
DOI: [https:// 10.15407/kvt196.02.027](https://10.15407/kvt196.02.027)

UDC 616.89-07-08(035):616-036.82:355.11:355.721

A.Ya. GLADUN¹, PhD (Engineering),
Senior Researcher of the Department of Complex Research
of Information Technologies and Systems
email: glanat@yahoo.com

Yu.V. ROGUSHINA², PhD (Phys&Math)
Senior Researcher of the Department of Automated Information Systems
ladanandraka2010@gmail.com

A.A. ANDRUSHEVICH³, Researcher at the Faculty
of Applied Mathematics and Computer Science
email: andrushevich@bsu.by

¹International Research and Training
Center for Information Technologies and Systems
of the National Academy of Sciences of Ukraine
and Ministry of Education and Science of Ukraine
40, Acad. Glushkov av., 03187, Kyiv, Ukraine

²Institute of Program Systems
of the National Academy of Sciences of Ukraine,
40, Acad. Glushkov av., 03187, Kyiv, Ukraine

³Belarusian State University,
4, Nezavisimosti av., 220030, Minsk, Republic of Belarus.

USING SEMANTIC MODELING TO IMPROVE THE PROCESSING EFFICIENCY OF BIG DATA IN THE INTERNET OF THINGS DOMAIN

Introduction. *The development of the Internet of Things (IoT), equipped with various electronic sensors and controllers that distantly operate with these things is an important step of a new technical revolution. In this article we look at the features of Big Data generated by the Internet of Things (IoT) technology, and also present the methodology for processing this Big Data with use of semantic modeling (ontologies) at all stages of the Big Data life cycle. Semantic modeling allows to eliminate such contradictions in these technologies as the heterogeneity of devices and things that causes the heterogeneity of the data types produced by them. Machine learning is used as an instrument for Big Data of analyzes: it provides logical inference of the rules that can be applied to processing of information generated by Smart Home system.*

The purpose of the article is to use deep machine learning, based on convolutional neural networks because this model of machine learning corresponds to processing of unstructured and complex nature of the IoT domain.

Results. *Proposed approach increases the efficiency of IoT Big Data processing and differs from traditional processing systems by using NoSQL database, distributed architectures and semantic modeling.*

© A.Ya. GLADUN, Yu.V. ROGUSHINA, A.A. ANDRUSHEVICH, 2019

ISSN 2663-2586 (Online), ISSN 2663-2578 (Print). Cyb. and comp. eng. 2019. № 2 (196)

27

Conclusion. *The conceptual architecture of the Big Data processing system for IoT and describe it on the example of the NoSQL database for Smart Home were given. This architecture consists of five independent levels. At each of these levels, a combined approach of semantic modeling and data mining methods can be used. Currently, this platform can be combined with a lot of open source components.*

Keywords: *Industry 4.0, Big Data, Internet of Things, ontology, Semantic Web, non-formal and informal learning.*

INTRODUCTION

Industry 4.0 is defined in [1] as a process of the digital transformation of industrial markets with smart manufacturing currently on the forefront.

The new capabilities of Industry 4.0 deal with intellectualization of digital technologies used in industrial processes. Specialists say about the phenomena of ‘smart anything’ in environment of people: from smart grid, smart buildings and smart plants, smart services and smart manufacturing and so on. Internet of things also is influenced by this tendency.

Various advanced digital technologies are already used in manufacturing for realization of Industry 4.0. It will lead to greater efficiencies and change traditional relations among suppliers and customers. In [2] nine most important technologies that build Industry 4.0 are defined:

- Big data and analytics;
- The cloud computing;
- Autonomous robots;
- Simulation;
- Horizontal and vertical system integration;
- The industrial Internet of things;
- Cybersecurity;
- Additive manufacturing;
- Augmented reality.

Industry 4.0 actively uses digital context for industrial objective therefore the tasks of collection and comprehensive evaluation of data from various distributed sources—production equipment and systems as well as enterprise- and customer-management systems— now become standard to semantic support of decision making processes in real-time mode.

Competencies can be used for adaptation of Industry 4.0 for semantic management of personnel.

Now a lot of research works, deal with this problem, are provided. For example, in [3] authors try to analyze the most significant aspects of the new forms of human work that they face in this Industry 4.0 revolution in order to know what is currently being done. With all the advances that have been made over time in the problem of knowledge age, the participation of organizations requires them to create and maintain environments that foster learning.

The development of the Internet of Things (IoT), equipped with various electronic sensors and controllers that distantly operate with these things is an important step of a new technical revolution.

The term «Internet of Things» was proposed in 1999 by K. Ashton. Now IoT signifies a complex system of interrelated computing devices, mechanical

and digital machines, objects, animals or people that are provided with unique identifiers and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction. IoT has evolved from the convergence of wireless technologies, microelectromechanical systems, microservices and the Internet. IoT components (devices — sensors, actuators, mobile devices etc. — and services) are heterogeneous and dynamic, with unknown nature of the network topology.

IoT proposes new technological infrastructure that expands the technology of wireless sensors, involves the Internet connecting for a lot of things around a person and distance management of these things [4].

However, IoT is a complex and heterogeneous environment that should evolve towards creating a more structured set of solutions, where “things” should be represented in some uniform way and be equally detectable, able to communicate with other objects, and also be directly integrated with the Internet infrastructure and with Web services irrespective of the specific method of connection [5].

Data collected by different sensors and devices is usually polysemantic (temperature, light, sound, video, etc.).

