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RESUMEN: La Teoria de la Informacion permite desarrollar una herramienta util para medir la interdependencia en la in formacion que brindan un grupo de clasificaciones. Aplicaremos aqui el metodo propuesto por Estabroot: (1967) a la muestra de 140 estrellass Be del trabajo de Jaschek et al. (1980), estudiando las clasificaciones por tipo espectral, en relación al sistema clasificatorio de. las Be propuesto por Jaschek, en el trabajo citado.

ABSTRACT: The Information Theory $i=$ a useful development tool to measure the correlation in the information of several classifications over the same of objects. In this work, we apply the method proposed by Estabrook (196?) to the sample of 140 Ee stars subdivided in five groups by Jascher et al. (1980). We study the possible dependence between this classification of Eee stars (J) and the Mk spectral classification (T).

## 1. FUNDAMENTAL CONCEPTS

Table I gives the numbers of those Ee stars which share the same classification. We can associate, with each "state" of Jaschek's classification (J), a distribution of

object at random from the collection of Be stars to which description has been assigned. The related expression is:

$$
\begin{gathered}
P\left(J_{i}\right)=\text { Number of Be stars with } J_{i} \text { classification } \\
\text { Total number of Be stars }
\end{gathered}
$$

In the same way, we can obtain $P\left(T_{m}\right)$ applied to the selection of stars with spectral type $T_{m}$. The results are presented in Tables 2 and 3.
table 1
Description of the stars which share the sane classification (J and T ).

| $I_{n}^{J_{i}}$ | 1 | II | III | IV | $v$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 80 | 3 | - | - | - | - |
| 80.5 | 2 | - | - | - | 1 |
| B 1 | 12 | - | - | - | 3 |
| B 2 | 17 | 1 | - | 1 | 8 |
| B J | 6 | 5 | - | 4 | 7 |
| B4 | 2 | - | 1 | 1 | 2 |
| 85 | 1 | - | 1 | 1 | 3 |
| 86 | 1 | 3 | - | 6 | 4 |
| 87 | - | 3 | - | 7 | 5 |
| 88 | - | 1 | 3 | 12 | 2 |
| 89 | - | - | 1 | 5 | 1 |
| 8 9.5 | - | - | - | 1 | 1 |
| A 0 | - | - | 1 | 1 | - |

It is possible to assign to each of these discrete distributions of probability a measure of entropy according to the Information Theory (IT). This is essentially a measure of how difficult it is to predict which one of the
claseifications's possible descriptions is applicable to some object randomly chosen from or set. Depending on their associated distributions of probability, different classifications will be assigned to different measures of entropy (Estabrook, 1967).

TABLE 2
Distribution of the probability associated with the classification $J_{i}$

| $\mathbf{U}_{1}$ | $P\left(d_{i}\right)$ |
| ---: | ---: |
| $I$ | 0.314 |
| II | 0.093 |
| III | 0.050 |
| IV | 0.279 |
| $V$ | 0.264 |

TABLE 3
Distribution of the probability associated with the classification $T_{0}$

| $\mathrm{T}_{\text {m }}$ | P( $\mathrm{ra}_{\mathrm{m}}$ ) |
| :---: | :---: |
| в 0 | 0.0214 |
| 8 0.5 | 0.0214 |
| ¢ 1 | :. 1071 |
| 3 こ | 2.1929 |
| 3 ! | :.1571 |
| 36 | :.0429 |
| 9 | 2.6427 |
| в 6 | 2.1000 |
| - 7 | 0.1071 |
| 3 غ | 0.1266 |
| 39 | 0.0500 |
| B 9.5 | 0.0143 |
| 10. | 0.0143 |

## Conditional probchilities associated mith clestofication'J

| $\mathrm{T}^{\text {c }}$ J | 1 | II ${ }^{\circ}$ | " Iti' | IV | $\nabla$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 30 | 1 | - | - | - | - | 0 |
| 9 0.5 | 0.667 | - | - | - | 0.333 | C.636 |
| $\geq 1$ | -.e.00 | - | - | - | 0.200 | 2.500 |
| 22 | 2.6x.) | 2.6:7 | - | . 037 | 0.296 | 3.e.t |
| 3 | 2.873 | 3.275 | - | 2.182 | 0.312 | 2.138 |
| E4 | 0.333 | -- | 2.167 | 2.167 | 0.335 | - 133 |
| 35 | 2.267 | - | 2.167 | 2.167 | c.50c | 1.243 |
| 36 | 0.167 | 0.214 | - | 2.429 | 0.286 | 1.350 |
| ${ }^{8} 7$ | - | -0.200 | $\square$ | 3.467 | 0.335 | 1.254 |
| 58 | -- | 0.055 | 2.167 | 0.667 | 0.111 | c.974 |
| B 9 | - | $\cdots$ | 2.143 | 3.714 | 0.145 | 0.796 |
| B 9.5 | - | - | - | 0.500 | 0.500 | 0.693 |
| A 0 | - | - | 0.500 | 0.500 | - | 0.695 |

