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Data Science Technologies for Vibrant Cities

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1 ABSTRACT

Smart Cities forced IT technologies make a significant step in their development. A new generation of agile knowledge based software applications and systems have been successfully designed and implemented. Wide capabilities of the agile applications were sufficient to meet the complete set of requirements of smart cities. Fast transformation of modern cities from smart cities to vibrant cities throws new even more complicated challenges to information technologies. While smart cities assumed wide usage of agile means and tools for solving applied tasks, applications for vibrant cities must provide agile environment for exploring and managing of all types of data, information and knowledge. Agile environment must be flexible enough to support iterative data processing and analyses procedures that can be easily reorganized or changed depending on context. The aim of agile environment creation and support is to extend a set of used mathematical, technological and program solutions. In the paper it is proposed to build applications for vibrant cities using agile data science methodologies and toolsets within the commonly used approaches for developing agile information systems.

2 INTRODUCTION

The history of the modern society formation contains a number of evolution and revolution stages that sequentially followed each other. The processes of society development at early stages were forced by the need to survive. The progress engine of the industrial and postindustrial information societies is desire to reduce amount of time and financial resources required for producing all kinds of commonly consumed and innovation products, to have easy access to resources sufficient to satisfy physical, cultural and spiritual needs, to reach high level of life safety. At the industrial stage the economical sphere was considered as the target sphere of the development, high level of social sphere development was archived at the postindustrial stage. Now the society has to solve a number of new problems arisen within the industrial and postindustrial stages. The great number of created and used technical objects can lead to a variety of technogenic dangers, the natural environment has been considerably damaged and needs recovery, amount of consumed natural resources has to be reduced and substituted by alternative sources, the social sphere needs further development and improvement.

To solve these problems new highly technological solutions that can substitute existing solutions in comparatively short period of time are required. Significant amount of resources is required to produce technologies that will provide new level of quality. The major part of the available resources is now spent to support the existing society infrastructure. To free the resources for archiving the new technological level of the society development all spheres of human activities have to be precisely coordinated. It assumes human collaboration in using technical and natural resources, products provision and consumption.

Cities and towns are centers of the modern society development. They reflect the state of the society, its latest achievements and trends of further evolution of the society. An essential part of citizens are open to all kinds of innovations that potentially can improve quality of their life. Cities and town provide fertile ground for new economical, organizational, technological and technical solutions creating, implementing and approving. High concentration of population in cities, citizens' active social positions, high dynamics of life, large variety of the consumed products and services, strong requirements to their quality and accessibility throws new challenges to cities and forces cities rapid development.

The overwhelming majority of citizen professional and private activities in the modern information society are part and parcel of all kinds of information consumption and production. They gather, store, process and analyze data, transform it into information and knowledge. The results of the researches of the leader IT companies, for example, International Data Corporation (IDC, http://www.idc.com/), showed that amount of produced data is doubling in size every two years and will reach 44 zettabytes by 2020 [1]. Data is created by more than 2 billion people and millions of enterprises, millions of sensors and communicating devices. Diverse software is created and used to analyze expanding data streams, find hidden values and dependencies in it. Mined information and knowledge create new challenges and provide wide opportunities to enhance the real world. Big amount of gathered data used in new ways provide huge potential for enterprises development. Ability of enterprises to derive benefits of data and to obtain competitive intelligence completely defines their demand by the society and further successful development.

IDC pointed out that in 2013 only 22% of available data was considered as a candidate for analysis, less than 5% of that was actually analyzed and less than 1% of it was really used. In order to increase amount of consumed data, enterprises have to be reorganized into companies designed for data, information and knowledge (DIK) transformation adaptable to ever changing rushing environment.

Well founded theories and techniques for analytical data processing have been developed in the sphere of data science. Data science is extraction of knowledge from data [2]. It includes models and methods drawn from many fields within the areas of mathematics, statistics, and information technologies. Data science techniques are used for researches in biological and medical sciences, social sciences, economics, business and finance that have rich data sources.

From the perspective of modern cities data science has to become an integral part of vibrant cities informational infrastructure that encompasses both physical and organizational structures needed for operation and evolution of the human society. It will take determination and skilled workforce to find the way and put to use data science for cities and towns welfare.