The Internet of Things is widely used in various areas of society. Health, environment, traffic, vehicles, aviation, manufacturing, defense, home automation, telecommunications are the most known examples of IoT applications. The number of electronic devices connected to the IoT is increasing every year. Analysts expect that the number of electronic devices connected to the IoT will grow up by 2020 from 50 to 100 billion. It is expected that the total amount of data generated as a result of mass usage of such devices will become than 35 zettabyte [6] and can be considered as Big Data.

The development of IoT devices, systems and solutions, huge amounts of heterogeneous and unstructured data is a contiguous process. This Big Data needs to be analyzed and processed in order to acquire hidden knowledge. The heterogeneity of IoT devices and systems causes additional problems in processing and analyzing Big Data generated by IoT.

ANALYSIS OF NON-FORMAL AND INFORMAL LEARNING

Among the key modern innovations in the world today is the concept of non-formal and informal education [7]. The current problem is the study of the systematic combination of all forms of education: formal, non-formal and informal. The UNESCO Education Glossary [8] contains the following definitions:

Learning — individual acquisition or modification of information, knowledge, understanding, attitudes, values, skills, competencies or behaviours through experience, practice, study or instruction.

Formal education is an institutionalized, deliberate and planned education through public organizations and recognized private institutions and, in their totality, creates a system of formal education of the state.

Non-formal education — education that is institutionalized, intentional and planned by an education provider. The defining characteristic of non-formal education is that it is an addition, alternative and/or a complement to formal education within the process of the lifelong learning of individuals. It is often

provided to guarantee the right of access to education for all. It caters for people of all ages, but does not necessarily apply a continuous pathway-structure; it may be short in duration and/or low intensity, and it is typically provided in the form of short courses, workshops or seminars. Non-formal education mostly leads to qualifications that are not recognized as formal qualifications by the relevant national educational authorities or to no qualifications at all. Non-formal education can cover programmes contributing to adult and youth literacy and education for out-of-school children, as well as programmes on life skills, work skills, and social or cultural development.

Informal learning — forms of learning that are intentional or deliberate but are not institutionalized. They are less organized and structured than either formal or non-formal education. Informal learning may include learning activities that occur in the family, in the work place, in the local community, and in daily life, on a self-directed, family-directed or socially-directed basis.

These definitions are intended to provide a general understanding of the concepts, but today they are not yet fully enshrined in Ukrainian legislation and do not satisfy the principle of legal certainty. These definitions indicate the key differences that distinguish one type of education from another. In particular, the main difference between formal and non-formal education is that the latter is an addition or alternative to the formal, as well as in the official recognition or non-recognition by the state or authorized non-state bodies of qualifications obtained on the basis of educational achievements. The main difference between information education and other types is that it is not institutionalized.

The Law of Ukraine "On Education" (Article 9. Forms of Education) [9] contains the norms concerning formal, non-formal and informal education:

1. A person exercises his right to education throughout his life through formal, and informal education. The state recognizes all these types of education, supports educational actors providing relevant educational services, and encourages the acquisition of education of all kinds.

2. Formal education — education acquired through educational programs in accordance with the levels of education, branches of knowledge, specialties (occupations) prescribed by the legislation, envisages the achievement of the results of the education of the corresponding level of education and the recognition of qualifications recognized by the state determined by the students of education.

3. Non-formal education — education acquired through educational programs and does not stipulate the awarding of state-recognized qualifications to the levels of education and obtaining an education document established by the legislation.

4. Informational education (self-education) — education, which involves the self-organized acquisition of certain competencies by the person, in particular during everyday activities related to professional, community or other activities, family or leisure activities.

5. Qualifications and learning outcomes acquired through non-formal and informal education can be confirmed and recognized in the system of formal education or in other cases stipulated by the legislation of Ukraine.

In Ukraine, as in other countries of the world today, the task is to legalize non-formal and informal education, as well as to create legislative preconditions for official recognition of educational results obtained in these types of education.

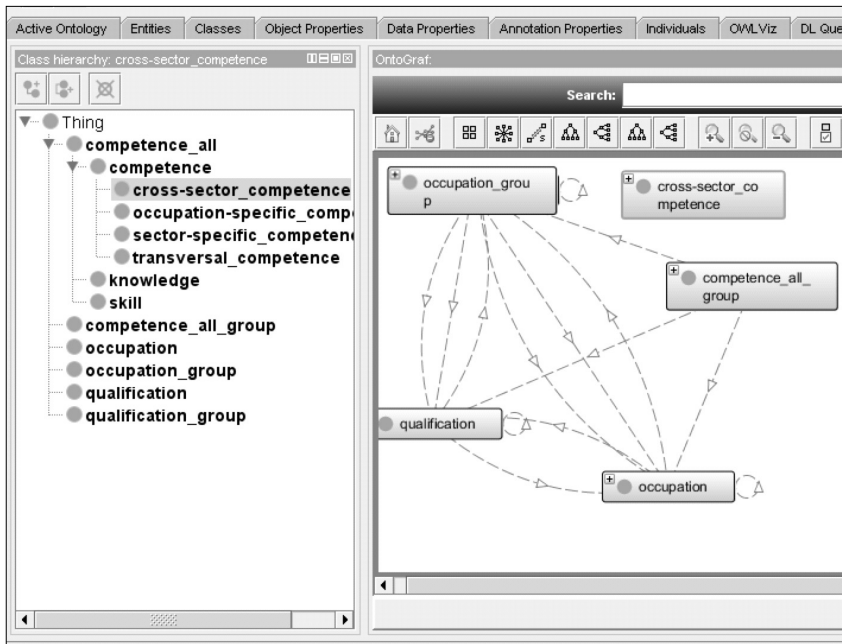


Fig.1. Ontology of competences (fragment).

