Algorithm for the Information Space Forming and the Evaluation of Input Objects Search Efficiency

Vadym Mukhin [1], Valerii Zavgorodnii [1], Yaroslav Kornaga [1], and Lesia Baranovska [1]

[1] *National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Peremohy Avenue, 37, Kyiv, 03056, Ukraine*

Abstract

Concept, algorithm and scheme of information space formation is considered in this paper. This algorithm involves the use of an information system, which is actually a software basis for maintaining the information space. Identification of the input object in the information space allows us to identify it univocally according to the relevant features. For this, an identification method based on consecutive analysis of the object's characteristics is used. Classification of the information objects in view to add them to the information space on basis of multidimensional discriminant analysis is considered. Efficiency analysis of the input objects search in information space is perform.

Keywords

information space, information object, parameters, discriminant analysis, object identification, search method

1. Introduction

Unified information space can be considered as the information model of a complex subject area. It includes the information objects, the links between them, the space environment and the processes for the creation the unified information space [1–4]. Unified information space is form as result of processing information about an object, received from various sources [5–9].

The contradiction arises between the heterogeneous nature of sensors for collecting features of objects and the requirement for unified data presentation [10, 11]. In this case, the same object, the parameters of which obtained from different sensors, should be identified uniquely anyway [12, 13].

An information object is a formal description of some object by its main parameters. It describes as a tuple of parameters of the object, and all values of parameters are determined by characteristics of real object. The information about objects in the unified information space changes in dynamic way [1, 14, 15]. The design of the unified information space allows us to provide a unified description of information objects for all users, and the all users will receive the same information object in the same way. This feature is the key factor for the unified information space [2, 16, 17].

The unified information space allows us to give the access to the common information without the limits for place and time. The computer system is form as the basis for unified information space and it performs the following main functions: transformation of information about objects and formation of unified in-formation space; to provide users with information about objects.

The creation of an information space is intended to provide access to some common information without the space and time limits. The basis of the information space is a set of computer systems, local networks, open networks (Internet), software (operating system, applications, databases, mail services, etc.). Also, the creation the information space is based on the mechanisms that combine the different information systems to each other.

XXI International Scientific and Practical Conference "Information Technologies and Security" (ITS-2021), December 9, 2021, Kyiv, Ukraine
EMAIL: v.mukhin@kpi.ua (V. Mukhin); v.zavhorodnii@kpi.ua (V. Zavgorodnii); ya.kornaga@kpi.ua (Y. Kornaga); lesia@baranovsky.org (L. Baranovska)
ORCID: 0000-0002-1206-9131 (V. Mukhin); 0000-0002-8347-7183 (V. Zavgorodnii); 0000-0001-9768-2615 (Y. Kornaga); 0000-0003-0024-8180 (L. Baranovska)

The main purpose of the information space is to unambiguously compare each input object to the respective information object in information space [18–21]. The identification of the input object in the information space allow us to uniquely identify it by the appropriate parameters. The identification method, based on a consecutive analysis of the parameters of the input object, can be used for this purpose [22–24].

Identification of the information object is performed by the external or internal parameters, taking into account the interaction of the information object in the information space. To do this, each information object is assigned a set of parameters that, to some extent, characterize the object, i.e. form the image of the information object. Similarly, an information request to input object is formulated as brief description [25–27].

Due to this, the procedure of the input object identification is just a simple comparison of its parameters with a certain image of the query [28–30]. In the case when the parameters of the input object in the necessary and sufficient way match the parameters of initial object, we may consider that the input object has been identified successfully.

2. Algorithm for the information space forming

We present an algorithm for the information space design that based on the information system (Fig. 1):