As was pointed out above, the information learned by assigning a classification to our set is equal to its initial entropy. We are now interested in learning about the classification called $J$. The measure of confusion (entropy) assigned to $J$ is an upper limit of the information that can be learned about $J . I f, i n$ an attempt to learn about $J$, we assign the classification $T$, we will be only successful insofar as $T$ contains information in common with J. After $T$ is given, it im possible with the IT, to determine the
conditional entropy in $J$. That is, the confusion determined by the conditional probability distributions for $J$ results from inspecting each of the states of $T$. Clearly, the conditional confusion in $J$ is, either equal to the original confusion in J , or less than the original confusion in J. In the former case $J$ and $T$ share no common information, but in the latter one, we derive a measure of the information held in common by $J$ and $T$ as the difference of the original confusion in $J$ minus the conditional confusion in $J$.

It is now possible to compute a measure of the interdependence from confusion measures with the following:

$$
d(J, T)=\frac{\text { Infor. held exclusively by } J+\text { Infor. held exclusively by } T}{\text { Total inforeation possessed by both } J \text { and } T}
$$

If its result is zero, $J$ and $T$ are identical. On the contrary, if its value is one, $J$ and $T$ are completely independent.

## 2. A SCHEMATIC VISUALIZATION OF INTERDEPENDENT MEASURE

In order to provide an intuitive understanding of the interdependent measures, the purely heuristic concept of an "Information space" will be used (Estabrook; 1967). Let us represent all the information about a study contained in the classification which is described as the area of a rectangle. Then, the information included in any single classification, J, can be represented as a subset of this rectangle (Figure 1).


The classification $J$ and $T$ can be represented on the information space as two sets (Figure 2). The information held in common by the classifications $J$ and, $T$ is labelled $C$. Then, A represents the information held exclusively by $T$, and $E$ that information held exclusively by J.


The measure of interdependence d(J,T) can be abstractly expressed as:

$$
d(J, T)=\frac{A+B}{A+B+C}
$$

If $A$ and $B$ are both empty (or nearly sol, the classifications $J$ and $T$ are the same. Ir other words $J$ and $T$ are highly correlated. If A ie empty or nearly so, but E is not, this means that the information contained in $J$ includes the information contained in T. In this case J is a refinement of T. That means that the classification represented by $J$ contains the classification represented by T (Figure 3 ).

the two
states of $T$

## 2. APPLICATION

Jaschek's classification: $J_{i}$, with $i=I, I I, I I I, I V$ and $V$. MK spectral type classification: $T_{m}$, with $m=E O, E O . \Xi, E 1$,

Table 1: Description of the stars which share the same classification ( $J$ arch $T$ ).

Table 2: Distribution of the probability associated with the classification $J_{i}$.
The unconditional entropy of $J_{i}$ is:
$H\left(J_{i}\right)=-\sum_{i} P\left(J_{i}\right) \cdot \operatorname{Ln}\left(F\left(J_{i}\right)\right)=1.442 \operatorname{nat}$
Here, Ln denotes the natural logaritm. Then, the unit of the entropy is nats, (Abramson, 1981).
Table 3: Distribution of the probatility associated with the classification $T_{m}$. The unconditional entropy of $T_{m}$ is:
$H\left(T_{m}\right)=-\sum_{m} F\left(T_{m}\right) \cdot \operatorname{Ln}\left(F\left(T_{m}\right)\right)=3.768$ nat
Table 4: Conditional protatilities acsoriated with
classification J.
In this table, the latest colum denotes the entropy of those cilassifications, calculated as followe:

$$
H\left(J / T_{m}\right)=-\sum_{i} F\left(J_{i} / T_{m}\right) \cdot \operatorname{Ln}\left(F\left(J_{i} / T_{m}\right)\right)
$$

4. CALCULATION OF THE CONDITIDNAL ENTROPY AND THE MEASURE OF THE INTERDEPENDENCE

The conctitional entropy of cazsification a atven Elassification Tis:

$$
H(J / T)=\sum_{m} H\left(J / T_{m}\right) \cdot F\left(T_{m}\right)=0.752 \text { nat }
$$



While, froe the 3.768 units of inforeation


$$
d(J, T)=\frac{0.752+3.078}{0.752+3.078+0.690}
$$

$$
d(J, T)=0.88 .3
$$

## CONCLUSIONS

From this analysis results:

1) Both classifications, $J$ and $T$, share in a small portion of the information about the characteristics of Ee stars.
2) As the value $d(J, T)=0 . \operatorname{BB}$, both classifications are highly independent. This means that to derive one group or state from one of the classifications, knowing the group or state in the other classification, has rot meaning in terms of IT.

ㅂ) The exclusive information of Jaschet's classification is greater than the exclusive information of MK spectral classification, according to the results obtained from the entropy.

Finally, according to this objetive comparison, we suggest that the Ee stars must be analyeed following the scheme given by Jascher: et al., because this one presents the minimal confusion (maximal information) and perinits a complete description of the characteristics of the Ee stars. Moreover, the simultaneous use of both classifications could be a result of undesirable redundancy ta deriver some properties of these objects.

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