

We end this lecture sequence with the most important property of expectations, namely linearity. The idea is pretty simple. Suppose that our random variable,  $X$ , is the salary of a random person out of some population. So that we can think of the expected value of  $X$  as the average salary within that population.

And now suppose that everyone gets a raise, and  $Y$  is the new salary. And generously, the new salary is twice the old salary plus a bonus of \$100. What happens to the expected value of the salary, or the average salary?

Well the new average salary, which is the expected value of  $2X$  plus 100, is twice the old average plus 100. So doubling everyone's salary and giving to everyone an additional \$100, what it does to the average is that it doubles the average and adds 100 to it.

This is the linearity property of expectation in one particular example. It's a most intuitive property, but it's worth also deriving it in a formal way. And the derivation proceeds through the expected value rule.

We're dealing here with a particular function,  $g$ , which is a linear function. So we're dealing with a linear function,  $ax$  plus  $b$ . And we're dealing with a random variable,  $Y$ , which is  $g$  applied to an original random variable,  $X$ .

So the expected value of  $Y$  can be calculated according to the expected value rule. It's the sum over all  $x$ 's of  $g$  of  $x$  times the probability of that particular  $x$ .

And we plug-in the specific form of the function,  $g$ , which is  $ax$  plus  $b$ . And then we separate the sum into two sums. The first sum, after pulling out a constant of  $a$ , takes this form. And the second sum, after pulling out the constant,  $b$ , takes this form.

Now, the first sum is  $a$  times the expected value of  $X$ . This is just the definition of the expected value. As, for the second sum, we realize that this quantity is equal to 1 because it is the sum of the probabilities of all the different values of  $X$ . And this concludes the proof of the linearity of expected values.

Notice that for expected values, what we have is that the expected value of  $Y$ , which is expected value

of  $g$  of  $X$ , is this same as  $g$  of the expected value of  $X$ . The expected value of a linear function is the same linear function applied to the expected value. But this is an exceptional case. This does not happen in general. It's an exceptional function  $g$  that makes this happen. This property is true for linear functions. But for non-linear functions, it is generally false.