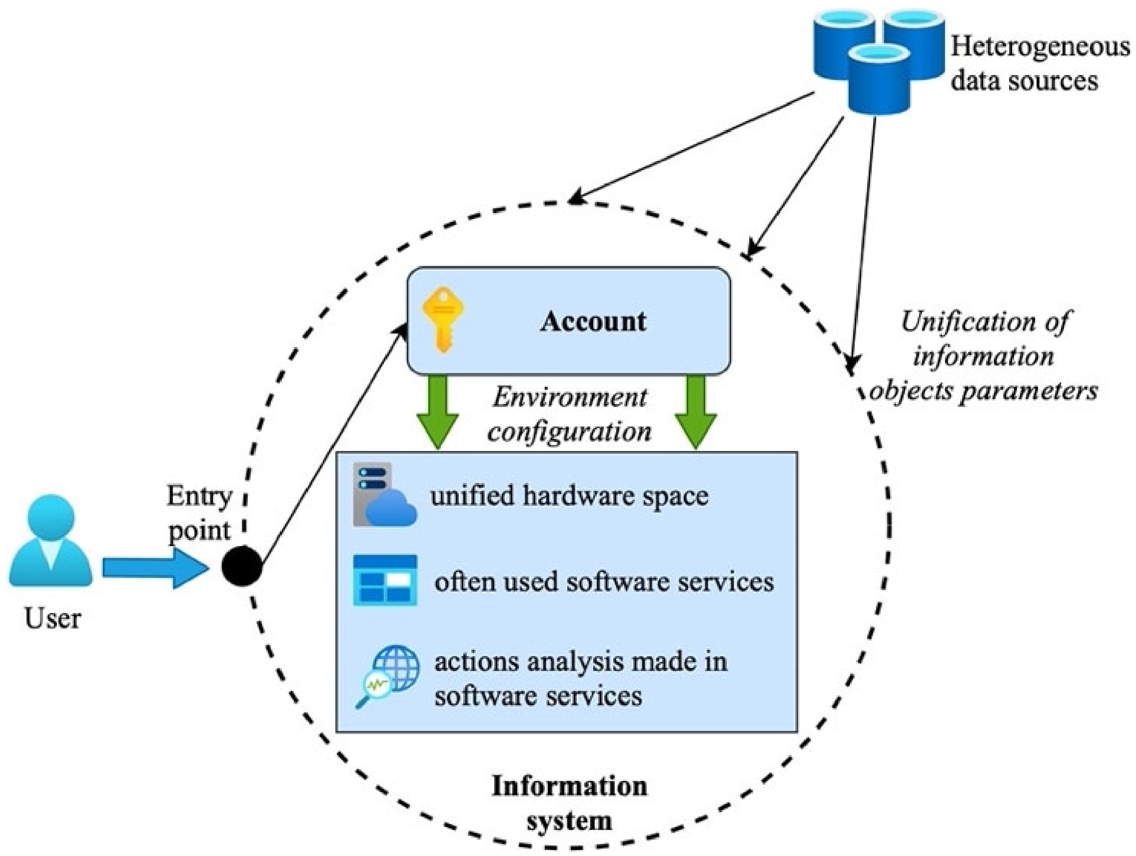

Figure 1: Algorithm for the information space formation

1. Information system is a distributed system that performs the conversion of information from various sources and usually it comes in different formats, into a single set of information object's parameters, by which users of information space can uniquely identify the input object.

2. The user's entry point into the information system is created. There may be many such entry points.

3. A single hardware space formed for the user regardless of the certain entry point. That is, to process the information request of any user, the same hardware is used.

4. The software tools are available to the user from anywhere.

5. Each user has an account, which contains the software tools that are often used by him, as well as his actions, including in relation to specific services.

6. User accounts are stored remotely and user may access them from the different login points.

7. The user enter into the information space via entry point, and there is performed the adjusting of his environment, i.e. the services that he often used are fixed, and his actions in for the specific services are analyzed.

8. As a result, the information system is present to the user as a single space, regardless of the current entry point.

Figure 2 shows the general scheme of the information space formation.

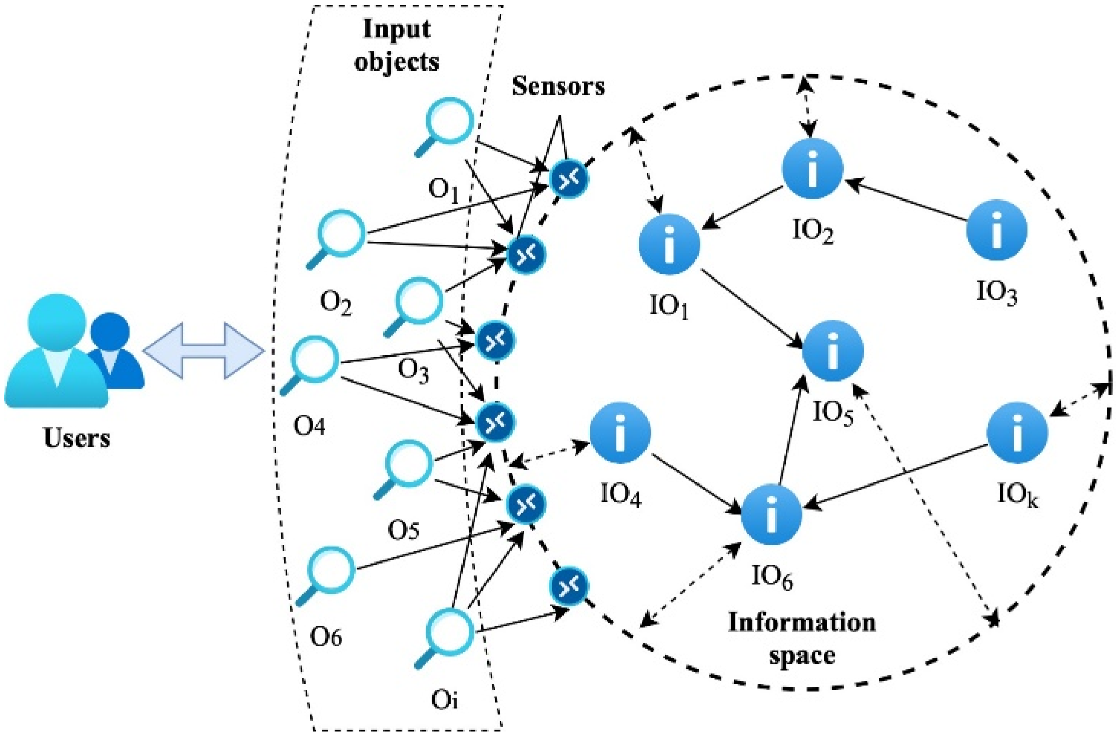

Figure 2: The general scheme of information space formation

The data collection in the information space and its formation is presented in the form of a graph, which reflects an integrated model of the information space, where the nodes of the graph correspond to the information objects, and arcs are the relationship between these objects.

Formally, such a model is described as:

$$IS = < IO, P, R, C >, \quad (1)$$

where IO is the set of information objects; P is the set of parameters of information objects; R is the set of connections types; C is mapping that specifies a certain relationship from set of relationships between the information objects.

We define the set of connections types as the union of the set of connections between information objects and the set of connections between the parameters of information objects:

$$R = R_1 \bigcup R_2, \quad (2)$$

where R_1 is the set of connections between information objects; R_2 is the set of connections between the parameters of information objects.

In turn, the single information space is a union of information spaces:

$$UIS = \bigcup_{i=1}^{m} IS_i, \quad (3)$$

where m is the number of information spaces.