3 DATA SCIENCE

Data Science has appeared more than 10 years ago as a response to acute need in theory for processing and analyses of data with 3Vs defining properties or dimensions - volume, variety and velocity. The term “Data Science” was introduced by Prof. William S. Cleveland [3]. Data science allow discover true business needs by taking ownership and management of the entire modeling process (Fig.1): collecting and managing data, information and knowledge, building / extending models and deploying models into production [4]. In narrow sense Data Science is a discipline targeted on extracting knowledge from data that can be used to predict and explain future and past observed events. Data science structure and goals are mostly defined by the DIKW (Data, Information, Knowledge and Wisdom) model, also known as DIKW Pyramid or DIKW Hierarchy [5, 6, 7]. The model represents structural and/or functional relationships between data, information, knowledge and wisdom. Two views [6, 8] of the DIKW model are shown in Fig.2.

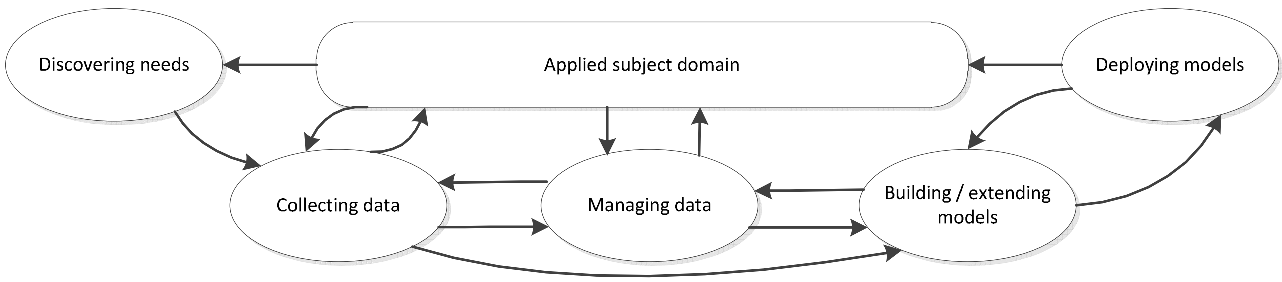
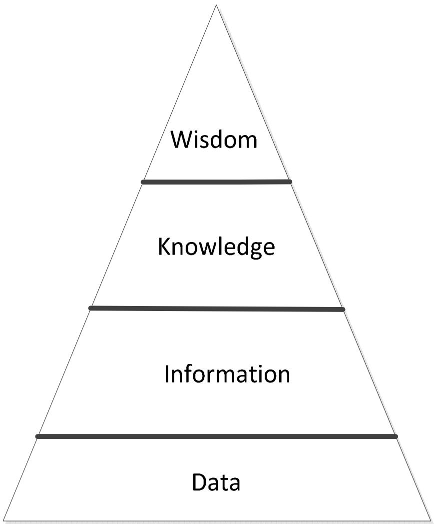


Fig. 1. Structure and steps of modeling process

Russell Ackoff' defines the terms used in the DIKW pyramid considering them as the key categories that form the content of the human mind: data is symbols; information is data that is processed to be useful; knowledge is application of data and information; wisdom is evaluated understanding of data, information and knowledge (Table 1).

The transitions between the nodes in the DIKW chain allow extract meaning from data and create data products. The transitions require single or multiple transformations of data, information, knowledge or wisdom. Data Science incorporates varying means capable to support complicated transformations. The techniques and theories used in data science refer to many fields, including math, statistics, data engineering, pattern recognition and learning, advanced computing, visualization, uncertainty modelling, data warehousing, and high performance computing. For example, John Hopcroft and Ravindran Kannan in

Foundations of Data Science [9] include into the list of the clustering techniques and algorithms a k-means algorithm, a greedy algorithm for k-center criterion clustering, spectral clustering, recursive clustering based on sparse cuts, kernel methods, agglomerative clustering, algorithms based on dense submetrices and communities calculation, flow methods, methods for finding local clusters without examining the whole graph and some other methods. The number of data science algorithms exceeds several thousand and is constantly increasing in response to new data, new applied problems and permanently changing requirements to the solutions.