EU Council Recommendation 2012 [7] highlights the issue of creating a systematic approach to "validation", increasing the visibility and value of learning beyond the formal education and training systems. The document developed 4 phases of validation for non-formal and informal learning. To specify the main features of validation, the recommendation defines four distinct phases: *identification*; *documentation*; *evaluation*; and *certification*.

The national qualifications frameworks are now being implemented in Europe. These frameworks can contribute to the implementation and integration of validation.

Today, the transformation of a market economy into a knowledge economy is taking place. Highly skilled professionals are the greatest value for the IT industry. In the process of learning, students study and apply in practice a variety of tools and Internet technology things, including: IoT devices and physical objects, equipped with IoT, consumer devices, sensors, gadgets and a wide range of Internet applications. [4]. Devices used for different learning systems generate a stream of Big Data that needs to be efficiently handled for decision making and the creation of intelligent learning systems.

We use for analysis an ontology of competences that use such main components and their types as it represented (Fig.1.)

This ontology specifies the types of competences, their level etc. and can be used as a base either for matching of various natural-language texts, or for their semantic mark-up.

We propose to use an additional ontology class — atomic competence [10], which is meant for correlating instances of different IO classes by assessing their semantic proximity. Atomic competence has the following properties:

– $a \in C$, where K is the set of IO class "Competence" and C_{atomic} is the set of atomic competences, i. e. $C_{atom} \subseteq C$;

– every competence can be represented by a set of atomic competences

$$\forall c \in C \exists a_i \in C_{atomic}, i = \overline{1, n}, k = \bigcup_{i=1}^n a_i;$$

– no atomic competence is a subset of another atomic competence
 $\forall a, b \in C, a \subseteq b \Rightarrow b \notin C_{atomic}$.

SEMANTICS IN IOT

The distribution of the IoT sensors gives rise to various data types, data formats and time measurements specifications that cause of problems deal with data integration. This problem can be overcome by Semantic Web solutions used for data representation with the single knowledge model. RDF, RDF Schema and OWL are the main means for knowledge representing on the Semantic Web [11, 12]. These languages represent only the conceptual data model and rules, but do not specify the particular formats of serialization.

Now some specific languages for semantic data representation such as Turtle, N3 and JSON-LD are developed. [13] emphasizes the importance of semantics for the knowledge representation of the IoT domain and provides an assessment of the various knowledge representation languages in terms of efficiency of their use (in the field of data exchange and processing). The author evaluates all actual semantic formats: extensible Markup Language (XML), Resource Description Framework (RDF), SenML, Notation3 (N3), Turtle, N-Triples and JavaScript Object Notation for Linked Data (JSON-LD). The latter — JSON-LD is an effective and modern solution for experimental results.

Unfortunately, semantic data representation alone is not enough to solve the IoT heterogeneity problem. We also need general dictionaries for representation of domain semantics. Ontologies are used in the Semantic Web domain to provide a common language for representation of various "things", their relationships, etc. The Ontology Semantic Sensor Network (SSN) developed by the W3C Semantic Sensor Network Incubator Group is the first step on this path. SSN ontology is used to represent sensors, their properties and observations (generated data), domains, etc. in very simple general terms and it is assumed that they will be used by all types of sensors all over the world.

A number of papers deal with attempts of development of IoT ontologies. A common knowledge base for IoT domain that supports semantic detection of IoT sensors and their service infrastructure is offered in [14]. Ontologies for an IoT domain consisting of ontologies of devices, domains and computations are offered in [15]. The development an IoT ontology that covers the following aspects of the IoT domain: IoT resources, IoT services, observation and measurement, physical locations, deployment platform, QoS, and tests for IoT services is described in [16].

In addition, some researchers propose semantic structures and IoT platforms. Barbero et al. [17] offers the conceptual IoT platform that uses such languages as XML and OWL.

INTERNET OF THINGS AND BIG DATA IN SMART LEARNING ENVIRONMENTS

Smart learning environments are equipped with digital components that create better, more efficient, and smoother learning process. Ideally, they create a perfect synergy between physical and digital realities, allowing students to absorb information from their environment and creating opportunities for seamless transitions between a variety of learning approaches: individual and group learning, formal and informal settings, in analog and digital formats. IoT can track whether homework was done and collect data about how much time a student needed to complete an assignment. This data can help teachers better understand whether their methods are working, which students need additional help, and which tasks they struggle with the most.

Big Data may provide the chance to say goodbye to much-maligned standardized testing. Data collected during routine tasks and classwork – processed with the help of AI tools – may offer greater insights into the skills and abilities of individual students compared to any standardized test. This alone could produce a tremendous restructuring of the entire education sector.

BIG DATA AND MACHINE LEARNING IN IOT

We propose to use machine learning (ML) algorithms to acquire the semantics of Big Data generated by IoT devices. IoT data should be considered as Big Data if it has some specific Big Data features from 5V set [18]:

- Volume — the large amounts of data;
- Velocity — the high-speed generation of new data;
- Variety — the heterogeneous data representation (various formats and types);
- Veracity — the level of data conformity to facts;
- Value — the pertinence to user needs.

Big Data in IoT differs from traditional Big Data by its specific characteristics in terms of data generation, data interoperability and data quality.

Speed, scalability, dynamics and heterogeneity are important issues for IoT data creating. Data quality can be measured using signs of uncertainty, redundancy, ambiguity and inconsistency of data [19].