Moreover, each single information space is presented as a graph:

$$UIS =< IS(IO, P, R, C), \tilde{R}, \tilde{C} >, \quad (4)$$

where IS is the set of information spaces; $\tilde{R}$ is the set of connections types, which is similar to expression (2) are the union of a set of connections between information objects of information spaces $\tilde{R}_1$ and the set of relationships between the parameters of information objects of information spaces $\tilde{R}_1$, i.e. $\tilde{R} = \tilde{R}_1 \cup \widetilde{R_2}$; $\tilde{C}$ is mapping that specifies a certain relationship of set of types between set of the information spaces IS.

For each input object $O_i = (i = \overline{1,m})$, that enters the inputs of the information space and information object $IO_j(j = \overline{1,k})$, which already are in the information space, the set of parameters $P_{i,j}$ is determined. In case when $P_{i,j} = P_i \cap P_j$ does not completely match the set of parameters O_i and IO_j, such an input object O_i is considered new and is added to the information space IS.

Otherwise in case when $P_{i,j} = P_i \cap P_j$ matches the set of parameters O_i and IO_j, such an input object O_i is considered identified and is not added to the information space IS.

Also, the links C_i between the new information object and the existing information objects of the information space IS are added. An important goal of the information space design is to transform the input information in the certain way when each information object in the information space will be present unambiguously.

The parameters of information objects in the information space should be defined in unified format and their number must be the same. The users of the information space should also perceive information objects unambiguously. Usually, the input data in the information space has heterogeneous nature. The goal of the internal mechanisms of the computer system is to transform the heterogeneous information coming in different formats and from different sources into a single set of parameters of information objects, by which the users of information space can uniquely identify the input object.

3. Classification of information objects in the information space

We use the multidimensional discriminant analysis to classify information objects in order to add them to the information space. To do this, for each information space we built a discriminant function in the following form:

$$d_{IS_h}^j = \alpha_0^h + \alpha_1 p_{1h}^j + \cdots + \alpha_n p_{nh}^j, \quad (5)$$

where $d_{IS_h}^j$ is the value of the discriminant function for j-th information object in h-th information space; p_{gh}^j are the parameters j-th information object that are significant (have a value other than NONE) for h-th information space, $g = \overline{1,n}$; α_0^h is the free coefficient of discriminant function, which corresponds to h-th information space, $h = \overline{1,l}$; α_g are the coefficients of the discriminant function, which correspond to the significant parameters of each information space, $g = \overline{1,n}$.

Then, for each information object $IO_j(j = \overline{1,k})$ in each information space $IS_h(h = \overline{1,l})$, we calculate the value of the discriminant function $d_{IS_h}^j$.

Then, based on a set of values $d_{IS_h}^j$ for each information space, we calculate the main statistical characteristics of the obtained values of discriminant functions: expected value $M(d_{IS_h})$ and dispersion $D(d_{IS_h})$. These characteristics make it possible to determine the affiliation of a new information object to a particular information space.

For each input object O_i, which should be added as a new information object IO_{new}, the values of discriminant functions are calculated $d_{IS_h}^{new}$ and are compared with the obtained statistical characteristics for each information space. New information object IO_{new} will be added to the information space in case when its characteristics meet the following condition:

$$M\left(d_{IS_h}\right) - D\left(d_{IS_h}\right) \leq d_{IS_h}^{new} \leq M\left(d_{IS_h}\right) + D\left(d_{IS_h}\right). \quad (6)$$

The implementation of the above discriminant analysis allow us determine the certain information space to which the new input information object should correspond.

4. Simulation of identification process for input objects in the information space

Let us analyze the effectiveness of the input objects search in the information space. We created an information space of 20,000 information objects for the experiments. The part of the missing parameters in the information objects (*NONE*) was set at the level 6%. After that, the information space was reconstructed by excluding of the duplicate information objects. We performs 100 experiments with certain probabilities (5, 10, 15, 20, and 25%, respectively), which reflects the fact that the parameter would not be read by sensors (*NULL*).

Let us consider the case when every of the 20,000 information objects is described by 7 parameters. Table 1 shows a fragment of 10 information objects ($IO_1 - IO_{10}$) of the information space (IS).

Table 1
A fragment of the is information space of 10 information objects

IO	Parameters						
	P1	P2	P3	P4	P5	P6	P7
IO1	2±0.2	2±0.7	3±0.4	6±0.4	7±0.6	10±0.6	11±0.4
IO2	2±0.2	6±0.7	NONE	6±0.9	9±0.8	9±0.7	NONE
IO3	2±0.3	5±0.4	4±0.1	8±0.2	5±0.9	10±0.3	8±0.5
IO4	5±0.4	6±0.6	NONE	7±0.4	5±0.6	8±0.5	NONE
IO5	1±0.7	6±0.3	5±0.9	7±0.8	5±0.8	8±0.5	10±0.9
IO6	5±0.4	4±0.4	3±0.7	6±0.4	5±0.9	8±0.4	8±0.1
IO7	NONE	4±0.5	7±0.6	6±0.2	9±0.2	6±0.4	8±0.9
IO8	3±0.4	2±0.6	3±0.8	4±0.2	6±0.5	6±0.6	11±0.4
IO9	2±0.3	3±0.4	5±0.6	5±0.5	8±0.6	8±0.2	NONE
IO10	4±0.7	4±0.2	5±0.3	4±0.5	7±0.5	6±0.9	10±0.9

In this case, the interval length for each parameter is 5 units, for example, for parameter P1 [1;6). The following results obtained:

The sensors read all parameters values for the input object and there was an unambiguous identification:

New object:
1.6 2.9 4.2 4.7 5.3 8.5 8.4
Search object:
IO 00603 1±0.6 2±0.6 4±0.6 4±0.6 5±0.6 8±0.4 8±0.5

The sensors read all parameters values of the input object and did not identify it, it means that no information objects corresponding to the following input object was found in the information space:

New object:
4.9 3.3 4.5 7.9 5.2 6.5 11.7
Search object:
Object absent!