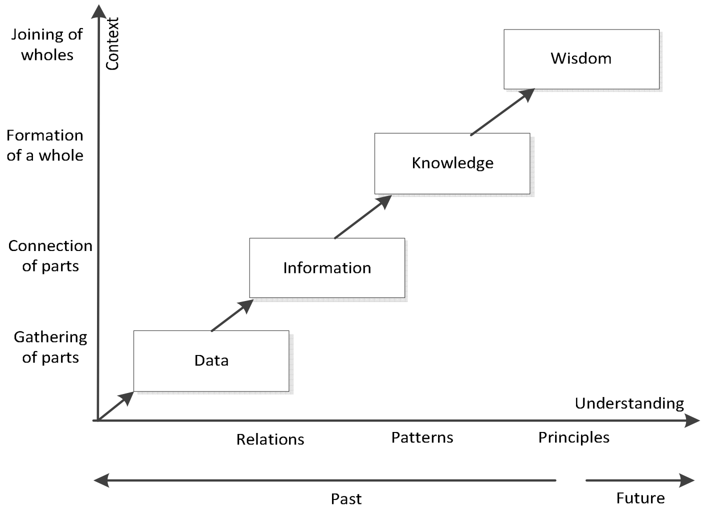


Fig. 2. Views of the DIKW model: left (a) DIKW hierarchy, right (b) DIKW chain.

№	Motion	Question to answer	Properties
1	data	-	Data is raw. It simply exists and has no significance beyond its existence (in and of itself). It can exist in any form, usable or not. It does not have meaning of itself.
2	infor-mation	who? what? where? when?	It is data that has been given meaning by way of relational connection. This meaning can be useful, but does not have to be. In computer parlance, a relational database makes information from the data stored within it.
3	know-ledge	how?	Knowledge is the appropriate collection of information, such that it is intent to be useful. Knowledge is a deterministic process. Knowledge can be amassed. This knowledge has useful meaning, but it does not provide for, in and of itself an integration such as would infer further knowledge. Synthesization of new knowledge from currently and previously held information and knowledge requires its understanding. Understanding is an interpolative and probabilistic process. It is cognitive and analytical.
4	wisdom	why?	Wisdom is an extrapolative and non-deterministic, non-probabilistic process. It calls upon all the previous levels of consciousness, and specifically upon special types of human programming (moral, ethical codes, etc.). It gives us understanding about which there has previously been no understanding, and in doing so, goes far beyond understanding itself.

Table 1. DIKW hierarhy notions description

4 SUBJECT DOMAIN MODELS

City and town infrastructure involves millions of various technical objects, natural objects and complexes of objects. IBM has developed a general intelligent semantic model (ISMP model) for smart cities [10] and a number of its customizations for separate regions. A fragment of the model is shown in Fig.2 (a).

Data about the objects is continuously gathered using embedded and external sensors. Behavior of the objects is defined by needs of solving applied problems and requires objects interaction. The results of the objects activities are influenced by the environment in which the objects are functioning. Influence factors can refer to economic, social, political spheres or the objects can be impacted by natural phenomena. Objects can be also affected by both predictable and unexpected events. The result of joint influence of totality of the factors and events on the objects' states, behavior and their capability to solve the end tasks at particular time and in particular place is considered as a situation [11].

From the point of view of modeling processes development and execution description of the subject domain of cities and towns infrastructure can be simplified to three key notions: measurements, objects and situations (Fig.2 (b)).

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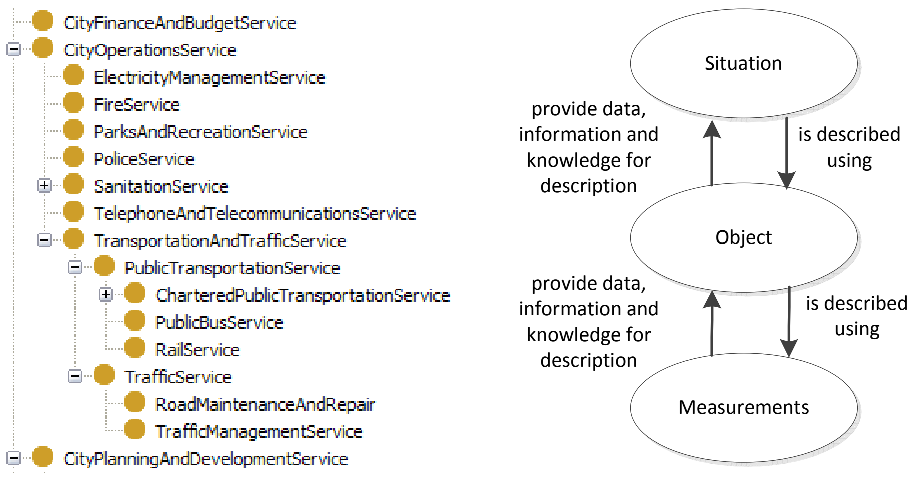

Fig. 2. Complex and simplified descriptions of the subject domain of city and town infrastructure. left (a) complex description, right (b) simplified description

High complexity of the notions required design and development of the specialized informational models for representing data, information and knowledge about each of the notions. The proposed models have four key features:

i) to build the models it is necessary and sufficient to have the results of the parameters measurements;

ii) the levels of the models are oriented on extracting knowledge out of data and information;

iii) relations between the notions are oriented on generalization of data, information and knowledge of the subject domain;

iv) representations of data, information and knowledge used in the models are completely compatible with representations of the results of the methods and algorithms that refer to data science.

