. Suppose the probability is at p_1, p_2, p_3, p_4 and p_5 , such that $\sum_{i=1}^5 p_i = 1$. Therefore, Y takes the value 0, 1 and 4, Y will take the value 0 when X is equal to 0. Therefore, the probability is p_3 . Y will take the value 1 when X is minus 1 or X is plus 1.

Therefore, this probability is p_2 plus p_4 and y is tilted the value 4 if X is minus 2 or plus 2 and that probability is p_1 plus p_5 . Therefore, expectation of Y is equal to 0 times p_3 plus 1 times p_2 plus p_4 plus 4 times p_1 plus p_5 .

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However, it is not necessary that we need to obtain the distribution of Y explicitly. We can get the Expectation as follows

$$E(Y) = E(X^2) = \sum_{i=1}^n x_i^2 p_i$$

with respect to the above example:

$$E(Y) = E(X^2) = (-2)^2 \cdot p_1 + (-1)^2 \cdot p_2 + 0 \cdot p_3 + 1^2 \cdot p_4 + 2^2 \cdot p_5$$

$$= 1 \cdot (p_1 + p_2) + 4 \cdot (p_4 + p_5)$$

We get the same result.

However, it is not necessary that we need to obtain the distribution of Y explicitly. We can do it, we can get the expectation as follows. Expectation of Y is equal to expectation of X square is equal to $\sum X^2 p_X$ that is I am changing the value from X to X square and multiplying by the probability of X and I am summing over X .

So with respect to the example, above example, expected value of Y is equal to expected value of X square is equal to minus 2 square times p_1 plus minus 1 square times p_2 plus 0

times p_3 plus 1 square times p_4 plus 2 square times p_5 . And we can see that this is equal to 1 times p_2 plus p_4 plus 4 times p_1 plus p_5 , that is, we get the same result.

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We may observe the same for a continuous case as well.
 For example: If $X \sim N(0,1)$ what is the Expectation of X^2 ?
 We do it as follows:

$$E(X^2) = \int_{-\infty}^{\infty} x^2 f(x) dx = \int_{-\infty}^{\infty} x^2 \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$
 (Note: The integrand is an even function)

$$E(X^2) = 2 \int_0^{\infty} x^2 \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$
 Put $x^2 = z \Rightarrow \frac{dz}{dx} = 2x \Rightarrow dx = \frac{dz}{2x} = \frac{dz}{2\sqrt{z}}$

$$\therefore E(X^2) = 2 \int_0^{\infty} x^2 \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

$$= 2 \int_0^{\infty} \frac{z}{\sqrt{2\pi}} e^{-z/2} \frac{dz}{2\sqrt{z}}$$

$$= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} z^{1/2} e^{-z/2} dz = \frac{1}{\sqrt{2\pi}} \int_0^{\infty} \frac{z^{3/2-1}}{2} e^{-z/2} dz$$

$$\therefore E(X^2) = \frac{1}{\sqrt{2\pi}} \frac{\Gamma(3/2)}{(1/2)^{3/2}} = \frac{1}{\sqrt{2\pi}} \frac{\frac{1}{2}\sqrt{\pi}}{1/2^{3/2}} \cdot 2^{3/2}$$
 Putting $\frac{1}{2} = \sqrt{\pi}$ we have

$$E(X^2) = \frac{1}{\sqrt{2\pi}} \frac{1}{2} \sqrt{\pi} \cdot 2^{3/2} = 1$$
 Therefore we get if $X \sim N(0,1)$ then $E(X^2) = 1$

We may observe the same for a continuous case as well. For example, if X is normal 0, 1, what is the expectation of X square? So we do it as follows. Expectation of X square is equal to minus infinity to infinity X square into $f(x)$, dx which is equal to minus infinity to infinity X square 1 over root over 2 Pi e to the power minus X square by 2 dx .

Now note that this is an even function, therefore expectation of X square is equal to 2 into integration 0 to infinity, X square 1 over root over $2\pi e$ to the power minus X square by 2 dx . Put X square is equal to z , therefore $dz dx$ is equal to $2x$. Therefore, dx is equal to dz upon $2x$ is equal to dz upon $2\sqrt{z}$.

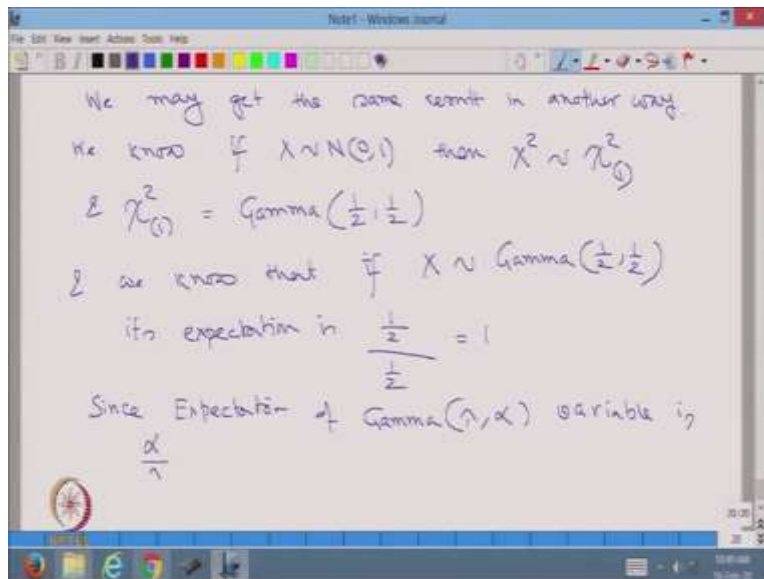
Therefore, expectation of X^2 is equal to $\int_0^\infty x^2 \frac{1}{\sqrt{2\pi e}} e^{-x^2/2} dx$ is same as $\int_0^\infty z \frac{1}{\sqrt{2\pi e}} e^{-z/2} dz$ put z in place of X^2 and we get $\int_0^\infty z \frac{1}{\sqrt{2\pi e}} e^{-z/2} dz = 2$. $\frac{1}{\sqrt{2\pi e}}$ cancels this 2.