In this case, the input object considered as a new information object and it can be added to the information space.

The sensors get the values for incomplete set of parameters of the input object (there are NULL values), but due to the interaction of information objects with each other in the information space, still there was a unique identification of the input object in the information space:

New object:
2.8 Null 2.6 5.8 5.9 6.4 8.3
Search object:
IO 01849 2±0.4 4±0.4 2±0.6 5±0.6 5±0.4 6±0.6 8±0.5
IO 04387 2±0.5 2±0.7 2±0.6 5±0.6 5±0.4 6±0.5 8±0.5
IO 05956 2±0.1 3±0.6 2±0.6 5±0.2 5±0.1 6±0.5 8±0.7
ReCreateObject:
2.8 2.2 2.6 5.8 5.9 6.4 8.3
Search object:
IO 04387 2±0.5 2±0.7 2±0.6 5±0.6 5±0.4 6±0.5 8±0.5

The sensors get the values for incomplete set of parameters of the input object but, despite the interaction of information objects with each other in the information space, the identification of the input object did not occur:

New object:
2.1 Null 5.3 Null Null 9.3 8.9
Search object:
IO 00391 2±0.9 None 5±0.8 8±0.3 6±0.1 9±0.9 8±0.4
IO 01210 2±0.1 3±0.8 5±0.2 5±0.6 6±0.1 9±0.2 8±0.9
IO 01460 2±0.7 2±0.4 5±0.9 6±0.9 7±0.8 9±0.2 8±0.9
IO 03248 2±0.2 6±0.6 5±0.6 6±0.3 8±0.6 9±0.5 8±0.6
IO 06463 2±0.4 2±0.5 5±0.2 8±0.5 6±0.6 9±0.6 8±0.6
IO 06791 2±0.4 4±0.4 5±0.5 4±0.7 9±0.3 9±0.9 8±0.8
IO 08241 2±0.7 6±0.9 5±0.1 7±0.8 7±0.1 9±0.6 8±0.2
IO 09634 2±0.7 6±0.3 5±0.9 8±0.6 6±0.9 9±0.7 8±0.7
IO 10339 2±0.8 None 5±0.6 4±0.1 7±0.6 9±0.9 8±0.1
IO 10744 2±0.2 6±0.2 5±0.6 4±0.5 8±0.5 9±0.1 8±0.6
IO 10806 2±0.1 4±0.2 5±0.5 8± 0.2 8±0.8 9±0.8 8±0.7
IO 11204 2±0.8 3±0.3 5±0.8 6±0.7 7±0.4 9±0.3 8±0.1
IO 12128 2±0.6 2±0.3 5±0.8 7±0.1 5±0.6 9±0.1 8±0.5
IO 12679 2±0.3 3±0.7 5±0.6 None 9±0.3 9±0.8 8±0.8
IO 13174 2±0.5 4±0.6 5±0.6 5±0.9 5±0.5 9±0.6 8±0.6
IO 13400 2±0.5 None 5±0.7 7±0.7 5±0.4 9±0.6 8±0.8
IO 14805 2±0.2 4±0.9 5±0.6 None None 9±0.7 8±0.9
IO 15221 2±0.6 5±0.1 5±0.1 4±0.5 6±0.2 9±0.1 8±0.5
IO 15884 2±0.4 5±0.9 5±0.5 7±0.3 6±0.3 9±0.8 8±0.2
IO 16132 2±0.5 2±0.1 5±0.2 None 8±0.2 9±0.1 8±0.6
IO 18388 2±0.1 5±0.7 5±0.8 7±0.1 8±0.1 9±0.9 8±0.6
ReCreateObject:
2.1 Null 5.3 Null 8.9 9.3 8.9
Search object:
IO 03248 2±0.2 6±0.6 5±0.6 6±0.3 8±0.6 9±0.5 8±0.6
IO 10744 2±0.2 6±0.2 5±0.6 4±0.5 8±0.5 9±0.1 8±0.6
IO 10806 2±0.1 4±0.2 5±0.5 8±0.2 8±0.8 9±0.8 8±0.7
IO 16132 2±0.5 2±0.1 5±0.2 None 8±0.2 9±0.1 8±0.6
IO 18388 2±0.1 5±0.7 5±0.8 7±0.1 8±0.1 9±0.9 8±0.6
ReCreateObject:
2.1 Null 5.3 6.1 8.9 9.3 8.9
Search object:
IO 03248 2±0.2 6±0.6 5±0.6 6±0.3 8±0.6 9±0.5 8±0.6
ReCreateObject:
2.1 2.5 5.3 6.1 8.9 9.3 8.9
Search object:

Object absent!

5. The sensors did not get the value of one or more parameters and after the interaction of the information objects between themselves in the information space it was found that this object did not have this parameter (NONE).

New object:
2.7 4.7 4.1 8.3 5.5 Null 7.6
Search object:
IO 12602 2±0.5 4±0.4 4±0.3 8±0.7 5±0.8 10±0.9 7±0.8
ReCreateObject:
2.7 4.7 4.1 8.3 5.5 Null 7.6
ReCreateObject:
2.7 4.7 4.1 8.3 5.5 Null 7.6
ReCreateObject:
2.7 4.7 4.1 8.3 5.5 None 7.6
Search object:
Object absent!