Descriptions of objects in the models are based on processing and analyses of the objects characteristics. Values of the characteristics are obtained as the results of measurements processing. Descriptions of the situations are built using the descriptions of objects that are directly or indirectly involved or can be involved into the situations or can potentially influence on them. The defined notions and the supported relations allow reflect the actual state of the cities and towns infrastructure sufficiently enough to solve the problems of the infrastructure understanding and in time management.

The schematical structures of the models for representing measurements (MIM), objects (OIM) and situations (SIM) are given in tables 2-4. The models are functional multilevel models that contain systematized data, information and knowledge about the notions. The general metainformation about the measurements, objects and situations is out of the presented models scope. The models are targeted on providing operational DIKW of the subject domain and results of their processing.

Level	Element of the model	Description	Provider / consumer
L1.1	Structured binary stream	Parameters of the initial structured binary streams received from the object	- / MIM
L1.2	Initial results of the parameters measurements	Results of the objects parameters measurements represented in the form of time series or separate measurements	- / MIM
L1.3	Pre-processed results of the parameters measurements	Results of the parameters measurements processing	- / MIM
L2.1	Segment based representation of the results of the parameters measurements	Representation of the time series of parameters measurements in the form of a sequence of piece-wise constant segments	MIM / OIM
L2.2	Class based representation of the results of the parameters measurements	Representation of the time series of parameters measurements in the form of a sequence of classified segments	MIM / OIM
L2.3	Alphabet based representation of the results of the parameters measurements	Representation of the time series of parameters measurements using a predefined alphabet	MIM / OIM

Table 2. Informational model of the results of object parameters measurements

The model can be build taking into account information about measurements time and location or without the time-space buinding.

Level	Element	Description	Provider / consumer

L1.1	Functional parameters measurements	The list of the results of the parameters measurements / results of measurements processing with the defined location in space and time	MIM / OIM
L1.2	Signal parameters measurements	The list of the results of the parameters measurements / results of measurements processing with the defined location in space and time	MIM / OIM
L2	Parameters characteristics	Characteristics of the objects calculated using the results of measurements processing	OIM / OIM
L3.1	Physical - oriented parameters estimations	Estimations of the results of measurements in the context of parameters physical nature	OIM / SIM
L3.2	Object – oriented parameters estimations	Estimations of the results of measurements in the context of the objects properties and state	OIM / SIM
L3.3	Complex parameters estimations	Estimations of the objects parameters in the context of the known dependencies of parameters behaviour	OIM / SIM
L4	Mismatches and deviations	Mismatches between the parameters expected and actual behaviour; deviations between parameters actual behavior and predefined patterns	OIM / SIM

Table 3. Informational model of objects

Informational model of the objects can be used to store and provide information about the whole object, its separate functional componemts, in particular, systems and subsystems, or separate structure elements, including blocks, agregates and nodes. Information about the objects can be obtained or improved on the base of the information about the objects components and elements.

Level	Element	Description	Provider / consumer
L1.1	Objects involved in a situation	List of the objects and description of the objects directly or indirectly involved into the situation	OIM / SIM
L1.2	Relations between objects	Relations between the objects involved into the situation	OIM / SIM
L2.1	Context dependent descriptions	Descriptions of the objects with consideration of the diverse factors that influence the situation	External sources / SIM
L2.2	Events dependent descriptions	Descriptions of the objects with consideration of separate events or sequence of events that influence the course and / or the intensity of the situation development	External sources / SIM
L3.1	Situation related processes	The list of the processes and the descriptions of the processes related to the situation lifecycle, including situation emergence, development and resolution	SIM / SIM
L4	Mismatches and deviations	Mismatches between the expected and actual evolution of the situation	SIM / SIM

Table 4. Informational model of the situations

Similarly to the model of the objects the model of the situations can be considered at different levels – the levels of elementary situations of different scales and the level of the whole situations.

Elements of models are supposed to be described using OWL / OWL Schemes to provide interpretability of data, information and knowledge at the machine level.