Therefore, we have $\frac{1}{\sqrt{2\pi}} \int_0^\infty z^{\frac{e}{2}-1} e^{-\frac{z}{2}} dz = \frac{1}{\sqrt{2\pi}} \int_0^\infty z^{\frac{3}{2}-1} e^{-\frac{z}{2}} dz$. Now this is a gamma integral and we know that $\int_0^\infty x^{\alpha-1} e^{-\lambda x} dx = \frac{\Gamma(\alpha)}{\lambda^\alpha}$.

Therefore, this expectation of X square is equal to 1 over root over $2 \pi \gamma^{3/2}$ divided by half to the power $3/2$ is equal to 1 over root over $2 \pi \gamma^{3/2}$ we write it as half $\gamma^{1/2}$ multiplied by 2 to the power $3/2$.

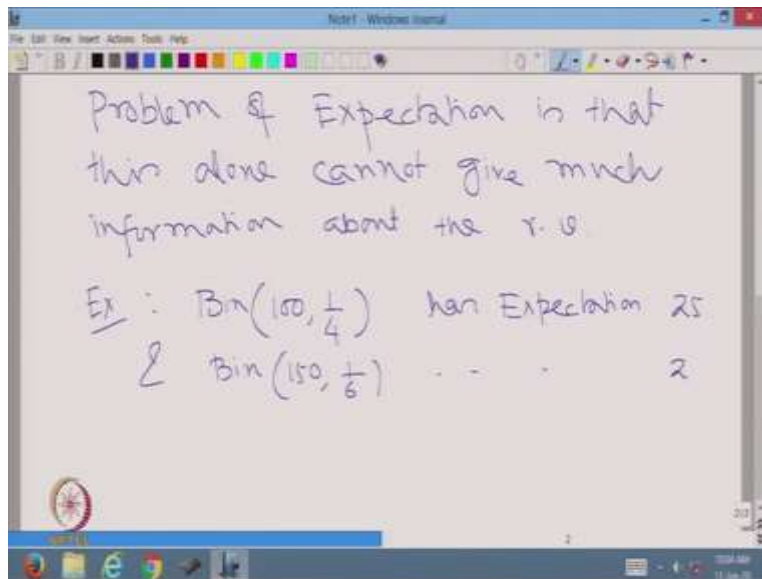
Putting $\gamma/2 = \sqrt{\pi}$, we have expectation of X^2 is equal to 1 over $\sqrt{2\pi}$ into $2\sqrt{\pi}$ which is equal to 1. Therefore, we get, if X is normal $0, 1$ then expectation of X^2 is equal to 1.

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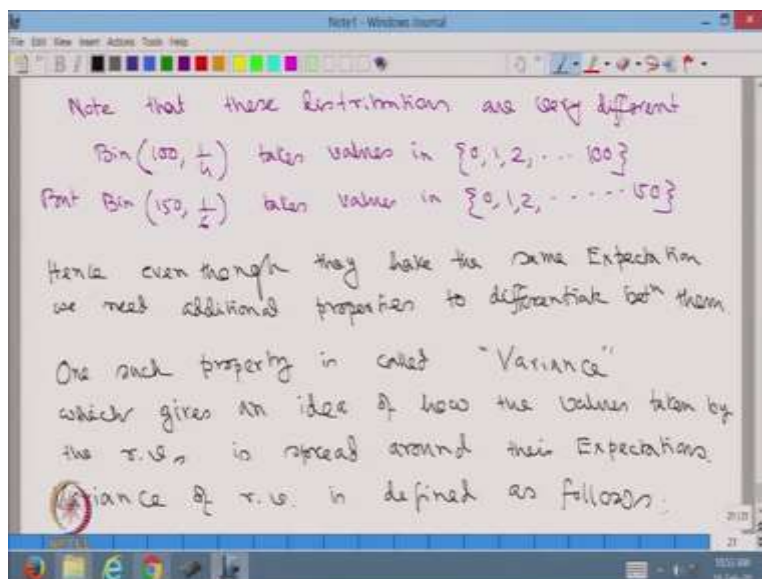
We may get the same result in another way. We know if X is normal $0, 1$, then X square is distributed as chi square with 1 degrees of freedom and chi square with 1 is equal to gamma half comma half. And we know that if X is distributed as gamma half comma half, its expectation is half over half is equal to 1, since expectation of gamma lambda comma alpha variable is alpha over lambda that we have seen already.

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Now problem of expectation is that this alone cannot give much information about the random variable. For example, binomial 100 comma 1 by 4 has expectation np which is 25 and binomial 150 comma 1 by 6 also has expectation 25.