The integrated results of the experiments allow us to draw conclusion about the effectiveness of the input objects search in the information space for 7 parameters of information object and the length of the interval of 5 units. They are presented in Table 2.

Table 2
Efficiency of search of input objects in information space at 7 parameters and length of an interval in 5 units

Probability that the parameter will not be read by sensors (NULL), %	Probability of identification of the input object, %
5	20
10	10
15	25
20	15
25	15

Table 2 shows the low level of the efficiency of input objects search in the information space for 7 parameters and for interval length of 5 units.

Next, we reduced the number of parameters that describe the information object, and with the same initial data to repeat the similar experiments with the number of parameters from 4 to 6. The results of the experiments are presented in Table 3.

Table 3
The efficiency for input objects search in the information space with an interval length of 5 units and the number of parameters from 4 to 6

Probability that the parameter will not be read by sensors (NULL), %	Probability of identification of the input object, %		
	Number of parameters, units		
	4	5	6
5	100	100	65
10	100	100	45
15	100	90	85
20	100	100	75
25	100	100	50

Table 3 shows the 100% probability for the input object identification in the information space for 4 parameters and the length of the interval of 5 units, i.e. there is no need to reduce the number of parameters. We design a graph on the data from Tables 2 and 3 in order to compare the efficiency of search of input objects in the information space for an interval length of 5 units and the number of parameters from 4 to 7 (Fig. 3).

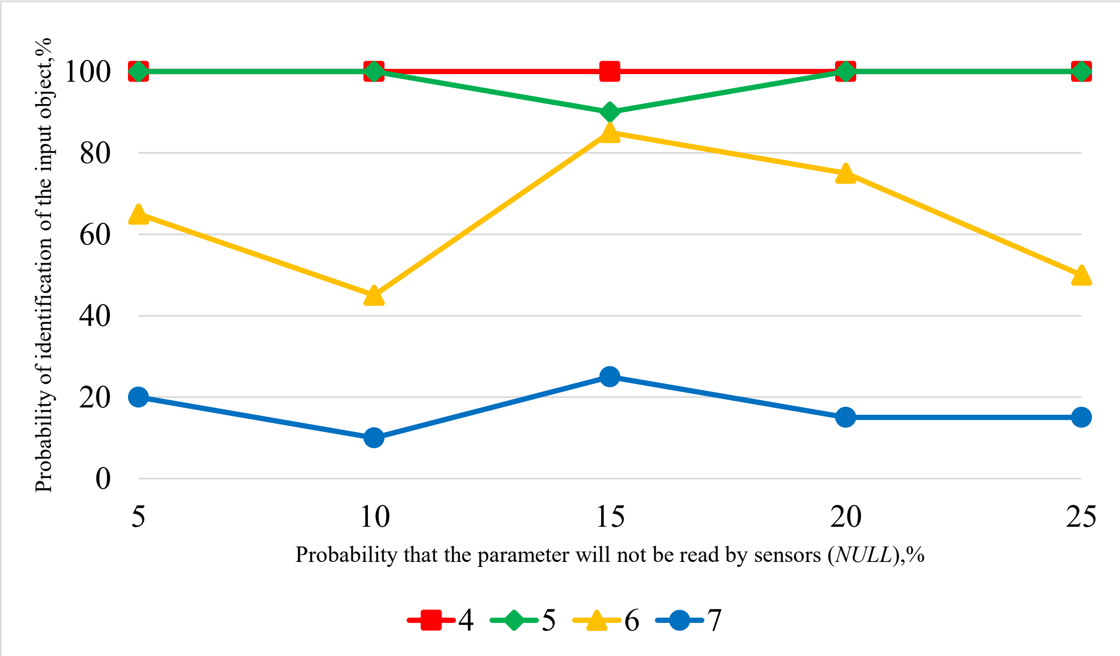

Figure 3: Graph of comparison of efficiency of input objects search in information space for interval length of 5 units and number of parameters from 4 to 7

Figure 3 shows the efficiency of the input objects search in the information space for an interval length of 5 units has next average values: for 4 parameters – 100%; for 5 parameters – 98%; for 6 parameters – 64%; for 7 parameters – 17%.

We may conclude from the above-mentioned that the reducing the number of parameters leads to a sharp increase in the efficiency of input objects search in the information space. Therefore, we decided to change the parameter value intervals lengths of the source objects in the information space with a constant value of the number of parameters.

Let us consider a case where each of the 20,000 information objects is described by 7 parameters with an interval length of 3 to 5 units. The results of the experiments are presented in Table 4.

Table 4

The efficiency of input objects search in information space for 7 parameters and interval length from 3 to 5 units

Probability that the parameter will not be read by sensors (NULL),%	Probability of identification of the input object, %		
	The length of the interval, units		
	3	5	3
5	100	75	20
10	100	40	10
15	95	50	25
20	100	65	15
25	100	50	15

We may conclude that increasing the length of the interval results in a strong decrease in the efficiency of input objects search in the information space. We design graph on the data in Table 4 in order to compare the efficiency of search of input objects in the information space for 7 parameters and the interval length from 3 to 5 units (Fig. 4).

