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An Algorithm For Selecting Informative Symbols Based On Determining The Measure Of Information In A Nominally Informed Space

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Abstract: The article reveals the issue of reducing the size of the phase of features describing objects, from data mining to brain cancer diseases. Initially, with the support of specialists in the field of medicine, 218 objects of the 4th class were conducted (it is a paid astrocytoma of the right hemisphere of the brain; Adenoma of the cellar region of the brain; Glioblastoma of the right-sided region of the brain; Meningioma of the right frontal region of the brain) and a training sample of 19 characters is formed. In this educational selection, the features characterizing the objects of the class are expressed as a nominal value. For this reason, this article proposes an algorithm for solving the problem of choosing a set of informative symbols based on determining the measurement of information in a nominal data space.

Keywords: Brain cancer, learning selection, nominal data space, informative signs.

INTRODUCTION:

The direction of choosing a set of informative symbols is considered one of the most relevant and important issues in the field of modern data analysis and artificial intelligence. This orientation is important in solving complex problems and providing more accurate forecasts, allowing for efficient and error-free analysis of large amounts of data. The process of identifying and selecting informative symbols is necessary to improve the efficiency and accuracy of data analysis, as well as optimize machine learning models [1-3].

Currently widely used in Data Mining, machine learning, artificial intelligence and many other fields, this field plays a key role in solving a wide range of problems, from medicine to banking, from climate change to e-commerce. Selecting informative symbols by extracting the most important and highly effective symbols from data reduces the number of uninformative symbols in data analysis and machine learning models and improves the accuracy of analysis, and a lot of scientific research is being conducted in this direction[3-18].

This area is also important for saving resources when working with large amounts of data, reducing calculation time and increasing the ability of models to generalize. As a result, the direction of choosing a set of informative signs, the development of modern technologies and the development of data analysis and artificial intelligence in the era of big data are the main ones[4-8].

The advanced work in the direction of selecting a set of informative signs is based mainly on extensive research in the field of artificial intelligence, data analysis, machine learning and Data Mining. The aim of these studies is to increase the efficiency of analysis by identifying and selecting the most important characteristics with high impact force from the available data[9-12].

In addition, algorithms developed in this direction are necessary to improve the efficiency of data analysis and machine learning models. These algorithms help reduce the number of uninformative characters in the data, analyze informative characters more accurately, and optimize models[13-18].

This article proposes a new approach to solving the problem of reducing the spatial size of symbols characterizing objects of a selective educational class, that is, an algorithm for selecting an informative symbol based on determining the measurement of information in a nominally informed space has been developed. This algorithm was then investigated in brain cancer, and positive results were obtained.

METHOD

In nominal character space, objects and their classes are given by $x_{p1}, x_{p2}, \dots, x_{pm_p} \in X_p, p = \overline{1,r}; \quad x_{pi} = (x_{pi}^1, \ x_{pi}^2, \dots x_{pi}^N), i = \overline{1, m_p}$.

Let the value indicating the similarity of objects in the space of symbols be defined in terms of $\rho^j(x_{pi,}x_{pq})$ and calculated based on formula (1), i.e.

$$\rho_{pi}^j(x_{pi,}x_{pq}) = \begin{cases} 1, \text{ if } & \left(x_{pi}^j - x_{pq}^j\right) = 0; \\ 0, & \text{otherwise} \end{cases} \qquad (1)$$

$p = \overline{1,r}; \ i \neq q = \overline{1, m_p}; j = \overline{1,N};$

This is a parameter of the magnitude vector (1), which has the following form $\rho_{pi}(x_{pi,}x_{pq}) = (\rho_{pi}^1(x_{pi,}x_{pq}), \rho_{pi}^2(x_{pi,}x_{pq}), \dots, \rho_{pi}^N(x_{pi,}x_{pq})$ is represented in the view.

Also $\lambda = (\lambda^1, \lambda^2, \dots, \lambda^N)$ is a vector bul whose components take the value 0 or 1.

If $\lambda^j = 1$, then the $j-$ component participates in computational work, otherwise the $j-$ component does not participate in computational work if $\lambda^j = 0$.

The following $\lambda = (\lambda^1, \lambda^2, \dots, \lambda^N)$ is represented by a set of ℓ informative vectors composed of vectors $\lambda \in \Lambda^\ell = \left\{\lambda: \sum_{j=1}^N \lambda^j = \ell, \ \lambda^j \in \{0,1\}, j = \overline{1,N}\right\}$.