These characteristics of IoT data should be considered in process of development of new model or structure for Big Data processing. In addition, streaming data transmission causes another big problem that should be considered in new IoT structures and models: streaming data also has its typical characteristics such as continuity, unordered data flow, unlimited data, and the absence of persistent data objects. Technological platforms and solutions for storing large IoT data have been developed only recently. Methods of Big Data storage also differ from traditional data storage methods. Such critical factors should be considered for IoT data storing: consistency, availability and sensitivity to data partitioning [20]. For example, Jiang et al. [21] offer an IoT-based storage environment that runs on cloud computing platforms. Li et al. [22] propose a solution for storing large IoT data based on NoSQL. Cecchin et al. [23] develop an IoT architecture that collects and processes IoT sensor data using MongoDB as storage mechanism for Big Data.

The literature also describes the use of machine learning algorithms in areas related to IoT. Khan et al. [24] and Altun et al. [25] use an artificial back-propagation neural network to recognize human activity, such as walking, sitting, running, etc. Choi et al. [26] use a neural network of reverse propagation for Smart Home applications. Lane et al. [27] offer deep learning networks and convolutional neural network models for processing data from IoT sensors.

Thereby, machine learning algorithms are widely used in areas related to IoT. However, these research works solve local and limited problems, and they are not suitable for data processing from heterogeneous IoT sensors and devices.

PROBLEM DEFINITION

The main idea of paper — we propose to use of competence ontology for retrieval and analyzing of Big Data from individual digital devices (mobile telephones etc.). Such data can characterize the level of person's competence for concrete proposal in situations with informal and non-formal education. We propose to match atomic competencies that are integrated into domain ontology.

Semantic representation (ontologies) that simulate the behavior and characteristics of IoT things is essential for the interoperability of these things, their discovery and selection for specific tasks.

The external ontology of IoT-things sensors (SSN ontology) for preliminary processing of heterogeneous unstructured and semi-structured Big Data generated by these sensors at the Extraction-Transformation-Loading (ETL) stage can be used. Methods of machine learning and logical inference can help in generation of the rules for Big Data processing.

REQUIREMENTS FOR SEMANTIC-ORIENTED IoT BIG DATA PROCESSING ARCHITECTURE

Overview of existing IoT platforms indicates the main directions of development of their functionality:

- Simulation of semantic data. Semantic Web allows to describe IoT domain by standard protocols and dictionaries. New frameworks support various aspects of semantic-oriented modeling, storage and processing of data oriented to semantics. However, one of their missing features is the use of logical inferences on knowledge and rule-based inference.

- Big Data analytics and machine learning: Big Data generated by IoT (as opposed to previous sensor systems with limited data storage and processing capabilities) needs in analysis of large volumes of data. Therefore, we plan to use not only Big Data analytics, but also modern ML approaches, such as deep learning.

The implementation of above functionalities can be realized if the following non-functional requirements are fulfilled:

- common IoT standards that increase requirements for interoperability. Therefore, the new IoT structure should be based only on common standards and refrain from developing its own solutions.

- system openness: higher interconnection and interoperability are possible only on base of open systems. Nowadays, a service-oriented approach where the functionality of the system can be accessed through standard Web services or by open API is required. Web services provide interconnectivity and openness.

Semantic data modeling is very suitable for IoT. To solve the problems of data modeling and management in complex information systems, recent works use innovative solutions based on Semantic Web technologies.

The Semantic Web use for sensors is analyzed in [28]. IoT is the next target for the Semantic Web, where heterogeneity is inherent in many types of sensor devices and their output signals, multiple communication protocols and data formats, etc.

MACHINE LEARNING FOR BIG DATA ANALYTICS

Deep learning is a particular learning model that combines well with unstructured and complex nature of the IoT domain. Deep neural networks are basically multilayered ones with a large number of cascading layers that have learning capabilities for hierarchical features. Deep learning works well in cases where the data set is huge and there has a large number of functions (for example, individual image pixels, individual elements or time series sequences, signals, etc.).

The main reason that makes deep learning the preferred choice for data researchers is that traditional neural network models are not scalable enough to provide solutions for Big Data. Meanwhile, deep neural networks usually do not require domain knowledge and characteristics, and also work well with Big Data, so directly submitting of raw data to deep learning model provides fast, scalable and more accurate data analysis solutions.

ARCHITECTURE OF THE SEMANTIC PROCESSING OF IOT BIG DATA

We propose the conceptual architecture of the system intended for semantic processing of IoT Big Data. It has multilevel structure for performing different independent tasks. System contains five basic levels, namely:

- (1) data collection,
- (2) extraction-transformation-loading (ETL),
- (3) logical inference based on semantic rules,
- (4) machine learning,
- (5) the result of the work of the levels from the lowest to the highest.

System processes the raw data from the sensors, adds semantics and rules, executes machine learning, and finally, carries out some actions.

The first level in the structure is the level of data collection, which is responsible for collecting all kinds of data from various sources, in particular from sensors. It can be considered as an input layer, since the platform uses this level to interact with sensors.

The incoming data is raw data, and the only task that this level performs is receiving and transmitting the raw data to the ETL level for processing.

$$\forall x \in T \exists d = \text{ETL}(x)$$

The second level in the structure is the level of ETL (Extract- Transform-Loading). Incoming data from the acquisition level is accepted by the ETL level for analysis. Since sensors of different types send data of different types and formats, the ETL level contains sensor drivers to receive and analyze data accordingly. For example, a humidity sensor and a temperature sensor send data in different formats.