5 DATA, INFORMATION AND KNOWLEDGE TRANSFORMATIONS

Modeling processes allow reveal and define the majority of the business processes. The processes assume application from one up to several hundreds of diverse methods and algorithms or their combinations. The processes are defined in terms of the subject domain. The set of the algorithms, their settings and the sequence of their application depend on the context of the solved problems. The set of the algorithms can be properly defined only during processes execution and has to be constantly adjusted.

Agile technologies based on agile concept introduced in [12] were developed within IT. They have been recently successfully spread to the area of data, information and knowledge processing and analyses [13]. The agile DIK processing is based on the idea of:

- defining taxonomies for data, information and knowledge and results of their processing systematization and classification;
- defining a system of patterns of different levels of abstraction to describe business processes of the applied subject domains and the subject domain of DIKW processing;
- detailing the patterns using logical rules according to processed data and available information and knowledge.

The considered approach can be successfully used in conditions of the limited number of high level business process. The restricting didn’t contradict the requirements of the smart cities [14]. For vibrant cities the task of apriori definition of the processes can be hardly solved. It generates a new need to build business processes in dynamics using logical rules and taxonomies.

A process can be described by defining the start point (SP), the end point (EP) and the path. The start point defines initial conditions in which the process is demanded and created. The end point is the target to be archived as the result of the process execution. The structure of the processes defined in dynamics can be both linear and non-linear.

According to the considered subject domain model the processes are described in a three dimensional space (Fig. 3). The dimensions are the type of the content, the type of the representation and scale of representation. Three types of content are considered: data, information and knowledge. For DIK representation MIM, OIM and SIM models can be used. The scale of DIK representation depends on the analyzed notion – measurements, objects or situations. In fig. 3 an example of the path that allows acquire data about a situation using initial measurements is given. The figure shows general direction of the path. In fact, the path defines the sequence of data, information and knowledge transformations implemented at different scales.

The transformation is a complete of major change in the structure and the contents of data, information or knowledge. The transformations can be of two types – vertical transformations and horizontal transformations. Transformation types are defined according to their references to the levels of JDL model (Data Fusion Model) [15]. The model was maintained by the JDL Data Fusion Group and has become the most widely-used method for categorizing data fusion-related functions. The levels of the model are: sub-object data assessment, object assessment, situation assessment, impact assessment, and process refinement. Horizontal transformations are transformations executed at one level of the JDL model. Transformations that support transitions between levels refer to horizontal transformations. In separate cases, for example, for the subject domain of measurements processing, sublevels are defined for the levels of the JDL model [16]. Transformations used for sublevel transitions are also considered as vertical transformations.

