STA286 Lecture 12

Neil Montgomery

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$$Cov(X, Y) = E(XY) - E(X)E(Y)$$

So, $X \perp Y$ implies Cov(X,Y) = 0, in which case the variance of the sum is the sum of the variances.

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It is a measure of *linear* relationship, in the following sense(s):

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- ▶ with high probability, smaller values of *X* and larger values of *Y* happen at the same time, then:
 - with high probability (X EX)(Y EY) will be **negative**.

correlation coefficient

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Positive and negative correlation mean the same as positive and negative covariance; in addition, the correlation of different pairs of distributions can be compared. Also:

$$-1 \leqslant \rho \leqslant 1$$

		X		
Y	-1	0	1	Marginal
-1	0.30	0.02	0.01	0.33
0	0.02	0.30	0.02	0.34
1	0.01	0.02	0.30	0.33
Marginal	0.33	0.34	0.33	1.00

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-1	0.30	0.02	0.01	0.33
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$$E(X) = E(Y) = 0$$
, so $Cov(X, Y) = E(XY)$.

		X		
Y	-1	0	1	Marginal
-1	0.30	0.02	0.01	0.33
0	0.02	0.30	0.02	0.34
1	0.01	0.02	0.30	0.33
Marginal	0.33	0.34	0.33	1.00

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In this case (tedious exercise) $\rho=$ 0.879.

		X		
Y	-1	0	1	Marginal
-1	0.30	0.02	0.01	0.33
0	0.02	0.30	0.02	0.34
1	0.01	0.02	0.30	0.33
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The probability is strongly concentrated along the "X = Y diagonal".

discrete example - negative correlation close to ${\bf 1}$

		X		
Y	-1	0	1	Marginal
-1	0.01	0.02	0.30	0.33
0	0.02	0.30	0.02	0.34
1	0.30	0.02	0.01	0.33
Marginal	0.33	0.34	0.33	1.00

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-1	0.01	0.02	0.30	0.33
0	0.02	0.30	0.02	0.34
1	0.30	0.02	0.01	0.33
Marginal	0.33	0.34	0.33	1.00

In this case (tedious exercise) $\rho = -0.879$.

The probability is strongly concentrated along the "X = -Y diagonal".

discrete exmaple - $X \perp Y$

		^		
Y	-1	0	1	Marginal
-1	0.1089	0.1122	0.1089	0.33
0	0.1122	0.1156	0.1122	0.34
1	0.1089	0.1122	0.1089	0.33
Marginal	0.33	0.34	0.33	1.00

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X and Y are indepedent (can be tediously verified.)

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X and Y are indepedent (can be tediously verified.)

Easy to show E(XY) = 0, so that $\rho = 0$.

discrete example - $\rho = 0$ but very much not independent!

		X		
Y	-1	0	1	Marginal
-1	0.00	0.00	0.25	0.25
0	0.50	0.00	0.00	0.50
1	0.00	0.00	0.25	0.25
Marginal	0.50	0.00	0.50	1.00

discrete example - $\rho = 0$ but very much not independent!

		X		
Y	-1	0	1	Marginal
-1	0.00	0.00	0.25	0.25
0	0.50	0.00	0.00	0.50
1	0.00	0.00	0.25	0.25
Marginal	0.50	0.00	0.50	1.00

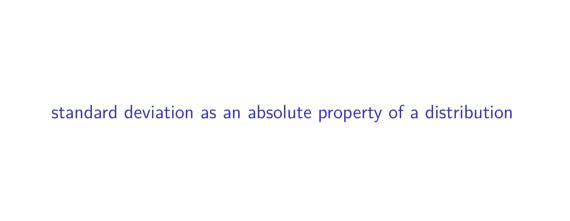
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X and Y are not independent.

But E(XY) = 0, so $\rho = 0$.



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E(X) and $E(X^2)$ provide information about X that limit its values and probabilities to some extent. Two examples are Markov's and Chebyshev's inequalities.

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Theorem (Markov): If $X \ge 0$ has expected value E(X), then:

$$P(X \geqslant t) \leqslant \frac{E(X)}{t}$$
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E(X) and $E(X^2)$ provide information about X that limit its values and probabilities to some extent. Two examples are Markov's and Chebyshev's inequalities.

Theorem (Markov): If $X \ge 0$ has expected value E(X), then:

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Theorem (Chebyshev): If $Var(X) = \sigma^2$ and $E(X) = \mu$:

$$P(|X - \mu| \geqslant t) \leqslant \frac{\sigma^2}{t^2}$$

Equivalently:

$$P(\mu - k\sigma < X < \mu + k\sigma) \geqslant 1 - \frac{1}{k^2}$$

example - "uniform on (0,1)"

Suppose X has the density f(x) = 1 on 0 < x < 1 and 0 otherwise.

Then
$$E(X) = \frac{1}{2}$$
 and $Var(X) = \frac{1}{12}$

Various applications of Markov's and Chebyshev's inequality for this example show how weak they really are — mainly useful in theory than in practice.