Consider the following scalar product, $(\rho_{pi}(x_{pi,}x_{pq}), \boldsymbol{\lambda}) = \rho_{pi}^1(x_{pi,}x_{pq})\lambda^1 + \rho_{pi}^2(x_{pi,}x_{pq})\lambda^2 + \dots + \rho_{pi}^N(x_{pi,}x_{pq})\lambda^N$ and $\boldsymbol{I}(\boldsymbol{\lambda}, x_{pi}, X_p) -$ let the values of the information measurement criterion be calculated as follows:

$$\boldsymbol{I}(\boldsymbol{\lambda}, x_{pi}, X_p) = \frac{1}{m_p - 1} \sum_{q=1}^{m_p} (\rho_{pi}(x_{pi,}x_{pq}), \boldsymbol{\lambda}), i \neq q; \qquad (2)$$

The value of this (2) expression X_p for all objects of the x_{pi} class will determine the information measure of the object.

Also, the criterion for determining the information measure of all objects of class X_p is expressed in terms of $\boldsymbol{I}(\boldsymbol{\lambda}, X_p)$ and calculated as follows:

$$\boldsymbol{I}(\boldsymbol{\lambda}, X_p) = \frac{1}{m_p} \sum_{i=1}^{m_p} \boldsymbol{I}(\boldsymbol{\lambda}, x_{pi}, X_p) = \frac{1}{m_p(m_p - 1)} \sum_{i=1}^{m_p} \sum_{q=1}^{m_p} (\rho_{pi}(x_{pi,}x_{pq}), \boldsymbol{\lambda}), i \neq q. \ (3)$$

To solve the problem of choosing informative symbols based on the identification of the information dimension of logos in the nominal information space (3), it is necessary to find a solution to the following optimization problem

$$\begin{cases} \max\limits_{\lambda} \boldsymbol{I}(\boldsymbol{\lambda}, X_p) \\ \lambda \in \Lambda^\ell = \left\{ \lambda: \sum\limits_{j=1}^{N} \lambda^j = \ell, \ \lambda^j \in \{0,1\}, j = \overline{1,N} \right\} \end{cases}$$

So, ℓ the informative vector $\lambda = (\lambda^1, \lambda^2, \dots, \lambda^N)$ is found - with this value, the optimization question is taken as the maximum value.

Voluntary, one-time for the class $X_p, p = \overline{1,r};$

$\boldsymbol{I}(\boldsymbol{\lambda}, x_{pi}, X_p) = \frac{1}{m_p - 1} \sum_{q=1}^{m_p} (\rho_{pi}(x_{pi,}x_{pq}), \boldsymbol{\lambda}), i \neq q;$ is considered.