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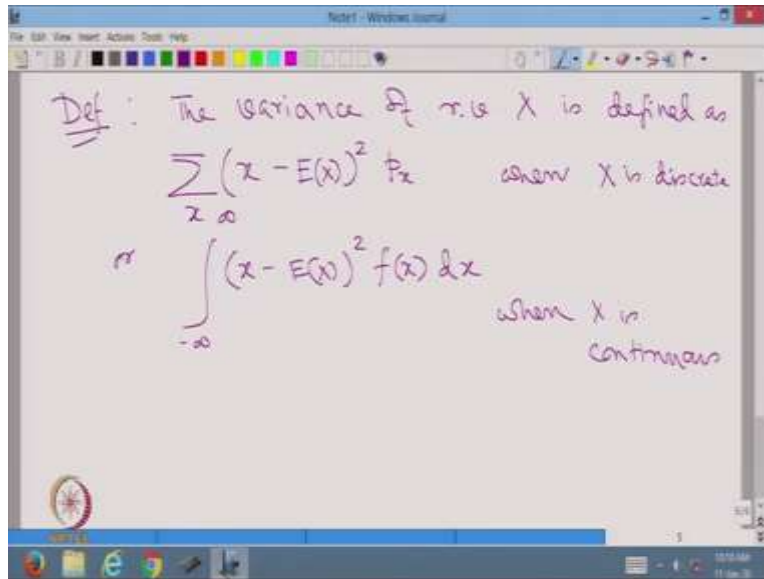


Note that, these two distributions are very different. Say, binomial 100 comma 1 by 4 takes values in 0, 1, 2, up to 100, but binomial 150, 1 by 6 takes values in 0, 1, 2, up to

150. Hence, even though they have the same expectation, we need additional properties to differentiate between them.

One such property is called variance which measures, which gives an idea of how the values taken by the random variables is spread around their expectations. Variance of a random variable is defined as follows.

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The image shows a handwritten definition of variance for a random variable X on a digital whiteboard. The text is written in purple ink. It starts with 'Def: The variance of r.v. X is defined as'. Then it shows two formulas. The first is a summation from $-\infty$ to ∞ of $(x - E(X))^2 p_x$, with the note 'where X is discrete'. The second is an integration from $-\infty$ to ∞ of $(x - E(X))^2 f(x) dx$, with the note 'where X is continuous'. The whiteboard has a toolbar at the top and a taskbar at the bottom.

Def : The variance of r.v. X is defined as

$$\sum_{-\infty}^{\infty} (x - E(X))^2 p_x \quad \text{where } X \text{ is discrete}$$
$$\text{or } \int_{-\infty}^{\infty} (x - E(X))^2 f(x) dx \quad \text{where } X \text{ is continuous}$$

Definition, the variance of a random variable X is defined as sigma over X , X minus expected value of X whole square into p_x when x is discrete and it is integration minus infinity to infinity, x minus expected value of x whole square into $f_x dx$ when x is continuous.

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Now there is a simpler form for Variance.

$$\sum_x (x - E(X))^2 p_x$$
$$= \sum_x \left(x^2 - 2xE(X) + (E(X))^2 \right) p_x$$

↑
is a constant

value of the r.v. X

$$= \sum_x x^2 p_x - \sum_x (2xE(X)) p_x + \sum_x (E(X))^2 p_x$$

$$= E(X^2) - 2E(X) \sum_x p_x + \sum_x (E(X))^2 p_x$$
$$= E(X^2) - 2(E(X))^2 + (E(X))^2$$
$$= \underline{E(X^2) - (E(X))^2}$$

Now there is a simpler form for Variance. I am showing it for discrete but the same will apply for continuous also. Sigma over x, x minus expected value of x whole square p_x , we can write it as sigma over x, x square minus 2x into expected value of x plus expected value of x whole square into p_x .

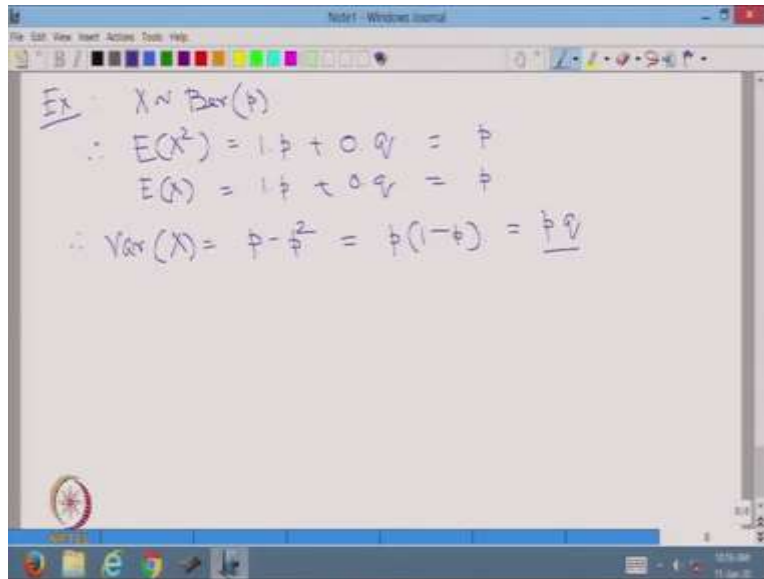
I want to emphasize on two things. One is that expected value of x is a constant. So we can take out of the summation as I will show later, but another thing is about notation, you can notice that here I am using small x which means value of the random variable x.

When we use capital x then that gives the name of the random variable. I have used it before also, but (())(19:51) did not explain. So in case some of you have the confusion, I am explaining it that when you are using small value that means it is a particular value that the random variable can take. But when you are using capital, then that is the name of the random variable. And as you can understand that here this is a possible value for the random variable, but x itself is the random variable.