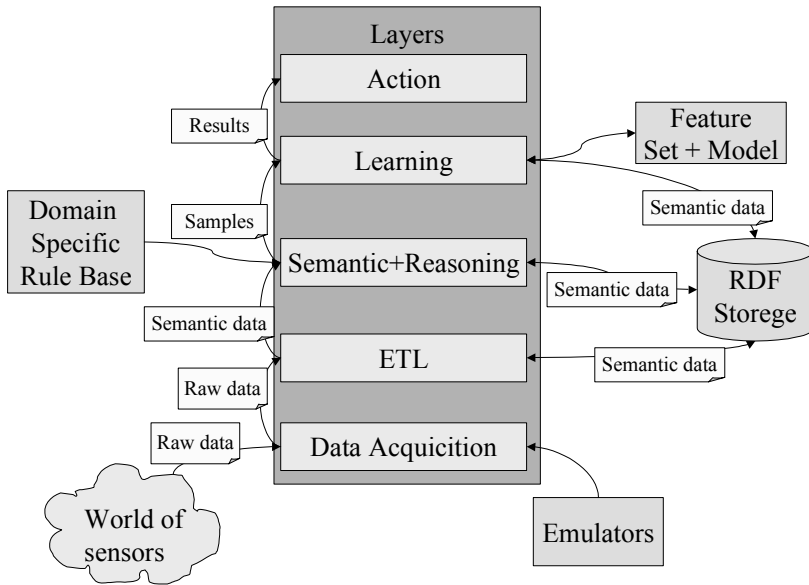


Fig. 2. Multilevel architecture of the semantic processing of IoT Big Data.

In addition, each sensor driver is responsible for receiving data in the correct form, the correct block and format, depending on the sensor, its type and version. For example, a temperature sensor from supplier A may provide data in units of degrees Celsius, while another sensor from supplier B may provide data in units of Fahrenheit. For this purpose, the ETL level is responsible for storing data in the correct type and format, regardless of the type of sensor, with the help of semantic technologies.

Data is converted to a semantic format RDF that is a basic language for describing statements. At this stage, artifacts from the sensor network ontology SSN are used together with ontology constructs.

The third level is the level of inference based on semantic rules. This layer uses semantically enriched data from the ETL layer that analyzed with the help of parsing rules defined by the corresponding drivers. The main purpose of the reasoning layer is to mark the domain boundaries and draw basic conclusions from the RDF data by use of the built-in reasoning mechanism. Two types of rules are used for semanticization of data from sensors. The first one is the rules of logical inference characteristic for RDF, RDFS and OWL (these oriented on particular language rules are automatically processed by inference engine). The second type are the rules specific to the domain or user.

For example, in a smart home environment, we can maintain a temperature of between 25 and 45 degrees Celsius. For this purpose, you can enter a domain rule "If the temperature is above 45 degrees Celsius, then activate the air conditioner or, if it is below 25, activate the heater." Domain-specific rules are just important for system as semantic ones. The fourth level is the level of learning. This level basically acquires features from data by machine learning techniques. This level consists of two sub-steps — preprocessing and learning. Various deep learning algorithms can be used for this purposes.

The last level is the action layer. The results of learning are used for selection of appropriate actions. For example, if the learning algorithm produces three different results using data of meteorological indications to determine the probability of rain, such as “low probability”, “average probability”, and “high probability” then user decides what actions are caused by each result - if rain has high probability then take an umbrella.

CONCLUSION

Implementing the new IoT infrastructure is a challenge. There are many options for this architecture and its components, but choosing the right technology and method is a difficult task. Now we can choose many open source components to create such structure. New features of such platform have two directions: semantics and analysis of Big Data.

In this article we reviewed and discussed the requirements for the Big Data processing platform architecture coming from IoT using new approaches to using Big Data semantics and analysis. The platform will combine the semantic infrastructure and Big Data and machine learning capabilities that will be implemented based on semantic data.

This platform is designed to provide effective support for all types of sensors in order to preserve data, substantiate the semantic rules for inferring these data and then use machine learning methods to obtain the best results from Big Data processing.

We plan to implement the structure with the above tools and methods. We will also use real-life examples of use in such areas as smart grids, e-health's, smart home, etc.

ACKNOWLEDGMENTS

"The work was prepared in accordance with the thematic plan of scientific research of the Tavria State Agrotechnological University named after D.Motorny (project of applied research at the expense of the State Budget "Theoretical foundation and development of the information system of semantic identification, documentation and processing of the results of non-formal and informal learning").

REFERENCES

1. Industry 4.0: the fourth industrial revolution — guide to Industrie 4.0. URL: https://www.i-scoop.eu/industry-4-0/#Industry_40_building_blocks_the_Industrial_Internet_of_Things. (Last accessed 20.05.2019).
2. Embracing Industry 4.0 and Rediscovering Growth. URL: <https://www.bcg.com/ruru/capabilities/operations/embracing-industry-4.0-rediscovering-growth.aspx>. (Last accessed 20.05.2019).
3. Bermúdez M.D., Juárez B. F. “Competencies to adopt Industry 4.0 for operations management personnel at automotive parts suppliers in Nuevo Leon”. In Proc. of the International Conference on Industrial Engineering and Operations Management (25–26th of Oct., 2017, Bogota). Bogota, 2017. P.736–747. URL: <http://ieomsociety.org/bogota2017/papers/117.pdf>. (Last accessed 20.05.2019).
4. A.Gladun, A. Andrushevich, A. Kurbatski. Ontological representation information objects, models and services in the Web Things. *Problems Informatization and Management*. 2015. No. 4 (issue 48). P. 28–41 (in Russian).