We multiply both parts of this equality by $m_p - 1$ ra then

$\boldsymbol{I}(\boldsymbol{\lambda}, x_{pi}, X_p)(m_p - 1) = \sum_{q=1}^{m_p}(\rho_{pi}(x_{pi,}x_{pq}), \boldsymbol{\lambda})$. We write by extending the right-hand side of this equality, then $\sum_{q=1}^{m_p}(\rho_{pi}(x_{pi,}x_{pq}), \boldsymbol{\lambda}) = \rho_{pi}^1(x_{pi,}x_{p1})\lambda^1 + \rho_{pi}^2(x_{pi,}x_{p1})\lambda^2 + \cdots + \rho_{pi}^N(x_{pi,}x_{p1})\lambda^N + \rho_{pi}^1(x_{pi,}x_{p2})\lambda^1 + \rho_{pi}^2(x_{pi,}x_{p2})\lambda^2 + \cdots + \rho_{pi}^N(x_{pi,}x_{p2})\lambda^N + \ldots + \rho_{pi}^1\left(x_{pi,}x_{pm_p}\right)\lambda^1 + \rho_{pi}^2\left(x_{pi,}x_{pm_p}\right)\lambda^2 + \cdots + \rho_{pi}^N\left(x_{pi,}x_{pm_p}\right)\lambda^N = \rho_{pi}^1(x_{pi,}x_{p1})\lambda^1 + \rho_{pi}^1(x_{pi,}x_{p2})\lambda^1 + \cdots + \rho_{pi}^1\left(x_{pi,}x_{pm_p}\right)\lambda^1 + \ldots + \rho_{pi}^2(x_{pi,}x_{p1})\lambda^2 + \rho_{pi}^2(x_{pi,}x_{p2})\lambda^2 + \cdots + \rho_{pi}^2\left(x_{pi,}x_{pm_p}\right)\lambda^2 + \ldots + \rho_{pi}^N(x_{pi,}x_{p1})\lambda^N + \rho_{pi}^N(x_{pi,}x_{p2})\lambda^N + \ldots + \rho_{pi}^N\left(x_{pi,}x_{pm_p}\right)\lambda^N = [\rho_{pi}^1(x_{pi,}x_{p1}) + \rho_{pi}^1(x_{pi,}x_{p2}) + \cdots + \rho_{pi}^1\left(x_{pi,}x_{pm_p}\right)]\lambda^1 + [\rho_{pi}^2(x_{pi,}x_{p1}) + \rho_{pi}^2(x_{pi,}x_{p2}) + \cdots + \rho_{pi}^2\left(x_{pi,}x_{pm_p}\right)]\lambda^2 + \ldots + [\rho_{pi}^N(x_{pi,}x_{p1}) + \rho_{pi}^N(x_{pi,}x_{p2}) + \ldots + \rho_{pi}^N\left(x_{pi,}x_{pm_p}\right)]\lambda^N = \sum_{q=1}^{m_p}\rho_{pi}^1(x_{pi,}x_{pq})\,\lambda^1 + \sum_{q=1}^{m_p}\rho_{pi}^2(x_{pi,}x_{pq})\,\lambda^2 + \ldots + \sum_{q=1}^{m_p}\rho_{pi}^N(x_{pi,}x_{pq})\,\lambda^N$ defining the total in the last expression as,

$a_{pi}^j = \sum_{q=1}^{m_p}\rho_{pi}^j(x_{pi,}x_{pq}), j = \overline{1, N}$, then the final amount becomes $\sum_{q=1}^{m_p}\rho_{pi}^1(x_{pi,}x_{pq})\,\lambda^1 + \sum_{q=1}^{m_p}\rho_{pi}^2(x_{pi,}x_{pq})\,\lambda^2 + \ldots + \sum_{q=1}^{m_p}\rho_{pi}^N(x_{pi,}x_{pq})\,\lambda^N = a_{pi}^1\,\lambda^1 + a_{pi}^2\,\lambda^2 + \cdots + a_{pi}^N\,\lambda^N = (a_{pi}, \boldsymbol{\lambda})$. Here is the last expression $a_{pi} = (a_{pi}^1, a_{pi}^2, \ldots, a_{pi}^N)$ and $\lambda = (\lambda^1, \lambda^2, \ldots, \lambda^N)$ the scalar product of its vectors.

So, $\boldsymbol{I}(\boldsymbol{\lambda}, x_{pi}, X_p)(m_p - 1) = (a_{pi}, \boldsymbol{\lambda})$. Based on this expression, the following is appropriate

$$I(\lambda, x_{pi}, X_p) = \frac{1}{m_p - 1}(a_{pi}, \lambda). \tag{4}$$

Here (4), $\boldsymbol{I}(\boldsymbol{\lambda}, x_{pi}, X_p)$ – functional, $\boldsymbol{\lambda}$ In the cross section of vector components, the x_{pi}- object is understood as a criterion for evaluating objects of the X_p class. The meaning of its meaning is understood as the fact that the x_{pi} object is evaluated by objects of the X_p class, and this is the contribution of this object to the formation of this class.

Also, $a_{pi} = (a_{pi}^1, a_{pi}^2, \ldots, a_{pi}^N)$ vector parameters $\lambda = (\lambda^1, \lambda^2, \ldots, \lambda^N)$ since it does not depend on the vector, they can be calculated in advance

$$a_{pi}^j = \sum_{q=1}^{m_p}\rho_{pi}^j(x_{pi,}x_{pq}), \mathrm{i} = \overline{1, \mathrm{m_p}},\ j = \overline{1, N}. \tag{5}$$

This turns expression (5) into a matrix if EIB $(m_p \times N)$ is written.

In the first row of the matrix, object x_{p1} is located at the level of similarity assessment in the cross section of the parameters of objects of class X_p, and in the second row, the second object x_{p2} is located at the level of similarity assessment in the cross section of the parameters of objects of class X_p and the m_p line contains the evaluation of the object x_{pm_p} in the context of similarity levels in the context of the parameters of objects of the X_p class.