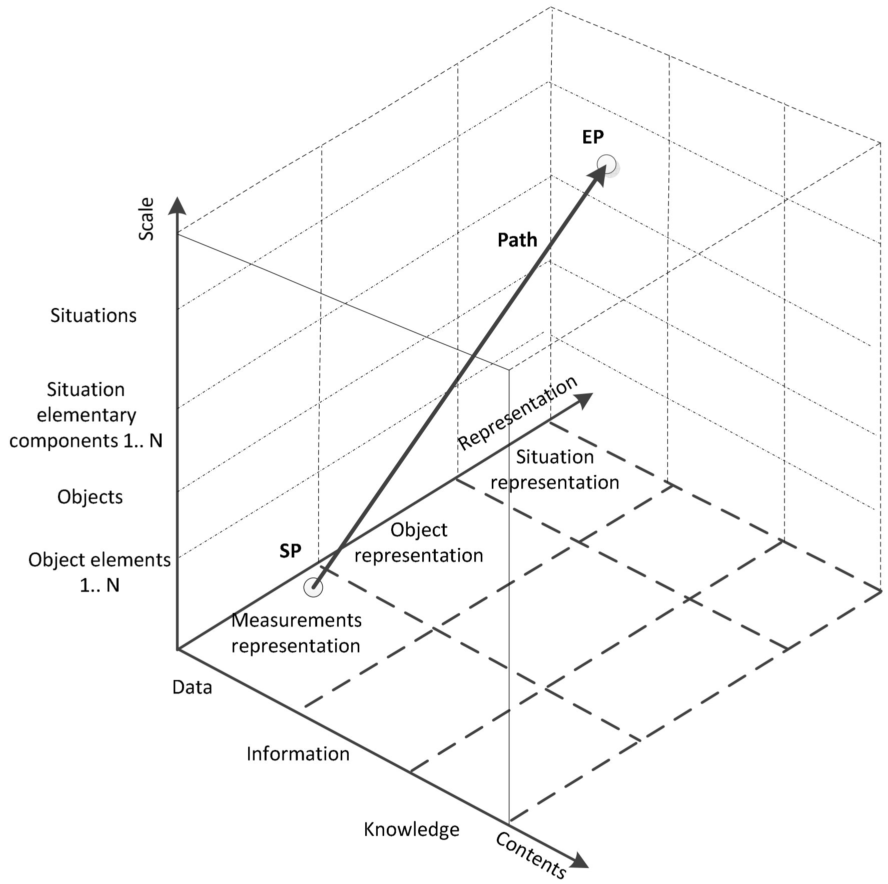

Fig. 3. 3D space for business processes representation

Six forms of transformations for DIKW are considered: “data” → “data”, “information → information”, “knowledge → knowledge”, “data → information”, “information → knowledge”, “data → knowledge”. The first three forms refer to horizontal transformations and the last three transformations are vertical transformations. In addition backward horizontal transformations “information → data”, “knowledge → information” are supported for neighboring scales.

The sequence of data, information and knowledge transformations at the scales of signals, objects and situations is given in Fig.4. It is a projection of the path shown in Fig.3 on the Contents and Scale axises. The path from the SP to the EP shown in the figure is a typical path that can be modified according to users needs. The results of DIKW processing can be generalized to the level of the subject domain. At the level of the subject domain dependencies between diverse situations can be reveiled. The set of the considered notions can be extended with the notion “wisdom”. To acquire and to use “wisdom” in the sequence of the transformations the definition of the notion is supposed to be narrowed. For different levels of JDL model term “wisdom” has different sense. It can be defined as “higher level knowledge” or “knowledge about knowledge”.

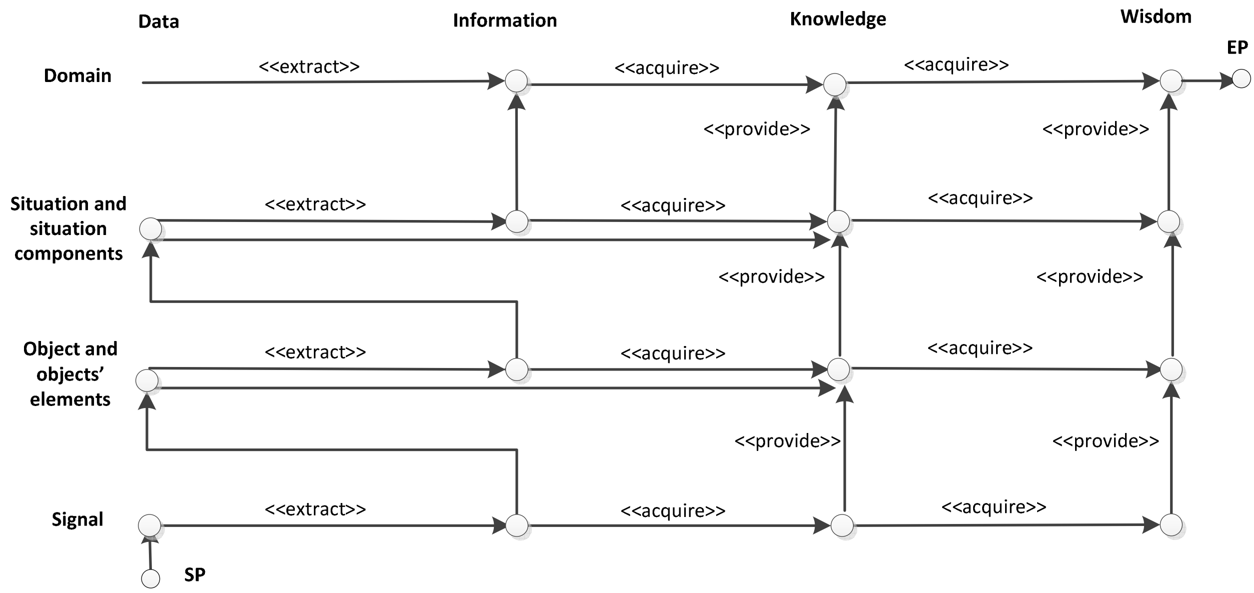

Fig. 4. The sequence of data, information and knowledge transformations at different scales

The set of the admissible operations for data, information and knowledge transformations is not limited. It can be defined for the applied subject domains according to the specialized requirements of the solved problems. For solving the majority of the problems three groups of operations are used: harmonization, integration and fusion. The operations are applicable to data, information and knowledge. According to [17] harmonization can be treated as standardization of data; the results of harmonization are supposed to be consumed by a great number of users. Integration is considered as association of data (access to sources of the information) for the decision making and modeling oriented on solving current problems. Fusion is a formal basis for expressing approaches and defining tools for associating data from various sources. Its purpose is to obtain information of higher quality; exact definition of "information quality" depends on a subject domain. Applicability of the groups of operations for implementing transformations is defined in Table 5.