5. J. Rogushina, A. Gladun "Semantic approach to the integration of the Web of Things" In Proceedings of the V-th Int. Scientific and technical conf. "Open semantic technologies for intelligent systems" — OSTIS 2015, Minsk, Belarus. P.70–75. (in Russian).
6. J. Borges Neto, T. Silva, R. "Assunc ao, R. Mini, and A. Loureiro Sensing in the collaborative internet of things" *Sensors*. 2015. vol. 15, no. 3. P. 6607–6632.
7. Cedefop (2015). European guidelines for validating non-formal and informal learning. Luxembourg: Publications Office. Cedefop reference series; №104. <http://dx.doi.org/10.2801/008370>.
8. UNESCO Glossary. URL: <http://uis.unesco.org/en/glossary>. (Last accessed 20.05.2019).
9. The Law of Ukraine "On Education" (Information from the Verkhovna Rada, 2017, № 38-39, art.380). URL: <https://zakon.rada.gov.ua/laws/show/2145-19>. (Last accessed 20.05.2019).
10. Rogushina J., Priyma S. Use of competence ontological model for matching of qualifications // Chemistry: Bulgarian Journal of Science Education, Volume 26, Number 2, 2017. P.216–228.
11. OWL2 Web Ontology Language Document Overview. W3C. 2009. URL: <http://www.w3.org/TR/owl2-overview/>. (Last accessed 20.05.2019).
12. Lassila O., Swick R. "Resource Description Framework (RDF) Model and Syntax Specification", W3C Recommendation. URL: <http://www.w3.org/TR/REC-rdf-syntax>. (Дата звернення: 20.05.2019).
13. X. Su, J. Riekk, J. K. Nurminen, J. Nieminen, and M. Koskimies, "Adding semantics to the internet of things," *Concurrency and Computation: Practice and Experience*. 2015. vol. 27, no. 8, P. 1844–1860.
14. S. N. A. U. Nambi, C. Sarkar, R. V. Prasad, and A. Rahim, "A unified semantic knowledge base for IoT," *2014 IEEE World Forum on Internet of Things (WFIoT)*, IEEE. 2014. P. 575–580.
15. S. Hachem, T. Teixeira, and V. Issamy, "Ontologies for the Internet of Things" *Proceedings of the 8th Middleware Doctoral Symposium on MDS'11*, ACM Press, 2011. P. 1–6.
16. W. Wang, S. De, G. Cassar, and K. Moessner, "Knowledge representation in the internet of things: semantic modelling and its applications" *Automatika Journal for Control, Measurement, Electronics, Computing and Communications*. 2013. vol. 54, no. 4. P.388–400.
17. C. Barbero, P. D. Zovo, and B. Gobbi, "A flexible context aware reasoning approach for IoT applications," in *IEEE 12th International Conference on Mobile Data Management*. 2011. P. 266–275.
18. T. Erl, W. Khattak, P. Buler (2018) *The Basics of Big Data: Concepts, Algorithms, and Technologies*. Dnipro: Business, Balans, Book, 2018. 312 p.(in Russian).
19. Y. Qin, Q. Z. Sheng, N. J. G. Falkner, S. Dustdar, H. Wang, and A. V. Vasilakos, "When it's a matter of data-centric Internet of Things" *Journal of Network and Computer Applications*. 2016. vol. 64, no. 4. P. 137–153.
20. M. Chen, S. W. Mao, and Y. H. Liu, "Big data: a survey" *Mobile Networks Applications*. 2014. vol. 19, no. 2. P. 171–209.
21. L. Jiang, L. D. Xu, H. Cai, Z. Jiang, F. Bu, and B. Xu "An IoT-oriented data storage framework in cloud computing platform" *IEEE Transactions on Industrial Informatics*. 2014. vol. 10, no. 2. P. 1443–1451.
22. T. Li, Y. Liu, Y. Tian, S. Shen, and W. Mao, "A storage solution for massive IoT data based on noSQL" *IEEE International Conference on Green Computing and Communications*, 2012, pp. 50–57.
23. C. Cecchinell, M. Jimenez, S. Mosser, and M. Riveill, "An architecture to support the collection of Big Data in the Internet of Things," in *IEEE World Congress on Services*, 2014, pp. 442–449.
24. M. Khan, Y.-K. Young-Koo Lee, S. Y. Lee, and T.-S. Tae-Seong Kim, "A triaxial accelerometer-based physical-activity recognition via augmented- signal features and a hierarchical recognizer" *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no.5, pp. 1166–1172, 2010.
25. K. Altun and B. Barshan, "Human activity recognition using inertial/magnetic sensor units" *Lecture Notes in Computer Science*, vol. 6219 LNCS, Springer Berlin Heidelberg, 2010, pp. 38–51.

26. J. Jonghwa Choi, D. Dongkyoo Shin, and D. Dongil Shin, "Research and implementation of the contextaware middleware for controlling home appliances" *IEEE Transactions on Consumer Electronics*, vol. 51, no. 1, pp. 301–306, 2005.
27. N. D. Lane, S. Bhattacharya, P. Georgiev, C. Forlivesi, and F. Kawsar, "In smartphones and Internet-based devices" *Int. Workshop on Internet of Things towards Applications*, ACM, 2015, pp. 7–12.
28. Gladun A., Rogushina Y., Subach I. An Ontology Modelling Human Resources Management for Innovational Domains. *Information Technology and Security*, 2018, vol.1, №6. P.15-25. URL: <http://its.iszzi.kpi.ua/article/view/153125>. (Last accessed 20.05.2019).

