# Analysis and Application of Semantic Networks in Education

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Abstract: The basis of any discipline is a set of didactic units. The task of the educational process management apparatus is to ensure compliance with the requirements for the order of the didactic units and their full implementation within the framework of the formation of the curriculum while minimizing its duration. A significant difficulty is the logical linking of didactic units with each other, since it is impossible to break the logic of presentation of materials of one discipline and there is a relationship between didactic units of different disciplines. The paper compares the topological characteristics of the concept graphs related to various disciplines. We develop the algorithm to implement the subject area model in the form of a semantic knowledge network. 125 concepts are analyzed that provide optimal mastering disciplines and establish the connection between them. A survey of the dynamics of the popularity of the term “network science” from 2004 to 2020 using Google Trends showed a steady trend of user interest. On average, 80 requests are executed (calculated in arbitrary units), with the largest volume of requests being 100.



## 1 INTRODUCTION

Education is the foundation of sustainable development and the main tool for creating a humane, equal and attentive society to human problems, in which each individual should have his or her human dignity. Obviously, the main reason for the emergence of education for sustainable development is the awareness of the need for changes in the educational paradigm in order to further sustainable development of society, the economy and preservation of the environment. Sustainable development education involves a transition to an economically and socially oriented learning model. This model should be based on broad interdisciplinary knowledge, which is based on an integrated approach to the development of society, and allows making and implementing decisions at the local and global levels. All these steps are aimed at improving the quality of life and do not threaten the ability of future generations to meet their needs.

Many researchers consider the problems of education modernization in the framework of sustainable development. In recent years, the interest in research concerning Education for Sustainable Development (ESD) has grown considerably. In research (Grosseck et al., 2019) using a bibliometric approach, analyzed 1813 papers on the subject, indexed by the Web of Science, between 1992 and 2018. The number of publications, authors, and journals has increased, proving that ESD has gained momentum over the period examined in the study. In study (Grosseck et al., 2019) illustrates two main research directions for the entire time span: integration of education into sustainable development and of sustainable development into education. In study (Holfelder, 2019) is to show that education must be thought of as something other than just training: considering education predominantly as subjectification holds the possibility for open and alternative futures. that education is more than training. The main message – education is more than training. Evaluation case studies in (Eilks, 2015) show that thoroughly combining the ESD framework with science teaching that follows a socio-scientific

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issues-based approach to education has great potential for helping students develop many general educational skills. In articles (Byrch et al., 2015; Morioka et al., 2006) has laid out the initiatives to contribute to global sustainability through reform and streamlining of the current technological paradigm and business. This reform is based on a future-oriented and global approach. In this initiative, industry and business plays a critical role as a link between technology, business and society. Leicht et al. (Leicht et al., 2018) presents an overview of ESD and highlights key issues related to ESD policy and practice. Topics include key ESD competencies and themes, policy, changes in the learning environment, teacher training, youth as lead actors, scaling-up action, and the monitoring of progress.

The epidemics, the destruction of the natural environment and climate change, the depletion of material and energy resources, the population explosion and lack of food, as well as the civilization crisis as a whole, are complex interdisciplinary problems of the humankind. New directions of science appear for their solution. The convergence of methods and interdisciplinary approaches is the main characteristic of these advanced scientific communities.

Supra-sectorial technologies (information, cognitive, nano-, bio-, social technologies) are currently actively developing. Thanks to them, new branches of science appear and serve as a new methodological basis for studying nature (Arshinov et al., 2011; Ahromeeva et al., 2013; Kovalchuk, 2011). Such interdisciplinary scientific fields lead to new directions in science such as risk management, sustainable development, new nature management, etc.

The quality of professional training of students in the modern sense determines their readiness and ability to use the acquired professional competencies to solve not only professional tasks, but also multidisciplinary tasks. Solving such problems contributes to sustainable development at the level of the country, region and the world as a whole. This implies updating the content and methods of professional training of specialists at a modern university taking into account the requirements of interdisciplinary integration and the implementation of sustainable development ideas (Shults and Tsyiganov, 2010; Solodova and Malinetskiy, 2013).

The work (Chekmarev, 2014) emphasizes that the competitive professional competence of university graduates in the labor market in the light of international requirements can be achieved subject to significant changes in the system of higher professional school. The articles (Sirenko, 2014, 2013) presents the ways of enriching the content of the academic discipline “Fundamentals of Information Technologies” with interdisciplinary components. The diffuse principle of penetration of general scientific and philosophical knowledge into the content of the academic discipline is substantiated. The characteristics of generalized tasks as a means of interdisciplinary integration are given. The results of experimental work on checking the effectiveness of the method of using generalized problems are analyzed.