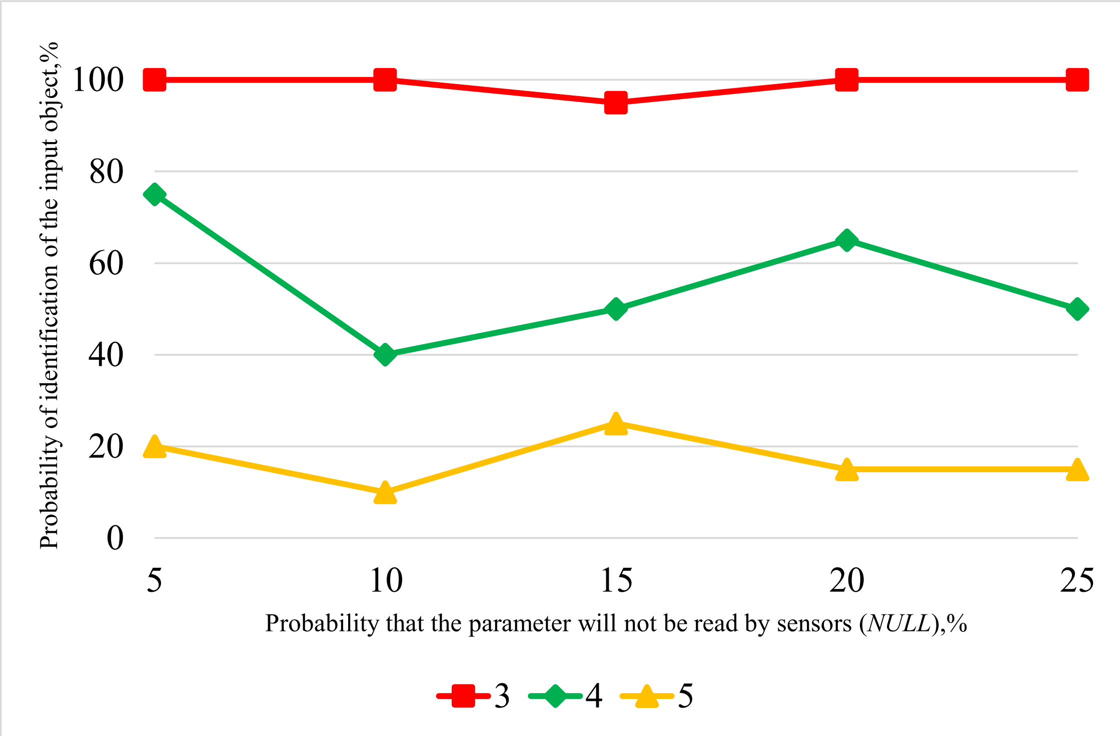

Figure 4: Graph of comparison of efficiency of input objects search in information space for 7 parameters and interval length from 3 to 5 units

Figure 4 shows that the efficiency of search of input objects in the information space for 7 parameters averaged: for interval length of 3 units – 99%; for interval length of 4 units – 56%; for interval length of 5 units – 17%.

We decided to perform the similar experiments for a small intervals length of, but for more parameters of the input objects in the information space.

We consider the case when every of the 20,000 information objects is described by 7 to 10 parameters with an interval length of 3 units. The results of the experiments are present in Table 5.

Table 5
Efficiency of input objects search in information space for 7 to 10 parameters and interval length of 3 units

Probability that the parameter will not be read by sensors (NULL), %	Probability of identification of the input object, %			
	Number of parameters, units			
	7	8	9	10
5	100	85	35	25
10	100	80	40	5
15	95	90	35	10
20	100	90	45	25
25	100	95	40	15

We design a graph on the data in Table 5 in order to compare the efficiency of search of input objects in the information space for 7 to 10 parameters and the interval length of 3 units (Fig. 5).

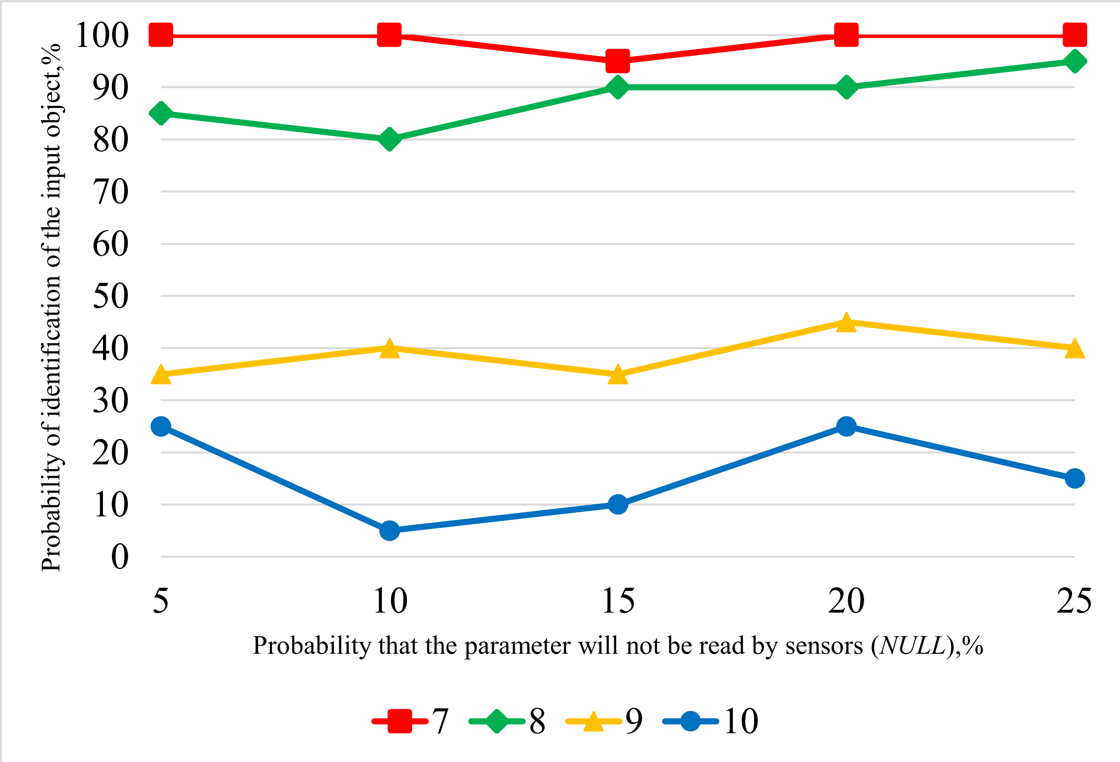

Figure 5: Graph of comparison of efficiency of input objects search in information space for 7 to 10 parameters and interval length of 3 units

Figure 5 shows that the efficiency of search of input objects in the information space for interval length of 3 units averaged: for 7 parameters – 99%; for 8 parameters – 88%; for 9 parameters – 39%; for 10 parameters – 16%.