That is why when I am writing expectation of x , I am putting it in capital X . So this is equal to $\sigma \sum x, x^2 P_x$ minus $\sigma \sum x$ to expected value of x P_x plus $\sigma \sum x$ expected value of x whole square into P_x which is equal to expected value of x^2 minus 2 into expected value of x as it is a constant we take out of the summation $\sigma \sum x, x P_x$ plus $\sigma \sum x$ expected value of x whole square times P_x .

And this we can write it as expected value of x^2 minus 2 into expected value of x whole square plus expected value of x whole square. Because once we take out expected value of x^2 out of the summation, the remaining things adds to 1 , is equal to expected value of x^2 minus expected value of x whole square. This is a very convenient formula for computing variance.

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The image shows a screenshot of a Windows Journal window titled "Notet - Windows Journal". The window contains handwritten mathematical derivations for the Bernoulli distribution. The text is as follows:

$$\begin{aligned} \text{Ex: } X &\sim \text{Ber}(p) \\ \therefore E(X^2) &= 1 \cdot p + 0 \cdot q = p \\ E(X) &= 1 \cdot p + 0 \cdot q = p \\ \therefore \text{Var}(X) &= p - p^2 = p(1-p) = \underline{pq} \end{aligned}$$

So let us give some example. X is Bernoulli with parameter p , therefore, expected value of x square is equal to 1 times p plus 0 times q is equal to p . And expected value of x is also 1 times p plus 0 times q is equal to p . This is obvious because x takes values only 1 and 0 , 1 with probability p and 0 with probability q . Therefore, variance of x is equal to p minus p square is equal to p into 1 minus p is equal to pq .

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Ex 2 Bin(n, p) $E(X) = np$

$$E(X^2) = \sum_{x=0}^n x^2 \binom{n}{x} p^x q^{n-x}$$

$$= \sum_{x=0}^n x^2 \frac{n!}{x!(n-x)!} p^x q^{n-x}$$

$$= \sum_{x=0}^n [(x(x-1)) + x] \frac{n!}{x!(n-x)!} p^x q^{n-x}$$

$$= \underbrace{\sum_{x=0}^n x(x-1) \frac{n!}{x!(n-x)!} p^x q^{n-x}}_{S} + \underbrace{\sum_{x=0}^n x \frac{n!}{x!(n-x)!} p^x q^{n-x}}_{E(X) = np}$$

$$E(X^2) = S + np \quad \text{where } S =$$

$$\sum_{x=0}^n x(x-1) \frac{n!}{x!(n-x)!} p^x q^{n-x}$$

$$= \sum_{x=0}^n \frac{n!}{(x-2)!(n-x)!} p^x q^{n-x}$$

$$= n(n-1)p^2 \sum_{x=2}^n \frac{(n-2)!}{(x-2)!(n-2-(x-2))!} p^{x-2} q^{(n-2)-(x-2)}$$

$$= n(n-1)p^2 \sum_{y=0}^{n-2} \frac{(n-2)!}{y!(n-2-y)!} p^y q^{(n-2)-y}$$

Sum of probabilities of Bin(n-2, p) = 1

Example 2, binomial n, p , we know expected value of x is equal to n times p . Therefore, expected value of x square we can compute as follows, this is sigma over x is equal to 0 to n x square $\binom{n}{x} p^x q^{n-x}$, is equal to sigma over x is equal to 0 to n x square into factorial n upon factorial x factorial n minus x p to the power x , q to the power n minus x .

Now we write it as sigma x is equal to 0 to n , x into x minus 1 plus x . So I am breaking x square into two parts, it is x into x minus 1 plus x into n factorial into x factorial into n

minus x factorial, p to the power x , q to the power n minus x , is equal to $\sum_{x=0}^n x$ is equal to 0 to n , x into x minus 1 into n factorial into x factorial n minus x factorial plus $\sum_{x=0}^n x$ is equal to 0 to n , x into n factorial, x factorial into n minus x factorial, p to the power x , q to the power n minus x .

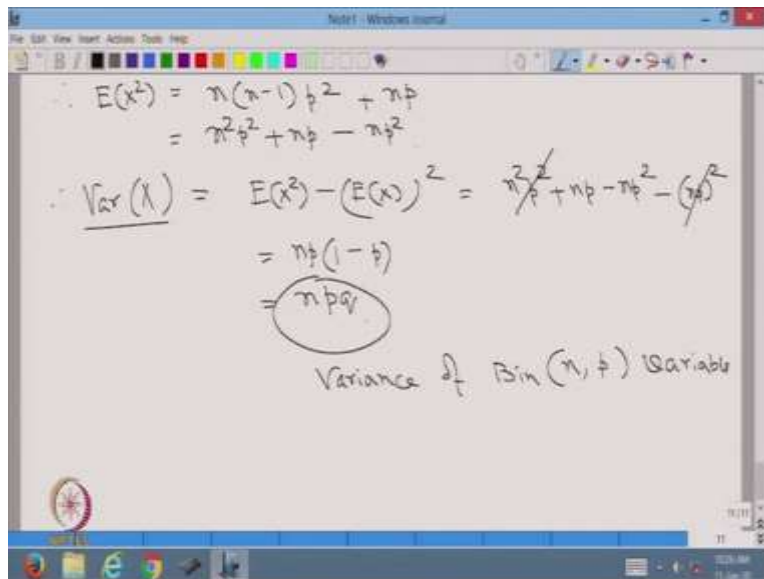
This part is, we know, is expected value of x which is is equal to np . So we need to calculate this part let us call it, say S , therefore, expected value of x square is equal to S plus np where S is equal to $\sum_{x=0}^n x$ is equal to 0 to n , x into x minus 1 into n factorial x factorial n minus x factorial p to the power x q to the power n minus x .