DIK	Data	Information	Knowledge
Data	harmonization	integration	fusion
Information	operations for inverse transformations	harmonization	fusion
Knowledge	operations for inverse transformations	operations for inverse transformations	harmonization

Table 5. Informational model of the situations

Harmonization, integration and fusion of DIK can be done using diverse groups of methods and algorithms. The procedures of the operations, methods and algorithms selection and estimation are based on application of logical rules. The logical rules check:

i) correspondence of the requirements to input data and processed data;

ii) correspondence of the expected results to the needs of the consumers;

iii) fitting the field of application;

iv) compliance to the restrictions;

v) fulfilment of preconditions before methods and algorithms execution;

vi) fulfilment of postconditions after methods and algorithms execution.

In addition logical rules can express recommendations for the methods and algorithms application in diverse conditions.

To use operations, methods and algorithms in transformations each of them must have complete OWL-based description. Logical rules have to be described using notations interpretable by inference machines.

The sequence of the transformations that defines the path (Fig. 3) is build as the result of solving an optimization problem. It is necessary to find the path in the 3D space for business processes representation that allows reach the end point from the start point. The logical rules defined for the operations are considered as restrictions. There are no limitations for optimization methods that can be used to solve the problem. They are selected mostly according to the available computational resources.

6 CASE STUDY

At the step of the smart cities development a considerable number of interconnected smart grids have been developed. They allow manage energy, water, transportation, public health and safety, and other aspects of a smart citis in concert to support operation of critical infrastructure [18, 19].The smart city is considered as an "organism" that is supposed to work together as an integrated whole [20, 21]. It is expected that vibrant cities using new integrated solutions and developed smart grids will transfer into a greater, highly responsive urban ecosystem. Ecosystems are communities of living organisms in conjunction with the nonliving components of their environment [22].

The results of the analyses of the urbant climate of several regions, for example, presented in [23], showed that the processes of land transformation and city growth determine radical changes in urban landscape morphology that affect air temperature and energy exchange. The influence of urbanization on local climate is much more intensive than, for example, global warming. The main cause of it is the rapidity of human made changes related to natural processes. The alteration of urban climate can be investigated by a network of sensors that monitor the climate parameters. The infractructure required for monitoring the state of the environment is rarely well supported. As the result, the time series' of hydrometeorological data are not available at a suitable spatial density at all desired scales [23]. It defines the need to build regular grids of envoronmental parameters using avaibable measurements. The data about the environmental parameters becomes outdated quickly. To have actual information about the ecosystem state at every turn it is nesseccary to recalculate the grids in operational mode.

The procedure of building regular grids of the parameters values includes preprocessing stage and regularization stage. The description of the stages and the transformations assumed for each of the stages can be found in [24, 25].

The preprocessing stage includes four main substages:

- describing initial measurements, sources of the measurements and related information in terms of the intelligent semantic model;
- quality control of the initial measurements using a set of computational procedures;
- exclusion of dupblicated values;
- reduction to standart vertical levels.

At each of the stages one or several methods and algorithms can be used. As an example lets consider the group of interpolation methods (Fig. 5) used in buisness processes executed at the preprocessing substages and the conditions of their application.