Experiments have shown that the probability of correct identification of the input object significantly depends on the number of its parameters, as well as on the interval length of the parameters of the input object.

Also, with the increase in the number of parameters of the source object and the intervals length of object parameters, the efficiency of search of input objects in the information space decreases significantly.

5. Comparison of the results obtained by machine learning and experimental data

The adequacy of the suggested method for input objects identification in the information space was checked using machine learning methods.

The multivariate logistic regression using the *LogisticRegression* class from the *Scikit-Learn* library was used to identify information objects. By default, it applies a one-on-one strategy for more than two classes.

To switch to multivariate logistic regression, the *multi_class* hyperparameter is set to "multinomial" and the *lbfgs* solver is selected.

By default, we apply applied l_2 regularization, which can be controlled with the hyperparameter C.

X = info_data ["InformationObject"] # prepared parameters vectors for information objects
Y = info_data ["IdentifiedObject"]
softamx_reg = LogisticRegression (multi_class = "multinomial", solver = "lbfgs", C = 10)
softmax_reg.fit (X, Y)

This method was applied, for example, for the input object with the parameters [2,3 4,6 4,2 5,4 9,1 8,1] and the following information object was obtained with a probability of 94.2%:

IO 04011 2±0.4 4±0.7 4±0.2 5±0.5 9±0.4 9±0.9 8±0.4

Thus, we can conclude that the results obtained with the suggested method of input objects identification in the information space are confirmed by the corresponding results obtained with the machine learning method.

6. Conclusion

We develop an algorithm for the information space formation on the information system, which is actually a software basis for maintaining the information space. Identification of the input object in the information space allow us uniquely identify it by the appropriate parameters. To do this, we suggest the method of identification based on step-by-step analysis of the object parameters.

References

[1] L. Zhu, C. Shi, and J. Guo, "Mapping discovery modeling and its empirical research for the scientific and technological knowledge concept in unified concept space," Cluster Computing, 2015, vol. 18 (1), pp. 103–112. doi:10.1007/s10586-013-0339-7

[2] L. Yakovis, "From unified information space to unified manufacturing control," Automation and Remote Control, 2016, vol. 77 (9), pp. 1689–1698. doi:10.1134/S0005117916090150

[3] S.A. Karin, "Integration in a single information space of diverse geospatial data," Informatsionno-upravlyayushchiye sistemy, 2012, vol. 2 (57), pp. 89–94. URL: http://www.i-us.ru/index.php/ius/article/view/13797

[4] Ozhereleva T.A. On the relationship of the concepts information space, information field, information environment and semantic environment. International Journal of Applied and Fundamental Research, Vol. 10, N 2/2014. P. 21–24. [in Russian] URL: https://applied-research.ru/ru/article/view?id=5989

[5] Tsvetkov V.Ya. Information field and information space. International Journal of Applied and Fundamental Research, Vol.1, N 3/2016. 455 p. [in Russian] URL: https://applied-research.ru/ru/article/view?id=8536

[6] A.V. Vincent, "Development of a model of a single information space to assess the reliability of its operation," Proceedings of the Kola Scientific Center of the Russian Academy of Sciences, 2011, vol. 7, pp. 65–70. URL: https://cyberleninka.ru/article/n/razrabotka-modeli-edinogo-informatsionnogo-prostranstva-dlya-otsenki-nadezhnosti-ego-funktsionirovaniya

[7] A. Mayorov, "Information objects in the information field," Educational Resources and Technologies, 2015, vol. 1 (9), pp. 66–73. URL: https://vestnik-muiv.ru/en/article/informatsionnye-obekty-v-informatsionnom-pole/

[8] K.V. Yakushenko, "Unified information space: theoretical approaches to the content of the concept," Belarus and world economic processes: Sat. scientific Art, 2014, vol. 11, p. 13–20. URL: https://elib.bsu.by/bitstream/123456789/134114/1/13-20.pdf

[9] V.Ya. Tsvetkov, "Information interaction", European Researcher, 2013, vol. 62, no. 11-1, pp. 2573–2577. URL: http://www.erjournal.ru/journals_n/1386019866.pdf

[10] V. Mukhin, Y. Komaga, V. Zavgorodnii, A. Zavgorodnya, O. Herasymenko, and O. Mukhin, "Social Risk Assessment Mechanism Based on the Neural Networks," IEEE International Conference on Advanced Trends in Information Theory, 2019, pp. 179–182. doi:10.1109/ATIT49449.2019.9030519

[11] H. Zhenbing, V. Mukhin, Ya. Kornaga, and O. Herasymenko, "Resource Management in a Distributed Computer System with Allowance for the Level of Trust to Computational Components", Cybernetics and Systems Analysis, 2017, vol. 53 (2), pp. 312–322. doi:10.1007/s10559-017-9931-9

