# An Informational Measure of Correlation 

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In a recently published paper "Una teoria de la certidumbre" M. Castañs (1955) defines the certitude of a discrete probability distribution as the quantity

$$
\begin{equation*}
\log n+\sum_{i=1}^{n} p_{i} \log p_{i} \tag{1}
\end{equation*}
$$

where $n$ is the number of discrete, mutually exclusive possibilities and $p_{1}, p_{2}, \cdots, p_{n}$ their respective probabilities. Writing this expression in the form

$$
\begin{equation*}
-\sum_{i=1}^{n} p_{i} \log \frac{1}{p_{i}}+n \frac{1}{n} \log n, \tag{2}
\end{equation*}
$$

we see that it represents the amount by which the entropy of the probability distribution $p_{1}, p_{2}, \cdots, p_{n}$ of $n$ discrete cases falls below its greatest possible value $\log n$, which is assumed when every $p_{i}$ has the same value $1 / n$. It is therefore the amount of information conveyed, to an individual who previously supposed that the $n$ possible discrete values $x_{1}, x_{2}, \cdots, x_{n}$ of a discrete variable $x$ were all equally likely, by the statement that their respective probabilities are $p_{1}, p_{2}, \cdots, p_{n}$ (Shannon, 1948, pp. 379, 623).

In a later paper, Castañs Camargo and Medina e Isabel (1956) consider two sets of discrete values, with probabilities $p_{1}, p_{2}, \cdots, p_{n}$ and $q_{1}, q_{2}, \cdots, q_{n}$ respectively, and with joint probabilities

$$
p_{i j}(i=1,2, \cdots, n ; \quad j=1,2, \cdots, m) .
$$

Here

$$
\begin{equation*}
p_{i}=\sum, p_{i j}, \quad q_{j}=\sum_{i} p_{i j} \tag{3}
\end{equation*}
$$

and it may be shown (Goldman, 1953) that

$$
\begin{equation*}
\sum_{i j} p_{i} q_{j} \log \left(p_{i} q_{j}\right) \leqq \sum_{i j} p_{i j} \log p_{i j} \tag{4}
\end{equation*}
$$

with equality only if $p_{i j}=p_{i} q_{j}$ for all $i$ and $q$. They then define the logarithmic index of correlation

$$
\begin{equation*}
r_{0}=\sum_{i j}\left(p_{i j} \log p_{i j}-p_{i} q_{j} \log p_{i} q_{j}\right) ; \tag{5}
\end{equation*}
$$

by (4), $r_{0} \geqq 0$.
It will be seen that $r_{0}$ also has a simple informational interpretation. It has been discussed from this point of view by McGill (1954). To an individual who previously supposed all the possible discrete values ( $x_{i}, y_{j}$ ) of a pair of variables $(x, y)$ to be equally likely, the statement that the probability distribution of $\left(x_{i}, y_{j}\right)$ is $p_{i j}(i=1,2, \cdots, n$; $j=1,2, \cdots, m)$ conveys an amount

$$
\sum_{i j} p_{i j} \log p_{i j}+\log m n
$$

of information. This is greater than the amount of the information which he received on being told only the separate probability distributions $p_{1}, \cdots, p_{n}$ and $q_{1} \cdots, q_{m}$ of $x$ and of $y$; and the former amount exceeds the latter by
$\sum_{i j} p_{i j} \log p_{i j}+\log m n-\left(\sum_{i} p_{i} \log p_{i}+\log n\right)$
$-\left(\sum_{j} q_{j} \log q_{j}+\log m\right)$

$$
\begin{aligned}
& =\sum_{i j} p_{i j} \log p_{i j}-\sum_{i j} p_{i} q_{j} \log p_{i}-\sum_{i j} p_{i} q_{j} \log q_{j} \\
& =r_{0} .
\end{aligned}
$$

It is easy to show, by applying a well known property (Shannon, 1948, sect. 6) of information, that the value of the information gain $r_{0}$ is unchanged if the prior opinion of equiprobable discrete values $\left(x_{i}, y_{j}\right)$ is replaced by the prior opinion that $x$ and $y$ are statistically independent ( $p_{i j}=p_{i} q_{j}$ ). Thus $r_{0}$ can be interpreted as an information gain which provides a measure of the correlation between $x$ and $y$.

For continuous variables $x$ and $y$ with joint probability density distribution $p(x, y)$ the corresponding quantity $r_{0}$ is given by the equation

$$
\begin{equation*}
r_{0}=\iint\{p(x, y) \log p(x, y)-p(x) q(y) \log [p(x) q(y)]\} d x d y \tag{6}
\end{equation*}
$$

where $p(x)$ and $q(y)$ are the probability density distributions of $x$ and $y$ taken separately. This is the amount of information conveyed, to any individual who previously supposed $x$ and $y$ to be independent, by the statement that their joint probability density distribution is $p(x, y)$.

It is independent of the probability density distributions $p_{0}(x), q_{0}(y)$ which express his prior opinions about the values of $x$ and $y$.

Although $r_{0}$ itself provides a logically very satisfactory measure of correlation, applicable whatever the form of $p(x, y)$, it is natural to ask whether something more closely resembling the classical coefficient of correlation can be derived from informational considerations. In the second paper referred to above (Castañs Camargo and Medina e Isabel, 1956), the two authors consider the quantity

$$
-2 r_{0}\left\{\sum_{i j} p_{i} q_{j} \log \left(p_{i} q_{j}\right)\right\}^{-1}
$$

which they call the "logarithmic coefficient of correlation." It appears on examination that this coefficient cannot be interpreted as an informational measure of correlation.