That is:

$$\begin{pmatrix} \sum_{q=1}^{m_p}\rho_{p1}^1(x_{p1,}x_{pq}) & \sum_{q=1}^{m_p}\rho_{p1}^2(x_{p1,}x_{pq}) \ldots & \sum_{q=1}^{m_p}\rho_{p1}^N(x_{p1,}x_{pq}) \\ \sum_{q=1}^{m_p}\rho_{p2}^1(x_{p2,}x_{pq}) & \sum_{q=1}^{m_p}\rho_{p1}^2(x_{p1,}x_{pq}) \ldots & \sum_{q=1}^{m_p}\rho_{p1}^N(x_{p1,}x_{pq}) \\ & \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots.. & \\ \sum_{q=1}^{m_p}\rho_{pm_p}^1\left(x_{pm_p,}x_{pq}\right) & \sum_{q=1}^{m_p}\rho_{pm_p}^2\left(x_{pm_p,}x_{pq}\right) \cdots & \sum_{q=1}^{m_p}\rho_{pm_p}^N\left(x_{pm_p,}x_{pq}\right) \end{pmatrix}$$

Therefore, while the path elements of this matrix are calculated in the sign section of the object being studied, the column elements represent the value of the objects in the sign section.

Using the above formulas (4) and (5), the evaluation criterion for all objects of class X_p $\boldsymbol{I}(\boldsymbol{\lambda}, X_p)$ is calculated as follows:

$$I(\lambda, X_p) = \frac{1}{m_p(m_p - 1)}\sum_{i=1}^{m_p}(a_{pi}, \lambda). \tag{6}$$

To solve the problem of selecting informative symbols using the recognition functionality of the nominal representation of information (6) of the cross-section of objects of class X_p, it is necessary to find a solution to the following optimization problem

$$\begin{cases} \frac{1}{m_p(m_p-1)}\sum_{i=1}^{m_p}(a_{pi},\lambda) \to max \\ \lambda \in \Lambda^\ell = \{\lambda: \sum_{j=1}^{N}\lambda^j = \ell, \ \lambda^j \in \{0,1\}, j = \overline{1,N}\} \end{cases} \tag{7}$$

This (7) solution to the optimization problem provides a solution to the problem of choosing a complex of informative symbols, which, on the one hand, gives the X_p class a value that determines the levels of interobject similarity, that is, gives objects their entire contribution to the formation of the $X_p$class, and, on the other hand, gives the maximum value

The target functional, i.e. the vertex (7), can be represented by decomposing it as follows

$$\frac{1}{m_p(m_p-1)}\sum_{i=1}^{m_p}(a_{pi},\lambda) = \frac{1}{m_p(m_p-1)}[(a_{p1},\lambda) + (a_{p2},\lambda) + \cdots + (a_{pm_p},\lambda)] = \frac{1}{m_p(m_p-1)}\left[\left(a_{p1} + a_{p2} + \cdots + a_{pm_p},\lambda\right)\right] = \left(\frac{1}{m_p(m_p-1)}a_{p1} + \frac{1}{m_p(m_p-1)}a_{p2} + \cdots + \frac{1}{m_p(m_p-1)}a_{pm_p},\lambda\right) = (a_p,\lambda).$$

Here $a_p = (a_p^1, a_p^2, \dots, a_p^N)$ the vector is written as

$$a_p = \frac{1}{m_p(m_p-1)}a_{p1} + \frac{1}{m_p(m_p-1)}a_{p2} + \cdots + \frac{1}{m_p(m_p-1)}a_{pm_p}.$$

While the components of this vector are

$$a_p^j = \frac{1}{m_p(m_p-1)}\sum_{i=1}^{m_p}\sum_{j=1}^{N}a_{pi}^j, j = \overline{1,N} \tag{8}$$

The vector a_p provided by (8), without prejudice to generality, is equal to a_p^j, $j = \overline{1,N}$ its components can be arranged in descending order, i.e. $a_p^{j_1} \geq a_p^{j_2} \geq \cdots a_p^{j_\ell} \geq a_p^{j_{\ell+1}} \geq \cdots a_p^{j_N}$.

The first ℓ member of this sequence will be$a_p^{j_1} \geq a_p^{j_2} \geq \cdots a_p^{j_\ell}$, (2.2.4) solving the optimization problem. In the literature, it is also referred to as an algorithm ordering algorithm.