Now we cancel x into x minus 1 with factorial x , so two terms will be cancelled. So what we are left with is x is equal to 0 to n , n factorial x minus 2 factorial n minus n p to the power x q to the power n minus x . Since, negative, factorial of a negative number has no meaning, therefore we can change the limit of the sum from x is equal to 2 to n .

So this becomes x is equal to 2 to n , n factorial x minus 2 factorial, n minus 2 minus x plus 2 factorial, p to the power x , q to the power n minus 2 minus x plus 2 , which is equal to, if we take n and n minus 1 common and therefore out of the summation and p square out of the summation, then we get, it is x is equal to 2 to n , n minus 2 factorial upon x minus 2 factorial with n minus 2 minus x minus 2 factorial, p to the power x minus 2 q to the power n minus 2 minus x minus 2 .

A small change of variable will make it $\sum_{y=0}^{n-2} n$ minus 2 factorial upon y factorial n minus 2 minus y factorial p to the power y q to the power n minus 2 minus y , what is this sum? This is sum of probabilities of binomial n minus 2 comma p . Hence this is equal to 1 . Therefore S comes out to be n into n minus 1 p square.

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The image shows a handwritten derivation of the variance of a binomial distribution within a software window titled "Notepad - Windows Journal". The derivation is as follows:

$$\begin{aligned} E(x^2) &= n(n-1)p^2 + np \\ &= n^2p^2 + np - np^2 \\ \therefore \text{Var}(X) &= E(x^2) - (E(x))^2 = \cancel{n^2p^2} + np - \cancel{np^2} - (np)^2 \\ &= np(1-p) \\ &= \textcircled{npq} \end{aligned}$$

Variance of Bin(n, p) Variable

Therefore, expected value of x square is equal to n into n minus 1 p square plus np is equal to n square p square plus n p minus n p square. Therefore, variance of x , which we write like that, is equal to expectation of x square minus expectation of x whole square is equal to n square p square plus n p minus n p square minus n p whole square.

So this cancels with this, therefore we are left with n p into 1 minus p which is equal to npq . So that is the variance of binomial n comma p variable.

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Ex: $Poi(\lambda)$

$$\begin{aligned} \therefore E(X^2) &= \sum_{x=0}^{\infty} x^2 \cdot e^{-\lambda} \frac{\lambda^x}{x!} \\ &= \sum_{x=0}^{\infty} x(x-1) \cdot e^{-\lambda} \frac{\lambda^x}{x!} + \sum_{x=0}^{\infty} x \cdot e^{-\lambda} \frac{\lambda^x}{x!} \\ &= \sum_{x=0}^{\infty} e^{-\lambda} \frac{\lambda^x}{(x-2)!} + \sum_{x=0}^{\infty} e^{-\lambda} \frac{\lambda^x}{(x-1)!} \\ &= \lambda^2 \sum_{x=2}^{\infty} e^{-\lambda} \frac{\lambda^{x-2}}{(x-2)!} + \lambda \sum_{x=1}^{\infty} e^{-\lambda} \frac{\lambda^{x-1}}{(x-1)!} \end{aligned}$$

Sum of probabilities for a Poisson r.v.

$$\begin{aligned} \therefore E(X^2) &= \lambda^2 + \lambda \\ \therefore \text{Variance}(X) &= \lambda^2 + \lambda - \lambda^2 \\ &= \lambda \end{aligned}$$

Let me do one more example from discrete case. Poisson with parameter lambda, therefore expected value of x square is equal to sigma x is equal to 0 to infinity x square into e to the power minus lambda, lambda power x upon factorial x is equal to in a very similar way we can write it as x is equal to 0 to infinity.

X into x minus 1 to e to the power minus lambda, lambda power x upon factorial x plus sigma x is equal to 0 to infinity, x e to the power minus lambda, lambda power x upon factorial x. This is, as before, is going to be expected value of x is equal to lambda. This on the other hand, we can write it as sigma x is equal to 0 to infinity, e to the power minus lambda, lambda power x upon x minus 2 factorial is equal to.

If we take lambda square out of the summation, sigma x is equal to 0 to infinity e to the power minus lambda, lambda to the power x minus 2 upon factorial x minus 2, sum of probabilities for a Poisson random variable. Therefore, this comes out to be lambda square, therefore expected value of x square is equal to lambda square plus lambda. Therefore, variance of x is equal to lambda square plus lambda minus lambda square is equal to lambda.

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Ex Continuous r.v.