However, it is a simple matter to obtain the desired result in the following way. Consider the probability density distribution

$$
\begin{equation*}
p(x, y)=\frac{1}{2 \pi} \sqrt{a b-h^{2}} e^{-\frac{1}{2}\left(\alpha x^{2}+2 h x y+b y^{2}\right)}, \tag{7}
\end{equation*}
$$

where $a>0, a b-h^{2}>0$. As is well known (Whittaker and Robinson, 1944), the classical correlation coefficient $r$ is given in this case by the equation

$$
\begin{equation*}
r=-h / \sqrt{a b} . \tag{8}
\end{equation*}
$$

To calculate the informational measure $r_{0}$, we first note that, in the notation already used above,

$$
\begin{align*}
& p(x)=\int_{-\infty}^{\infty} p(x, y) d y=\sqrt{\frac{\alpha}{\pi}} e^{-\alpha x^{2}} \\
& q(y)=\int_{-\infty}^{\infty} p(x, y) d x=\sqrt{\frac{\beta}{\pi}} e^{-\beta y^{2}}, \tag{9}
\end{align*}
$$

where

$$
\alpha=\left(a b-h^{2}\right) / 2 b, \quad \beta=\left(a b-h^{2}\right) / 2 a .
$$

Equation (6) then gives, after a short calculation (Shannon, 1948, p. 54),

$$
\begin{align*}
r_{0} & =-\log \frac{2 \pi e}{\sqrt{a b-\bar{h}^{2}}}+\log \sqrt{\frac{\pi e}{\alpha}}+\log \sqrt{\frac{\pi e}{\beta}}  \tag{10}\\
& =\frac{1}{2} \log \frac{a b}{a \bar{b}-h^{2}}
\end{align*}
$$

and from (8) and (10) we see that, for the distribution (7)

$$
\begin{equation*}
r=\sqrt{1-e^{-2 \tau_{0}}} \tag{11}
\end{equation*}
$$

It is easy to verify that the same result follows when $p(x, y)$ is given the more general form

$$
\begin{align*}
p(x, y)=\frac{1}{2 \pi} \sqrt{a b-h^{2}} & \exp \left\{-\frac{1}{2}\left[a\left(x-x_{0}\right)^{2}\right.\right.  \tag{12}\\
& \left.\left.+2 h\left(x-x_{0}\right)\left(y-y_{0}\right)+b\left(y-y_{0}\right)^{2}\right]\right\}
\end{align*}
$$

We can now define the informational coefficient of correlation $r_{1}$ by the equation

$$
\begin{equation*}
r_{1}=\sqrt{1-e^{-2 r_{0}}} \tag{13}
\end{equation*}
$$

where $r_{0}$ is given by (6). This coefficient reduces to the classical correlation coefficient in the case (12); it lies between 0 and 1 whatever the distribution $p(x, y)$. It is zero whenever $x$ and $y$ are statistically independent, since then $r_{0}=0$, and it is 1 whenever $x$ and $y$ are fully correlated, in the sense that each determines the value of the other uniquely.

An important advantage of the informational measures of correlation $r_{0}$ and $r_{1}$ in physical applications is that they are independent of the particular manner in which the measure numbers $x$ and $y$ are assigned to the two physical quantities under examination; in mathematical terms $r_{0}$ and $r_{1}$ are invarient under a transformation $x^{\prime}=f(x), y^{\prime}=g(y)$ of the variables $x$ and $y$ into new variables $x^{\prime}$ and $y^{\prime}$ respectively. The invariance of $r_{0}$ was pointed out by Jeffreys (1946) many years ago. In fact, since

$$
\begin{aligned}
& \iint p(x, y)[\log p(x)+\log q(y)] d x d y \\
&=\iint p(x) q(y)[\log p(x)+\log q(y)] d x d y
\end{aligned}
$$

Eq. (6) can be written in the equivalent form

$$
\begin{equation*}
r_{0}=\iint p(x, y) \log \left\{\frac{p(x, y)}{p(x) q(y)}\right\} d x d y \tag{14}
\end{equation*}
$$

Here $\log \{p(x, y) / p(x) q(y)\}$ is invariant under the above transformation, and hence its mathematical expectation $r_{0}$ is invariant; the invariance of $r_{1}$ follows immediately by (13).

Because of its interpretation in terms of quantity of information, $r_{0}$ seems to provide a more natural measure of correlation than $r_{1}$, but $r_{1}$ has the advantage that it is an informational measure of correlation which can be regarded as a generalization of an already familiar concept, viz. the ordinary correlation coefficient of a normal distribution.

## SUMMARY

Informational considerations lead to a natural generalization of the classical correlation coefficient of a normal distribution. The generalized coefficient, here called the informational coefficient of correlation, is a function of the joint probability density distribution $p(x, y)$ of the two variables $x$ and $y$, is invariant under a change of parameterization $x^{\prime}=f(x), y^{\prime}=g(y)$, and reduces to the classical correlation coefficient when $p(x, y)$ is normal.

Received: April 8, 1957

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