The algorithm for selecting a complex of informative symbols using this method will differ in complexity, that is, the number of calculations and placements will be equal to $N + \frac{N(N-1)}{2}$.

An algorithm based on the ordering of n nominal characters

1-step. Input parameters $x_{pi}^1, x_{pi}^2, \dots x_{pi}^N, p = \overline{1,r}; \ i = \overline{1,m_p}$; is loading.

2-step. Based on the following formula $\rho_{pi}(x_{pi,}x_{pq}) = (\rho_{pi}^1(x_{pi,}x_{pq}), \rho_{pi}^2(x_{pi,}x_{pq}), \dots, \rho_{pi}^N(x_{pi,}x_{pq}))$ vector components are being formed:

$$\rho_{pi}^j(x_{pi,}x_{pq}) = \begin{cases} 1, \text{ if } & \left(x_{pi}^j - x_{pq}^j\right) = 0; \\ 0, & \text{otherwise} \end{cases}$$

$p = \overline{1,r}; \ i \neq q = \overline{1,m_p}; j = \overline{1,N};$

3-step. Using the following formula $a_{pi} = (a_{pi}^1, a_{pi}^2, \dots, a_{pi}^N)$ vector parameters all

$p = \overline{1,r}; \mathrm{i} = \overline{1,\mathrm{m_p}}$, *calculated for* $j = \overline{1,N}$:

$$a_{pi}^j = \sum_{q=1}^{m_p}\rho_{pi}^j(x_{pi,}x_{pq});$$

4-step. Here $a_p = (a_p^1, a_p^2, \dots, a_p^N)$ The vector is expressed in the following terms,

$$a_p = \frac{1}{m_p(m_p-1)}a_{p1} + \frac{1}{m_p(m_p-1)}a_{p2} + \cdots + \frac{1}{m_p(m_p-1)}a_{pm_p}$$

its components are all $p = \overline{1,r}$; *for* $j = \overline{1,N}$ this formula is calculated based on:

$$a_p^j = \frac{1}{m_p(m_p-1)}\sum_{i=1}^{m_p}\sum_{j=1}^{N}a_{pi}^j, j = \overline{1,N};$$

5-step. Then, a_p vector a_p^j, $j = \overline{1,N}$ the components are arranged in descending order, so $a_p^{j_1} \geq a_p^{j_2} \geq$

$\cdots a_p^{j_\ell} \geq a_p^{j_{\ell+1}} \geq \cdots a_p^{j_N}$. The first ℓ -term of this would be $a_p^{j_1} \geq a_p^{j_2} \geq \cdots a_p^{j_\ell}$; solution to the optimization problem.

6-step. $I(\lambda, X_p)$ is calculared. Where the maximum value of the functional is $I(\lambda, X_p) = a_p^{j_1} + a_p^{j_2} + \cdots + a_p^{j_\ell}$, and the components of the vector λ are equal

$$\lambda^{j_1} = \lambda^{j_2} = \cdots = \lambda^{j_\ell} = 1, \lambda^{j_{\ell+1}} = \lambda^{j_{\ell+2}} = \cdots = \lambda^{j_N} = 0 .$$

While the value of the functional obtained using the described X_p algorithm gives all objects of the class their contribution to its formation, the second side provides a solution to the problem of choosing a set of informative features that gives the maximum value in determining the degree of similarity of the studied objects.

As a result of the study of this developed algorithm for brain cancer, a set of informative signs with $\ell = 6$ was selected, and this is: x^2 – dizziness; x^6 – itching, pain in the face; x^{11} – tinnitus; x^{12} – speech disorders; x^{18} – nausea; x^{19} – decreased sensitivity in the hands and feet.

CONCLUSION

In conclusion, the article proposes a new approach to solving the problem of reducing the size of the space of features characterizing the objects of an educational sample class, that is, an algorithm for selecting informative features based on determining the measure of information in a nominally informative space has been developed.

Then this algorithm is applied to brain cancer, that is, to 218 objects of 4 classes with the support of specialists in the field of medicine (Anaplastic astrocytoma of the right frontal region of the brain; Adenoma of the cellular region of the cranial xiasm; glioblastoma of the right region of the forehead of the skull; Meningioma of the right frontal region of the skull) and experimental studies on a training sample of 19 characters selected a set of informative characters with l=6.

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