Received 10.01.2019

ЛІТЕРАТУРА

1. Industry 4.0: the fourth industrial revolution — guide to Industrie 4.0. URL: https://www.i-scoop.eu/industry-4-0/#Industry_40_building_blocks_the_Industrial_Internet_of_Things. (Дата звернення: 20.05.2019).
2. Embracing Industry 4.0 and Rediscovering Growth. URL: <https://www.bcg.com/ru-ru/capabilities/operations/embracing-industry-4.0-rediscovering-growth.aspx>. (Дата звернення: 20.05.2019).
3. Bermúdez M.D., Juárez B. F. "Competencies to adopt Industry 4.0 for operations management personnel at automotive parts suppliers in Nuevo Leon". In Proc. of the International Conference on Industrial Engineering and Operations Management (25–26th of Oct., 2017, Bogota). Bogota, 2017. P.736–747. URL: <http://ieomsociety.org/bogota2017/papers/117.pdf>. (Дата звернення: 20.05.2019).
4. А. Гладун, А. Андрушевич, А. Курбацкий "Онтологическое представление информационных объектов, моделей и сервисов в Web of Things". Проблемы информатизации и управления. 2015. № 4 (48). С. 28–41.
5. Ю. Рогущина, А. Гладун "Семантический подход к интеграции объектов Web of Things" Труды V-ой Межд. научно-технический конф. «Открытые семантические технологии для интеллектуальных систем» — OSTIS 2015, Минск, Республика Беларусь. С.70–75.
6. J. Borges Neto, T. Silva, R. "Assunc ao, R. Mini, and A. Loureiro Sensing in the collaborative internet of things" *Sensors*. 2015. vol. 15, no. 3. P. 6607–6632.
7. Cedefop (2015). European guidelines for validating non-formal and informal learning. Luxembourg: Publications Office. Cedefop reference series; №104. <http://dx.doi.org/10.2801/008370>. (Дата звернення: 20.05.2019).
8. UNESCO Glossary. URL: <http://uis.unesco.org/en/glossary>. (Дата звернення: 20.05.2019).
9. Закон України «Про освіту» (Відомості Верховної Ради, 2017, № 38-39, ст.380).URL: <https://zakon.rada.gov.ua/laws/show/2145-19>. (Дата звернення: 20.05.2019).
10. Rogushina J., Priyama S. Use of competence ontological model for matching of qualifications. *Chemistry: Bulgarian Journal of Science Education*. Vol. 26, Number 2. 2017. P. 216–228.
11. OWL2 Web Ontology Language Document Overview. W3C. 2009. URL: <http://www.w3.org/TR/owl2-overview/>. (Дата звернення: 20.05.2019).
12. Lassila O., Swick R. "Resource Description Framework (RDF) Model and Syntax Specification", W3C Recommendation. URL: <http://www.w3.org/TR/REC-rdf-syntax>. (Дата звернення: 20.05.2019).
13. X. Su, J. Riekkki, J. K. Nurminen, J. Nieminen, and M. Koskimies, "Adding semantics to the internet of things," *Concurrency and Computation: Practice and Experience*. 2015. vol. 27, no. 8, P. 1844–1860.
14. S.N.A.U. Nambi, C. Sarkar, R.V. Prasad, and A. Rahim, "A unified semantic knowledge base for IoT," *2014 IEEE World Forum on Internet of Things (WFIoT)*, IEEE. 2014 P. 575–580.
15. S. Hachem, T. Teixeira, and V. Issamy, "Ontologies for the Internet of Things" *Proceedings of the 8th Middleware Doctoral Symposium on MDS'11*, ACM Press, 2011. P. 1–6.
16. W. Wang, S. De, G. Cassar, and K. Moessner, "Knowledge representation in the internet of things: semantic modelling and its applications" *Automatika Journal for Control, Measurement, Electronics, Computing and Communications*. 2013. vol. 54, no. 4. P.388–400.

17. C. Barbero, P. D. Zovo, and B. Gobbi, "A flexible context aware reasoning approach for IoT applications," in IEEE 12th International Conference on Mobile Data Management. 2011. P. 266–275.
18. Т. Эрл, В. Хаттак, П. Булер (2018) Основы Big Data: концепции, алгоритмы и технологии. Днепр: Бизнес, Баланс, Бук, 2018. 312с.
19. Y. Qin, Q. Z. Sheng, N. J. G. Falkner, S. Dustdar, H. Wang, and A. V. Vasilakos, "When it's a matter of data-centric Internet of Things" *Journal of Network and Computer Applications*. 2016. vol. 64, no. 4. P. 137–153.
20. M. Chen, S. W. Mao, and Y. H. Liu, "Big data: a survey" *Mobile Networks Applications*. 2014. vol. 19, no. 2. P. 171–209.
21. L. Jiang, L. D. Xu, H. Cai, Z. Jiang, F. Bu, and B. Xu "An IoT-oriented data storage framework in cloud computing platform" *IEEE Transactions on Industrial Informatics*. 2014. vol. 10, no. 2. P. 1443–1451.
22. T. Li, Y. Liu, Y. Tian, S. Shen, and W. Mao, "A storage solution for massive IoT data based on noSQL" *IEEE International Conference on Green Computing and Communications*, 2012, pp. 50–57.
23. C. Cecchinell, M. Jimenez, S. Mosser, and M. Riveill, "An architecture to support the collection of Big Data in the Internet of Things," in IEEE World Congress on Services, 2014, pp. 442–449.
24. M. Khan, Y.-K. Young-Koo Lee, S. Y. Lee, and T.-S. Tae-Seong Kim, "A triaxial accelerometer-based physical-activity recognition via augmented- signal features and a hierarchical recognizer" *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no.5, pp. 1166-1172, 2010.
25. K. Altun and B. Barshan, "Human activity recognition using inertial/magnetic sensor units" *Lecture Notes in Computer Science*, vol. 6219 LNCS, Springer Berlin Heidelberg, 2010, pp. 38–51.
26. J. Jonghwa Choi, D. Dongkyoo Shin, and D. Dongil Shin, "Research and implementation of the contextaware middleware for controlling home appliances" *IEEE Transactions on Consumer Electronics*, vol. 51, no. 1, pp. 301–306, 2005.
27. N. D. Lane, S. Bhattacharya, P. Georgiev, C. Forlivesi, and F. Kawsar, "In smartphones and Internet-based devices" *Int. Workshop on Internet of Things towards Applications*, ACM, 2015, pp. 7–12.
28. Gladun A., Rogushina Y., Subach I. An Ontology Modelling Human Resources Management for Innovational Domains. *Information Technology and Security*, 2018, Vol.1, №6. P. 15–25. URL: <http://its.iszzi.kpi.ua/article/view/153125>. (Дата звернення: 20.05.2019).