Interdisciplinary integration in higher education institutions has to be an important component of introducing sustainable development ideas into the training of modern specialists. The problems of sustainable development itself are multidisciplinary.

Such integration will solve the significant contradictions of education, namely the contradiction between the vast knowledge and limited human possibilities. The optimal combination of computer science and other academic disciplines within the same topic will provide conditions for a significant increase of the level of the educational process.

Jurgena and Cedere (Jurgena and Cedere, 2018) concluded that students have a large non-used potential to understand more deeply the nature of science and acquire the knowledge important for their future lives and work. Recently, a lot of talk has been going on about the transition to a knowledge-based society. Knowledge management systems are evolving and knowledge management professionals are employed in large corporations. Unfortunately, in the discussions of this topic higher education is not considered (Kumar and Agrawal, 2011; Boca and Mukaj, 2016). This is unacceptable, because knowledge is created, systematized and accumulated in universities, and then passed on to the next generation of people.

The learning process is the management of the process of student’s knowledge accumulation and systematization. Only a few researchers focus their attention on this fact (Martins et al., 2019; Fazey et al., 2013; Sanguankaew and Ractham, 2019; Vlasenko et al., 2021). An automated learning environment based on semantic knowledge networks is largely capable of solving a wide range of knowledge management tasks at the university. A feature of the modern stage in the development of educational systems is the necessity of expending the use of formal methods for presenting knowledge and organizing the learning process. The achievements of cybernetic, synergetic and the theory of artificial intelligence are the basis of these scientific directions. Many objects of cognitive research are networks. Alternatively, you can imagine them like that.

In the 1940s, scientists who study the human brain hypothesized that its unique properties are due not to the characteristics of individual nerve cells, but to the structure of the connections between them (Semerikov et al., 2018). To date, research on networks of a very different nature – biological, physical, social and economic – has been collectively called network science, or the science of networks.

Over the past two decades, many studies have focused on the network science methodology as an extensive scientific field of studying complex systems (for example, (Malineckiy, 2013; Barrat, 2008; Soloviev et al., 2016; Liu et al., 2010)). Complex systems contain several components that interact with each other, producing complex behaviour.

The human brain and the cognitive processes occurring in it are an example of a complex system. These processes provide memory and language (for example, (Sporns, 2011; Baronchelli et al., 2013; Beckage and Colunga, 2015; Jones, 2016; Solé et al., 2010; Wulff et al., 2019; Boccaletti et al., 2006; Borge-Holthoefer and Arenas, 2010)). The foundation of network science is mathematical graph theory. It is contains powerful quantitative methods for studying systems such as networks (for example, (Carrington et al., 2015)).

At this stage in the development of the education system, the priority is to find ways to improve the learning process, its content and structure. Receiving a fundamental and holistic education can be only as result of the learning process at the level of new quality. In this case, the content of various disciplines should reflect the logic and structure of knowledge ties between disciplines. In the absence of intersubjective communications, the knowledge will be fragmentary, unsystematic. Cognitive networks are not only a tool for cognition, but can also a basis for controlling student's knowledge.

In different historical periods, many variants of semantic knowledge networks that take into account the specifics of intellectual activity have been created. In the "precomputer era" the prototype of semantic knowledge networks was used to formalize logical reasoning. At the beginning of the twentieth century, in psychology, graphs were first used to represent hierarchies of concepts and inherit properties, model human memory and intellectual activity. In the early 60-s the first machine implementations of semantic networks were made. One of the first systems of practical importance (Masterman, 1961) contained 100 primitive types of concepts for solving the problem of automatic translation. Dictionary of 15 000 concepts was defined.

At present, semantic knowledge networks are widely used in solving many different problems, in particular when building knowledge bases, in problems of machine translation and processing of text in a natural language. Due to the wide range of use of such graphs, there is a need for their refinement – an increase in the number of nodes and an increase in the connectivity between them.

Actual modern studies are devoted to the use of semantic networks in the field of education. For example, in the work (Xie et al., 2015) the interdisciplinary of applied mathematics is quantitatively analyzed by using statistical and network methods on the corpus PNAS 1999–2013. Czerkawski (Czerkawski, 2014) discusses the potential Semantic Web for teacher education.