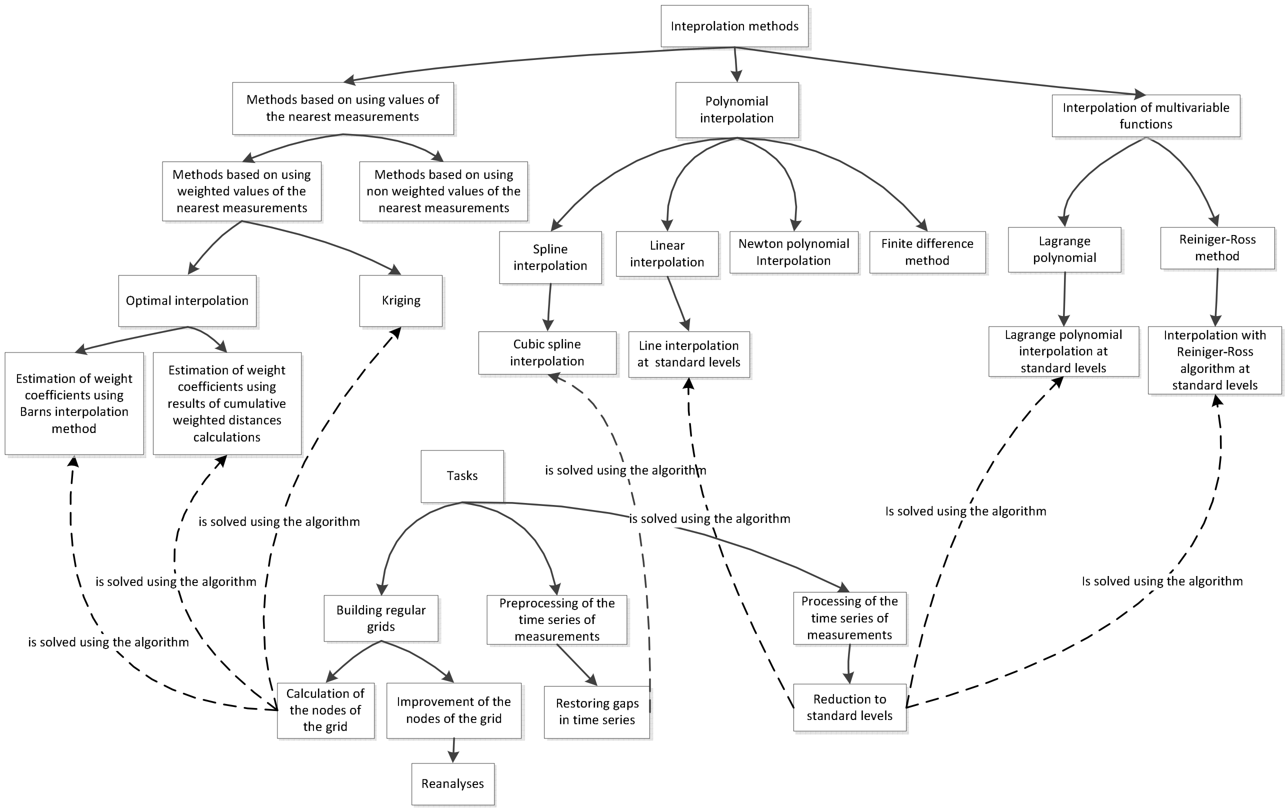

Fig. 5. The hierarchy of the interpolation algorithms and their relations to the solved tasks

At the stage of excuding the dublicated values initial measurements or the values of the interpolated profiles can be analyzed. In the second case the cross-linear interpolation methods are aplied to match the values of the profiles.

Time series of measurements may have gaps. To restore the gaps in time series the cubic spline interpolation method is included into the sequence of methods executed within the buisness processes of the preprocessing stage.

Reduction to standart levels can be fulfilled using linear, Lagrange or Reiniger-Ross interpolation methods [23]. The method is selected according to the number of the dimensions of the measurements. The complete list of the dimensions include latitude, longitude, hight or depth, time.

The hierarhy of the interpolation methods and algorithms used in buisness processes for monitoring the state of the environment and their relations to the solved tasks is partly represented in Fig.5.

7 CONCLUSION

In the paper an approach to transition of modern cities from smart cities toward vibrant cities is discussed. It is proposed to build applications for the vibrant cities using agile data science methodologies and toolsets. It is suggested to use standard approaches for developing agile information systems that must be flexible enough to support iterative data processing and analyses procedures that can be easily reorganized or changed depending on context.

Key problems of building applications for vibrant cities by means of using agile data science methodologies and toolsets within the commonly used approaches for developing agile information systems are discussed.

Main advantages of suggested approach are following:

- flexibility. Possibility of interaction with other components provided by external developers. The set of used components can be easily replaced by any other components with similar functionality;
- scalability. New information and knowledge can be added to a system using standard editors;
- high level of integration with other information systems. System can be implemented as a separate service and is included into a set of other services;

- low cost of development and support. Ready solutions are used for implementation of vibrant city applications. Only few new components are required.

Future work is to be oriented on expansion of the knowledge base and development of new algorithms for dealing with data, information and knowledge in the frames of vibrant city concept. Creation of big knowledge bases allow to solve such problems as estimation of current state of the city ecosystem in terms of existing and future problems, i.e. to solve real city problem on “wisdom level”.

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