STAT 22000 Lecture Slides Correlation

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Strong Association



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Large spread of *Y* when *X* is known

Small spread of *Y* when *X* is known

Correlation r is a numerical measure of the *direction* and *strength* of the **linear** relationship between two numerical variables.

"r" always lies between -1 and 1; the strength increases as you move away from 0 to either -1 or 1.

- *r* > 0: positive association
- *r* < 0: negative association
- $r \approx 0$: very weak linear relationship
- large |r|: strong linear relationship
- r = -1 or r = 1: only when all the data points on the scatterplot lie exactly along a straight line



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Positive Correlations



Negative Correlations



Formula for Computing the Correlation Coefficient "r"

The correlation coefficient r(x_1, y_1) (or simply, correlation) is defined as: (x_2, y_2) (x_3, y_3) : (x_n, y_n) where s_x and s_y are respectively the sample SD of Xand of Y.

Usually, we find the correlation using softwares rather than by manual computation.

Why *r* Measures the Strength of a Linear Relationship?



What is the sign of
$$\left(\frac{x_i - \bar{x}}{s_x}\right) \left(\frac{y_i - \bar{y}}{s_y}\right)$$
??

Here r > 0; more positive contributions than negative.

What kind of points have large contributions to the correlation?

Correlation *r* Has No Unit

$$r = \frac{1}{n-1} \sum_{i=1}^{n} \underbrace{\left(\frac{x_i - \bar{x}}{s_x}\right)}_{z-\text{score of } x_i \ z-\text{score of } y_i} \underbrace{\left(\frac{y_i - \bar{y}}{s_y}\right)}_{z-\text{score of } y_i}.$$

After standardization, the *z*-score of neither x_i nor y_i has a unit.

- So r is unit-free.
- So we can compare r between data sets, where variables are measured in different units or when variables are different.
 E.g. we may compare the

r between [swim time and pulse],

with the

r between [swim time and breathing rate].

Changing the units of variables does not change the correlation coefficient r, because we get rid of all the units when we standardize them (get *z*-scores).

E.g., no matter the temperatures are recorded in $^{\circ}F$, or $^{\circ}C$, the correlations obtained are equal because

$$C = \frac{5}{9}(F - 32).$$



Sometimes one use the *X* variable to predict the *Y* variable. In this case, *X* is called the *explanatory variable*, and *Y* the *response*. The correlation coefficient *r* does not distinguish between the two. It treats *x* and *y* symmetrically.

$$r = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{s_x} \right) \left(\frac{y_i - \bar{y}}{s_y} \right)$$

Swapping the *x*-, *y*-axes doesn't change *r* (both r = 0.74.)



The scatter plot below shows a *perfect nonlinear* association. All points fall on the quadratic curve $y = 1 - 4(x - 0.5)^2$.



No matter how strong the association, the *r* of a <u>curved</u> relationship is NEVER 1 or -1. It can even be 0, like the plot above.

Correlation Is VERY Sensitive to Outliers

Sometimes a single outlier can change *r* drastically.



For the plot on the left, $r = \begin{cases} 0.0031 & \text{with the outlier} \\ 0.6895 & \text{without the outlier} \end{cases}$

Outliers that may remarkably change the form of associations when removed are called **influential points**.

Remark: Not all outliers are influential points.

When Data Points Are Clustered ...



In the plot above, each of the two clusters exhibits a weak negative association (r = -0.336 and -0.323).

But the whole diagram shows a moderately strong positive association (r = 0.849).

- This is an example of the Simpson's paradox.
- An overall *r* can be misleading when data points are clustered.
- Cluster-wise *r*'s should be reported as well.

The 4 data sets below have identical \overline{x} , \overline{y} , s_x , s_y , and r.

	Dataset 1		Dataset 2		Dataset 3		Dataset 4	
	x	У	x	У	x	У	x	У
	10	8.04	10	9.14	10	7.46	8	6.58
	8	6.96	8	8.14	8	6.77	8	5.76
	13	7.58	13	8.75	13	12.76	8	7.71
	9	8.81	9	8.77	9	7.11	8	8.84
	11	8.33	11	9.26	11	7.81	8	8.47
	14	9.96	14	8.10	14	8.84	8	7.04
	6	7.24	6	6.13	6	6.08	8	5.25
	4	4.26	4	3.10	4	5.36	19	12.50
	12	10.84	12	9.13	12	8.15	8	5.56
	7	4.82	7	7.26	7	6.42	8	7.91
	5	5.68	5	4.74	5	5.73	8	6.89
Ave	9	7.5	9	7.5	9	7.5	9	7.5
SD	3.16	1.94	3.16	1.94	3.16	1.94	3.16	1.94
r	0.82		0.82		0.82		0.82	

Always Check the Scatter Plots (2)



- In Dataset 2, y can be predicted exactly from x. But r < 1, because r only measures linear association.
- In Dataset 3, *r* would be 1 instead of 0.82 if the outlier were actually on the line.

The correlation coefficient can be misleading in the presence of outliers, multiple clusters, or nonlinear association.

Correlation Indicates Association, Not Causation



Questions

- Why do both variables have to be numerical when computing their correlation coefficient?
- If the law requires women to marry only men 2 years older than themselves, what is the correlation of the ages between husbands and wives?