Отримано: 10.01.2019

А.Я. Гладун¹, канд.техн.наук, старш. наук. співроб.,
відд. комплексних досліджень інформаційних технологій та систем
email: glanat@yahoo.com

Ю.В. Рогущина², канд.фіз.-мат. наук, старш. наук. співроб.,
відд. автоматизованих інформаційних систем
e-mail: ladanandraka2010@gmail.com

А.А. Андрушевич³, науковий співробітник
факультету математики та комп'ютерних наук
e-mail: andrushevich@bsu.by

¹ Міжнародний науково-навчальний центр інформаційних
технологій та систем НАН України та МОН України,
пр. Аккад. Глушкова, 40, м. Київ, 03187, Україна

² Інститут програмних систем НАН України,
пр. Акад. Глушкова, 40, м. Київ, 03187, Україна

³ Білоруський державний університет,
пр. Незалежності, 4, м. Мінськ, 220030, Республіка Білорусь

ВИКОРИСТАННЯ СЕМАНТИЧНОГО МОДЕЛЮВАННЯ ДЛЯ ОБРОБ ОБРОБЛЕННЯ BIG DATA В ДОМЕНІ ІНТЕРНЕТУ РЕЧЕЙ

Вступ. Важливим кроком нової технічної революції є розвиток Інтернету речей (IoT), обладнаного різними електронними давачами та контролерами, які дистанційно працюють з цими речами. У статті розглянуто особливості Big Data, створених за технологією Інтернету речей, а також презентовано методологію оброблення цих великих даних з використанням семантичного моделювання (онтології) на всіх етапах життєвого циклу великих даних. Семантичне моделювання дає змогу усунути такі суперечності в цих технологіях, як неоднорідність пристроїв і речей, що зумовлює неоднорідність типів даних, які їх виробляють. Машинне навчання використовують як інструмент для аналізу великих даних: він забезпечує логічне виведення правил, які можуть бути застосовані до оброблення інформації, що генерується системою Smart Home.

Метою статті є використання глибокого машинного навчання, ґрунтованого на згорткових нейронних мережах, оскільки ця модель машинного навчання відповідає обробленню неструктурованого та складного домену IoT.

Результати. Запропонований підхід підвищує ефективність оброблення великих даних IoT і відрізняється від традиційних систем оброблення за допомогою бази даних NoSQL, розподілених архітектур і семантичного моделювання. Запропоновано використовувати глибоке машинне навчання, що базується на нейронних мережах, пристосованих для неструктурованих даних IoT. Запропоновану концептуальну архітектуру системи оброблення великих даних для IoT описано на прикладі бази даних NoSQL для Smart Home.

Висновки. Запропонована архітектура системи оброблення великих даних для IoT складається з п'яти незалежних рівнів. На кожному з цих рівнів можна використовувати комбінований підхід семантичного моделювання та методів інтелектуального аналізу даних. Зазначену платформу можна поєднувати з великою кількістю відкритих компонентів.

Ключові слова: Індустрія 4.0, Великі дані, Інтернет речей, онтологія, семантичний Web, неформальне та інформальне навчання.

*А.Я. Гладун*¹, канд.техн.наук,

старш. науч. сотр., отд. комплексных исследований
информационных технологий и систем

e-mail: glanat@yahoo.com

*Ю.В. Рогущина*², канд.физ.-мат. наук, старш. науч. сотр.,

отд. автоматизированных информационных систем

e-mail: ladanandraka2010@gmail.com

*А.А. Андрушевич*³, науч. сотр.

факультета прикладной математики и компьютерных наук

e-mail: andrushevich@bsu.by

¹Международный научно-учебный центр информационных

технологий и систем НАН Украины и МОН Украины,

пр. Академика Глушкова, 40, г. Киев, 03187, Украина

²Институт программных систем НАН Украины,

пр. Академика Глушкова, 40, г. Киев, 03187, Украина

³Белорусский государственный университет,

пр. Независимости, 4, г. Минск, 220030, Республика Беларусь

ИСПОЛЬЗОВАНИЕ СЕМАНТИЧЕСКОГО МОДЕЛИРОВАНИЯ ДЛЯ ОБРАБОТКИ BIG DATA В ДОМЕНЕ ИНТЕРНЕТА ВЕЩЕЙ

Рассмотрена специфика Big Data, которые генерирует технология Интернет вещей, а также представлена методология их обработки семантического моделирования (онтологий) на всех этапах жизненного цикла больших данных. Семантическое моделирование позволяет устранить такие противоречия в технологиях, как гетерогенность устройств и данных. Предлагается использование машинное обучение для анализа Big Data, создаваемых информационной системой умного дома. Предложено использовать глубокое машинное обучение, базирующееся на сверточных нейронных сетях, приспособленных для неструктурированных данных IoT. Представлены новые подходы для обработки больших данных, которые повышают эффективность обработки Big Data в IoT. Представлена концептуальная архитектура системы обработки больших данных для Интернета вещей на примере сгенерированной базы данных NoSQL для умного дома. Данная архитектура состоит из пяти независимых уровней, каждый из которых может использовать семантическое моделирование.

Ключевые слова: *Индустрия 4.0, Большие данные, Интернет вещей, онтология, семантический Web, неформальное и информальное обучение.*