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Short communication

One More Geometric Interpretation of Pearson's Correlation

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Abstract

It is known that Pearson's correlation coefficient r is equal to the cosine of the angle between the vectors \vec{x} and \vec{y} describing the centered data. We use this known fact to show that r describes how closer the corresponding unit vector $\vec{e}_x = \frac{\vec{x}}{\|\vec{x}\|}$ is to the y -unit vector $\vec{e}_y = \frac{\vec{y}}{\|\vec{y}\|}$ than to its opposite $-\vec{e}_y$: namely, r is equal to the (scaled) difference between the squared distances $d^2(\vec{e}_x, -\vec{e}_y)$ and $d^2(\vec{e}_x, \vec{e}_y)$. In particular, the correlation is positive if \vec{e}_x is closer to \vec{e}_y and negative if \vec{e}_x is closer to $-\vec{e}_y$.

Known geometric interpretation: correlation as the cosine of the angle between two centered data vectors. It is known that the sample Pearson's correlation r is equal to $\cos(\alpha)$, where $\alpha \stackrel{\text{def}}{=} \angle(\vec{x}, \vec{y})$ is the angle between the centered data vectors $\vec{x} \stackrel{\text{def}}{=} (X_1 - \bar{X}, \dots, X_n - \bar{X})$ and $\vec{y} \stackrel{\text{def}}{=} (Y_1 - \bar{Y}, \dots, Y_n - \bar{Y})$; see, e.g., Rodgers and Nicewander [1].

Specifically, in terms of these vectors \vec{x} and \vec{y} , the correlation

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X}) \cdot (Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \cdot \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}$$

can be described as $r = \frac{\vec{x} \cdot \vec{y}}{\|\vec{x}\| \cdot \|\vec{y}\|}$. Since for every two vectors \vec{a} and \vec{b} , the scalar (dot) product is equal to $\vec{a} \cdot \vec{b} = \|\vec{a}\| \cdot \|\vec{b}\| \cdot \cos(\angle(\vec{a}, \vec{b}))$, the vector-based expression for r leads to the desired formula $r = \cos(\alpha)$.

Towards a new interpretation. The angle between the two vectors \vec{x} and \vec{y} is the same as the angle between the corresponding unit vectors $\vec{e}_x \stackrel{\text{def}}{=} \frac{\vec{x}}{\|\vec{x}\|}$ and $\vec{e}_y \stackrel{\text{def}}{=} \frac{\vec{y}}{\|\vec{y}\|}$. Thus, for these unit vectors, $\vec{e}_x \cdot \vec{e}_y = \|\vec{e}_x\| \cdot \|\vec{e}_y\| \cdot \cos(\alpha) = \cos(\alpha)$. Therefore,

$$d^2(\vec{e}_x, \vec{e}_y) = \|\vec{e}_x - \vec{e}_y\|^2 = (\vec{e}_x)^2 + (\vec{e}_y)^2 - 2\vec{e}_x \cdot \vec{e}_y = 2 - 2\cos(\alpha) = 2 - 2r$$

and

$$d^2(\vec{e}_x, -\vec{e}_y) = \|\vec{e}_x - (-\vec{e}_y)\|^2 = (\vec{e}_x)^2 + (\vec{e}_y)^2 + 2\vec{e}_x \cdot \vec{e}_y = 2 + 2\cos(\alpha) = 2 + 2r.$$

So, we conclude that

$$r = \frac{1}{4} \cdot (d^2(\vec{e}_x, -\vec{e}_y) - d^2(\vec{e}_x, \vec{e}_y)).$$

In other words, the correlation coefficient describes whether the unit centered data vector \vec{e}_x corresponding to X_i is closer to the similar vector \vec{e}_y corresponding to Y_i or to the opposite vector $-\vec{e}_y$. In particular, the correlation is positive if \vec{e}_x is closer to \vec{e}_y and negative if \vec{e}_x is closer to $-\vec{e}_y$.

Comment. The above formula for r is a particular case of a more general formula presented in Batyrshin [2].

References

- [1] Rodgers, J. L., and Nicewander, W. A., Thirteen ways to look at the correlation coefficient, *The American Statistician*, 1988; 42(1): 59-66.
- [2] Batyrshin, I., Constructing time series shape association measures: Minkowski distance and data standardization, Proceedings of the 1st BRICS Countries Congress on Computational Intelligence BRIC-SCCI 2013, Recife, Brazil. September 811, 2013. <http://arxiv.org/pdf/1311.1958v3>.