Dunn (Dunn, 2013) presents a theoretical method for the integration of semantic knowledge network utilization into the classroom. This paper will also introduce insights from Cognitive Linguistics as to how the brain best learns vocabulary. The method of Dunn (Dunn, 2013) springs from the fields of psychology and neuroscience as well as inspiration from educators who are building new teaching styles. The purpose of the method detailed in this paper is to inspire other educators to incorporate cognitive linguistic insights into their classes as well as further the discourse on integrating this field into the teaching of English as a second or foreign language.

Teng et al. (Teng et al., 2012) formulate recipe recommendations using ingredient networks. Researchers have shown how information about cooking can be used to glean insights about regional preference sand modifiability of individual ingredients, and also how it can be used to construct two kinds of networks, one of ingredient complements, the other of ingredient substitutes. These networks test which ingredients work well with each other and which ones are better to replace. Allows you to predict which of a pair of related recipes will work best for the user.

Traditionally, researchers formed networks of semantic knowledge manually. This is labour intensive. Such networks contain a small number of nodes, but they have an important advantage - they are checked manually. An alternative approach is the automatic construction of a semantic network based on an external source generated by Internet users (Zesch et al., 2008). A striking example of such a source is the Wiktionary (Wiktionary Statistics, 2020).

In (Kiv et al., 2014) a new stylistic-mathematical approach (SMA) for analysis of translation works was introduced. It was postulated that the important requirement to translation is its compliance with the language in which the translation was done from the point of view of Zipf's laws and information characteristics. According to SMA any translation should satisfy at least to the following requirements:

- The sense of the translation version must exactly reflect the intention of the author of original text.
- It is necessary to find the equivalent constructions in the translation version for idioms and other specific expressions in the original text.
- The translator should reach the appropriate difference between Zipf's constants for the original text and for the translation.

A computer program for application of Zipf's Laws was developed for analysis of English and Russian literary texts. This program uses the algorithms of texts data processing from the Microsoft products, such as Microsoft C#, Microsoft SQL 2008. The Microsoft SQL 2008 was chosen because it is enough powerful full-text modules, realized on more than 10 languages, The algorithm realized in the developed program allows processing any texts in order to present them as tables of database with necessary parameters. As a result of uniting capabilities of these products, the client-server structure of the program, where the program is a client and Microsoft SQL2008 is a server was obtained. The user enables to specify a set of search criteria. The program gets the answers and outputs from the server in the comfortable to user form.

This program was applied to compare different translations of the famous play of William Shakespeare "Hamlet. Prince of Denmark" (Shakespeare, 1985). Various characteristics of this work given by critics were accounted. They analyzed these translations from the point of view of the exact reflection of Shakespeare's ideas, preservations of original thoughts, and the quality of the translation language. Then Zipf's constants were estimated for the original text and translations taken from (Shakespeare, 1985) (Edition of 1828). In table 1 one can see the obtained results.

We see that table 1 Zipf's constants are varied from 0.0954 (that is close to English language) to 0.0684 (that is close to Russian language). On the basis of these results and semantic analysis performed by other researchers it was come to conclusion that the translation of Pasternak satisfied the conditions of the high level translation described above. His translation is the most closely to the native Russian language. At the same time in this translation Pasternak reproduced the music and the spirit of Shakespeare's masterpiece (Shakespeare, 1985). The opposite translation approach we see in the Radlova's translation. She tried do not omit any word in the original text. As a result she did not reproduce in Russian version the sense of Shakespeare's work and her text is closer to the structure of English language.

Thus, all of these works are devoted to the integration of semantic knowledge networks in teaching. The increasing information volumes of the educational material of the disciplines dictate the need to use cognitive modelling to solve complex problems of training and teaching.

## 2 MATERIALS AND METHODS

There are various ways of representing knowledge, in particular, such visual methods for describing knowledge in the subject field: semantic networks, graphs of conceptual dependencies, scripts, frames, conceptual graphics and ontology.

Ontologies are an effective means of representing and organizing knowledge. For the formal specification of concepts and relationships, researchers use ontologies. Ontologies characterize a specific subject area. Ontology consists of terms (concepts), their definitions and attributes, as well as associated axioms and inference rules.

Formally, ontology is a relation:

$$O = < T, R, F >,$$

where $T$ – concepts (terms) of the subject area described by the ontology $O$, $R$ – relationship between terms of the subject area, $F$ – functions of interpretation, given on terms and relations of the ontology.

Let us determine the definitions that are important for this work: "semantic knowledge network", "semantic network", "network model", "cognitive map", "cognitive network", "cognitive scheme". Figure 1 shows a diagram of the types of cognitive schema.

