STA286 Lecture 12

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

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- with high probability, smaller values of X and larger values of Y happen at the same time, then:
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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:

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

discrete example - positive correlation close to 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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$E(X) = E(Y) = 0$, so $\mathrm{Cov}(X, Y) = E(XY)$.

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

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

discrete example - negative correlation close to 1

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

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

discrete exmaple - $X \perp Y$

	X			
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

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		X		
Y	-1	0	1	Marginal
-1	0.00	0.00	0.25	0.25
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X and Y are not independent.

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

standard deviation as an absolute property of a distribution

mean and SD aren't unique, but they do say something

$E(X)$ 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 $X \geqslant 0$ 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 $X \geqslant 0$ has expected value $E(X)$, then:

$$P(X \geqslant t) \leqslant \frac{E(X)}{t}.$$

Theorem (Chebyshev): If $\mathrm{Var}(X) = \sigma^2$ 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 $\text{Var}(X) = \frac{1}{12}$

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