① Consider Exp(λ) $E(X) = \frac{1}{\lambda}$

What is $E(X^2)$

$$= \int_0^{\infty} x^2 \lambda e^{-\lambda x} dx = \frac{1}{\lambda} \int_0^{\infty} (\lambda x)^2 e^{-\lambda x} dx$$

$$= \frac{1}{\lambda^2} \int_0^{\infty} (\lambda x)^2 e^{-\lambda x} d(\lambda x)$$

$$= \frac{1}{\lambda^2} \int_0^{\infty} z^2 e^{-z} dz = \frac{1}{\lambda^2} \int_0^{\infty} z^{3-1} e^{-z} dz = \frac{\Gamma(3)}{\lambda^2} = \frac{2}{\lambda^2}$$

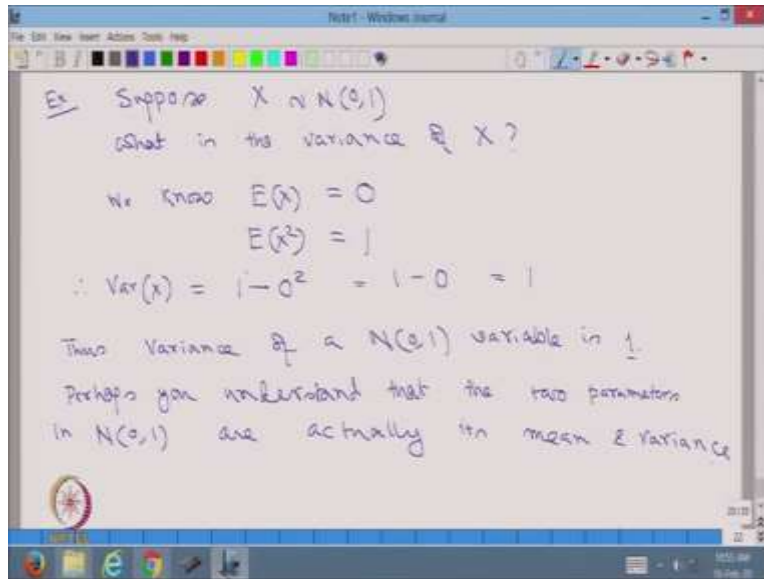
$\text{Var}(X) = \frac{2}{\lambda^2} - \frac{1}{\lambda^2} = \frac{1}{\lambda^2}$ Exp(λ) Variable

Example of continuous random variables, consider exponential lambda, we know that expected value of x is equal to 1 upon lambda. Question is what is expected value of x square? This is equal to integration 0 to infinity x square into lambda e to the power minus lambda x dx is equal to 1 upon lambda into 0 to infinity lambda x whole square into e to the power minus lambda x dx is equal to 1 upon lambda square 0 to infinity lambda x square e to the power minus lambda x into d lambda x.

Now this is is equal to 1 upon lambda square 0 to infinity z square e to the power minus z dz is equal to 1 upon lambda square 0 to infinity z to the power 3 minus 1 e to the power minus z dz. This is coming out to be gamma 3 upon lambda square. Now gamma 3 is equal to factorial 2, therefore this is 2 upon lambda square.

Therefore, variance of x when x is exponential lambda variable is equal to 2 upon lambda square minus expected value of x whole square, which is 1 upon lambda square is equal to 1 upon lambda square. So this is the variance of exponential lambda variable.

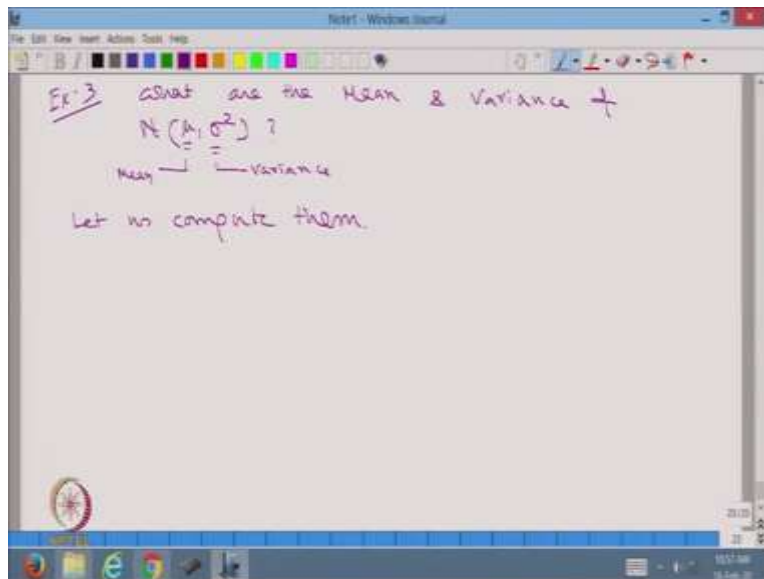
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Example, suppose is distributed as normal 0, 1, what is the variance of x? We know expectation of x is equal to 0 and expectation of x square is equal to 1. Therefore, variance of x we can understand is 1 minus 0 square is equal to 1 minus 0 is equal to 1.

Thus, variance of a normal 0, 1 variable is 1. Now perhaps you understand that the two parameters in normal 0, 1 are actually its mean and variance.

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So example 3, what are the mean and variance of normal μ comma σ^2 ? So we understand that the mean is going to be μ and variance is going to be σ^2 . Let us compute them.

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$$E(x) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} x e^{-\frac{1}{2} \frac{(x-\mu)^2}{\sigma^2}} dx$$

Put $\frac{x-\mu}{\sigma} = z \quad \therefore x = \mu + \sigma z \quad \therefore \frac{dx}{dz} = \sigma$
or $dx = \sigma dz$

$$E(x) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} (\mu + \sigma z) e^{-\frac{1}{2} z^2} \sigma dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\mu + \sigma z) e^{-\frac{1}{2} z^2} dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \mu e^{-\frac{1}{2} z^2} dz + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sigma z e^{-\frac{1}{2} z^2} dz$$

$$\mu + \sigma \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z e^{-\frac{1}{2} z^2} dz = \mu + \sigma \cdot 0 = \mu$$

Expectation of x is equal to $\frac{1}{\sqrt{2\pi}\sigma}$ integration minus infinity to infinity x into e to the power minus half x minus μ whole square upon σ^2 dx .