[12] V. Mukhin, V. Zavgorodnii, Y. Kornaga, A. Zavgorodnya, I. Krylov, A. Rybalochka, V. Kornaga, and R. Belous, "Devising a method to identify an incoming object based on the combination of unified information spaces," Eastern-European Journal of Enterprise Technologies, 2021, vol. 3, no. 2(111), pp. 35–44. doi:10.15587/1729-4061.2021.229568

[13] M. Gershkovich, and T. Biryukova, “Problems of Identification of Information Objects in Distributed Data Arrays,” Systems and Means of Inform., 2014, vol. 24(1), pp. 224–243. doi:10.14357/08696527140114
[14] T. Wang, L. Liu, N. Liu, H. Zhang, L. Zhang, and S. Feng, “A multi-label text classification method via dynamic semantic representation model and deep neural network,” Applied Intelligence, 2020, vol. 50 (8), pp. 2339–2351. doi:10.1007/s10489-020-01680-w
[15] Y. Pan, G. Hu, J. Qiu, Y. Zhang, S. Wang, D. Shao, and Z. Pan, “FLGAI: a unified network embedding framework integrating multi-scale network structures and node attribute information,” Applied Intelligence, 2020, vol. 50 (11), pp. 3976–3989. doi:10.1007/s10489-020-01780-7
[16] WD Yu, ST Cheng, CM Wu, and HR Lou, “A self-evolutionary model for automated innovation of construction technologies,” Automation in Construction, 2012, vol. 27, pp. 78–88. doi:10.1016/j.autcon.2012.04.018
[17] G. Nagpal, M. Uddin, and A. Kaur, “A Comparative Study of Estimation by Analogy using Data Mining Techniques,” JIPS, 2012, vol. 8 (4), pp. 621–652. doi:10.3745/JIPS.2012.8.4.621
[18] M. Arenas, BC Grau, E. Kharlamov, S. Marciuska, and D. Zheleznyakov, “Enabling Faceted Search over OWL 2 with SemFacet,” In OWLED, 2014, pp. 121–132. URL: https://marceloarenas.cl/publications/owled2014.pdf
[19] T. Teraoka, “Organization and exploration of heterogeneous personal data collected in daily life,” Human-Centric Computing and Information Sciences, 2012, vol. 2 (1), pp. 1–15. doi:10.1186/2192-1962-2-1
[20] RJ Little, and DB Rubin, “Statistical analysis with missing data”, 2019, P. 793. John Wiley & Sons. doi:10.1002/9781119482260
[21] T. Cheng, HW Lauw, and S. Paparizos, “Entity synonyms for structured web searc,” IEEE transactions on knowledge and data engineering, 2011, vol. 24 (10), pp. 1862–1875. doi:10.1109/TKDE.2011.168
[22] P. Zuiev, R. Zhyvotovskyi, O. Zvieriev, S. Hatsenko, V. Kuprii, O. Nakonechnyi, M. Adamenko, A. Shyshatskyi, Y. Neroznak, and V. Velychko, “Development of a complex methodology for processing various types of data in intellectual systems to support decision-making,” Eastern-European Journal of Enterprise Technologies, 2020, vol. 4, no. 9(106), pp. 14–23. doi:10.15587/1729-4061.2020.208554
[23] V. Mukhin, V. Zavgorodnii, O. Barabash, R. Mykolaichuk, Y. Kornaga, A. Zavgorodnya, and V. Statkevych, “Method of Restoring Parameters of Information Objects in a Unified Information Space Based on Computer Networks,” International Journal of Computer Network and Information Security, 2020, vol. 12 (2), pp. 11–21. doi:10.5815/ijcnis.2020.02.02
[24] M. Arenas, BC Grau, E. Kharlamov, Š. Marciuška, and D. Zheleznyakov, “Faceted search over RDF-based knowledge graphs,” Journal of Web Semantics, 2016, vol. 37, pp. 55–74. doi:10.1016/j.websem.2015.12.002
[25] BC Grau, E. Kharlamov, S. Marciuska, D. Zheleznyakov, and M. Arenas, “SemFacet: Faceted Search over Ontology Enhanced Knowledge Graphs,” International Semantic Web Conference, 2016. URL: http://ceur-ws.org/Vol-1690/paper75.pdf
[26] S. Ferré, and A. Hermann, “Semantic search: Reconciling expressive querying and exploratory search. In International semantic Web conference, Springer, Berlin, Heidelberg, 2011, pp. 177–192. doi:10.1007/978-3-642-25073-6_12
[27] A. Dodonov, V. Mukhin, V. Zavgorodnii, Ya. Kornaga, and A. Zavgorodnya, “Method of searching for information objects in unified information spac,” Systemresearch and information technologies, 2021, vol. 1, pp. 34–46. doi:10.20535/SRIT.2308-8893.2021.1.03
[28] A.N. Logunov, and G.L. Logunova, “Choice of recognition attributes when searching hidden objects,” Eastern-European Journal of Enterprise Technologies, 2012, vol. 5, no. 9(59), pp. 21–25. doi:10.15587/1729-4061.2012.4622
[29] A. Dodonov, V. Mukhin, V. Zavgorodnii, Y. Kornaga, A. Zavgorodnya, and O. Mukhin, “Method of Parallel Information Object Search in Unified Information Spaces,” International Journal of Computer Network & Information Security, 2021, vol. 13 (4), pp. 1–13. doi:10.5815/ijcnis.2021.04.01
[30] S. Ferré, A. Hermann, and M.Ducassé, “Semantic faceted search: Safe and expressive navigation in RDF graphs,” [Research Report] PI 1964, 2011, pp.27. URL: https://hal.inria.fr/inria-00554093