Put $x - \mu$ upon σ is equal to z . Therefore, x is equal to $\mu + \sigma z$. Therefore, dx is equal to σdz .

Therefore, expectation of x is equal to $\frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} (\mu + \sigma z) e^{-\frac{z^2}{2}} \sigma dz$ is equal to now σ gets cancelled $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\mu + \sigma z) e^{-\frac{z^2}{2}} dz$ is equal to $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \mu e^{-\frac{z^2}{2}} dz + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sigma z e^{-\frac{z^2}{2}} dz$.

Now if I take out μ , we get the integration to be the integration of the normal, standard normal PDF. Therefore, this gives us $\mu + \sigma \times \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z e^{-\frac{z^2}{2}} dz$ and this is the expectation of normal 0, 1 variable, therefore 0. Therefore, the end result is $\mu + \sigma \times 0$ is equal to μ . Thus, we get that expected value of x is equal to μ .

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What is the variance of X ?

$$E(X^2) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} x^2 e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx$$

Put $\frac{(x-\mu)}{\sigma} = z \quad \therefore x = \mu + \sigma z \quad \therefore dx = \sigma dz$

$$\therefore E(X^2) = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} (\mu + \sigma z)^2 e^{-\frac{1}{2}z^2} \sigma dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\mu^2 + 2\mu\sigma z + \sigma^2 z^2) e^{-\frac{1}{2}z^2} dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \mu^2 e^{-\frac{1}{2}z^2} dz + \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} 2\mu\sigma z e^{-\frac{1}{2}z^2} dz + \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z^2 e^{-\frac{1}{2}z^2} dz$$

The first term is μ^2 times the integral of the standard normal PDF, which is 1. The second term is 0 because the integrand is an odd function. The third term is σ^2 times the integral of z^2 times the standard normal PDF, which is 1.

$$\therefore E(X^2) = \mu^2 + \sigma^2$$

$$\therefore \text{Var}(X) = E(X^2) - (E(X))^2$$

$$= \mu^2 + \sigma^2 - \mu^2$$

$$= \sigma^2$$

What is the variance of x ? Expectation of x square is equal to $\frac{1}{\sqrt{2\pi}\sigma}$ minus infinity to infinity x square e to the power minus half x minus μ by σ whole square dx . Put x minus μ by σ is equal to z . Therefore, x is equal to μ plus σz and as before. Therefore, dx is equal to σdz .

Therefore, expected value of x square is equal to $\frac{1}{\sqrt{2\pi}\sigma}$ minus infinity to infinity μ plus σz whole square into e to the power minus half z square

$\sigma^2 dz$ is equal to $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (\mu^2 + 2\mu z + \sigma^2 z^2) e^{-\frac{z^2}{2}} dz$.

Is equal to $\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \mu^2 e^{-\frac{z^2}{2}} dz + \frac{2\mu}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z e^{-\frac{z^2}{2}} dz + \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z^2 e^{-\frac{z^2}{2}} dz$.

Now this is, I am integrating a constant μ^2 with the normal, standard normal PDF. Therefore, this will give me μ^2 . This is effectively computing the expected value of standard normal which we know is equal to 0 and this is expectation of x square when x is standard normal. Therefore, this integration will give us 1 and therefore the outcome is from this σ^2 we get σ^2 .

Therefore, expected value of x square is equal to $\mu^2 + \sigma^2$. Therefore, variance of x is expectation of x square minus expectation of x whole square is equal to $\mu^2 + \sigma^2 - \mu^2 = \sigma^2$.

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Properties of Variance

① For any constant $c \neq E(X)$

$$V(X) < E(X-c)^2$$

Proof: $E(X-c)^2 = E(X - E(X) + E(X) - c)^2$

$$= E(X - E(X))^2 + E(E(X) - c)^2 + 2E(X - E(X))(E(X) - c)$$

$$= V(X) + \frac{E(E(X) - c)^2}{>0}$$

$\therefore V(X) < E(X-c)^2$

Let us now investigate certain properties of variance. For any constant c not equal to expected value of x , variance of x is less than expected value of x minus c whole square. This is very simple since expected value of x minus c whole square is equal to expected

value of x minus expected value of x plus expected value of x minus c whole square is equal to expected value of x minus expected value of x whole square plus expected value of x minus c whole square plus 2 times expected value of x minus expected value of x into expected value of x minus c .

Since this is a constant and expected value of x minus expected value of x is going to be 0, because this is expected value of x minus expected value of x is equal to, because it is a constant. Therefore, it is expected value of x minus expected value of x is equal to 0.

Therefore what we are getting is equal to this term is variance of x plus this term is a positive quantity. It is greater than 0 therefore, variance of x is less than expected value of x minus c whole square.

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② If X is a r.v. then $\text{Var}(aX+b) = a^2 \text{Var}(X)$

Prf: $E(aX+b) = E(aX) + b = aE(X) + b$

$$\therefore \text{Var}(aX+b) = E(aX+b - aE(X) - b)^2$$

$$= E(a(X - E(X)))^2$$

$$= E(a^2 (X - E(X))^2)$$

↑
constant

$$= a^2 E(X - E(X))^2$$

$$= a^2 \text{Var}(X)$$

∴ Variance is not affected by change of origin however, it is affected by the scale

Property 2, if x is a random variable, then variance of ax plus b is equal to a square into variance of x . Proof, expected value of ax plus b is equal to expected value of ax plus b is equal to a times expected value of x plus b .

Therefore, variance of ax plus b is equal to expected value of ax plus b minus a times expected value of x minus b whole square, which is equal to expected value of a into x minus expected value of x plus 0 because they cancel each other square, is equal to expected value of a square into x minus expected value of x whole square.

Now since this is a constant, and we know that constant times expectation, expectation of a constant times a random variable is constant times expectation of the random variable. Therefore, we write it as a square into expected value of x minus expectation of x whole square is equal to a square into variance of x . Therefore, variance is not affected by change of origin. However, it is affected by the scale.

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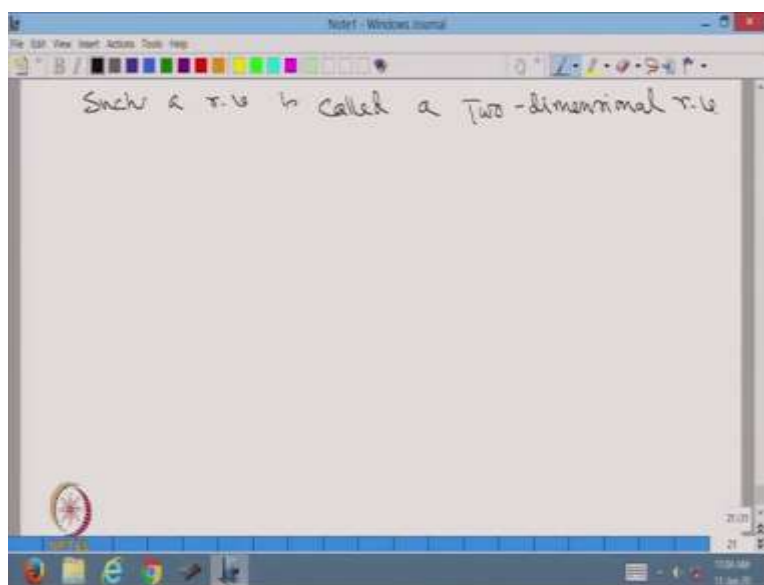
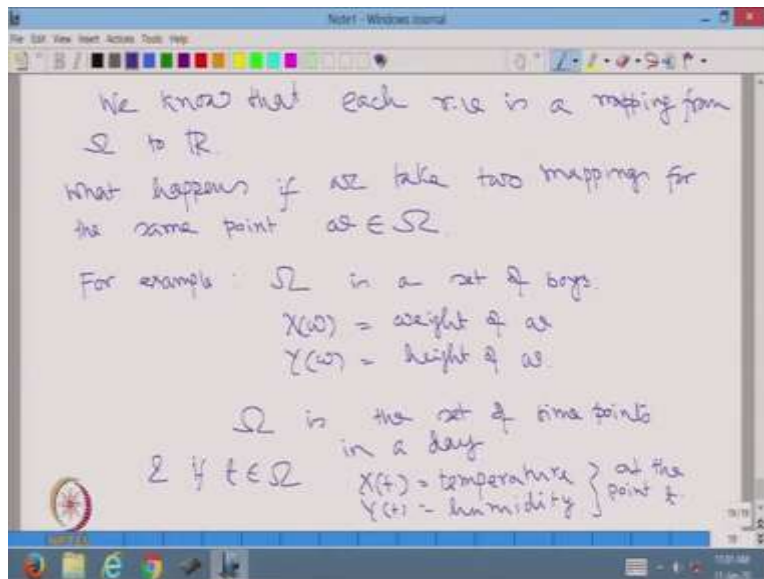
Ex: Suppose the temperature in Centigrade is given by C while in Fahrenheit given by F .
 We know that $F = C \times \frac{9}{5} + 32$
 $\therefore \text{Var}(F) = \frac{9^2}{5^2} \text{Var}(C)$

Note: ① The positive square root of Variance is called the standard deviation of the r.v.
 ② We generally denote the Variance by σ^2 & standard deviation is denoted by σ .

Example, suppose the temperature in centigrade is given by C while in Fahrenheit given by F . So if we consider these two to be the random variables, then we know that F is equal to C into 9 by 5 plus 32. Therefore, variance of F is equal to 9 square upon 5 square into variance when it is measured in terms of centigrade.

The positive square root of variance is called the standard deviation of the random variable. We generally denote the variance by sigma square. Sigma square, because variance has to be always positive, so the positiveness of the measurement is taken care of by the square and standard deviation is denoted by plus sigma.

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So, so far we have discussed mean and variance of a random variable and we know that each random variable is a mapping from Ω to \mathbb{R} . What happens if we take two mappings for the same point ω belonging to Ω ?

For example, Ω is a set of boys and $X(\omega)$ is equal to weight of ω and $Y(\omega)$ is equal to say height of ω . In a similar way, if Ω is the set of time points in a day and if t is a time point belonging to Ω , X_t is equal to temperature and Y_t is equal to humidity at the point t .

In practice, we often consider such two different random variables and that is important because we may like to see the relationship between these two random variables for illustration how much the weight of a person is affected by his or her height. Such a random variable is called a two-dimensional random variable and I shall start with that in the next class. Okay, students. Thank you so much.