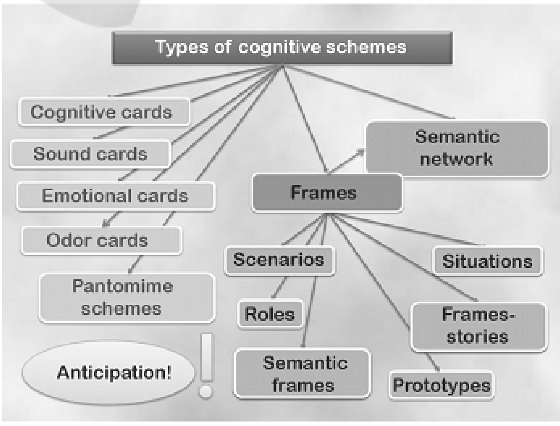


Figure 1: Cognitive scheme type chart.

Cognitive maps are a concept of cognitive psychology pioneered by Tolman (Tolman, 1948). A cognitive map is an active, information-seeking structure.

Table 1: Zipf's constants for different translations of "Hamlet. Prince of Denmark".

| Author and translators | Year | Zipf's constant | Comments |
|---|---|---|---|
| Shakespeare | 1603 | 0.1191 | Original |
| Pasternak | 1940 | 0.0684 | Translation |
| Romanov | 1899 | 0.0882 | Translation |
| Averkiev | 1895 | 0.0827 | Translation |
| Kroneberg | 1925 | 0.0837 | Translation |
| Lozinski | 1933 | 0.0877 | Translation |
| Radlova | 1937 | 0.0954 | Translation |

In our work, the concepts of "semantic knowledge network" and "semantic network" are identical.

In cognitive science, the network is one of the most common types of information models. Typically, a network consists of two components – nodes as network elements and edges, reflecting the interaction between the elements. Using these simple components, you can describe a wide range of objects of different nature and complexity. The network concept is the foundation of network models. In such models, all relationships are clearly distinguished. These relations constitute the framework of knowledge of the subject area, the model of which must be created. This class of models includes semantic networks, functional networks, and frames (frame representation).

Although the terminology and structure are different, there are similarities inherent in almost all semantic networks:

- Different nodes of one concept belong to different values, if not it is marked that they relate to one concept.
- Edges of semantic networks create relationships between concept nodes (marks above arcs indicate the type of relationship).
- Relations between concepts can be linguistic cases, such as "agent", "object", "recipient" and "instrument" (others mean temporal, spatial, logical relations).
- The concepts are organized by level in accordance with the degree of generalization.

An associative approach to knowledge representation defines an object value in terms of its connections (associations) with other objects. Thus, when a person perceives an object and discusses it. At this time, the brain maps the object of perception into a certain concept (figure 2 (Babkin et al., 2006)). This concept is part of general knowledge about the world. Therefore, it is associated with various associations with other concepts. Associations define properties and behaviour of the perceived object.

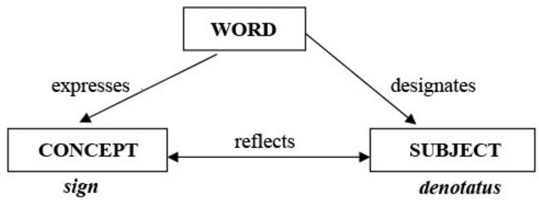


Figure 2: The relationship of the concept, subject and word denoting this subject (Babkin et al., 2006).

Scientists have developed semantic networks within a scientific field that relates to the representation of knowledge to model human thinking. This area of research has arisen within the general problem of artificial intelligence. It focuses on the development of specialized languages and graphical tools for representing declarative or static domain knowledge. The results of research in the field of semantic networks have been refined and successfully used in the construction of conceptual models and relational database schemes.

Semantic networks are the most powerful mathematical model for representing knowledge about a subject area, one of the most important areas of artificial intelligence. Currently, the scientific literature describes many alternative representations of semantic network models. Researchers use them to solve a variety of problems in a variety of software.

In general, a semantic network is an expression:

$$S = (O, R_1, R_2, \ldots, R_k),$$

where $O$ is a set of objects of a specific subject area, $R_i | i = 1 \ldots n$ is a set of relationships between objects, $i$ is the type of relationship.

In the general case, a semantic network is understood as a certain graph $G_s = (V_s, E_s)$, in which the set of vertices $V_s$ and the set of edges Es are divided into separate types that have special semantics characteristic of a particular subject area. In this situation, the set of vertices can correspond to objects or entities of the considered domain and have the corresponding explicit names of these entities instead of the vertex numbers. Such names should allow unambiguous identification of the corresponding objects,

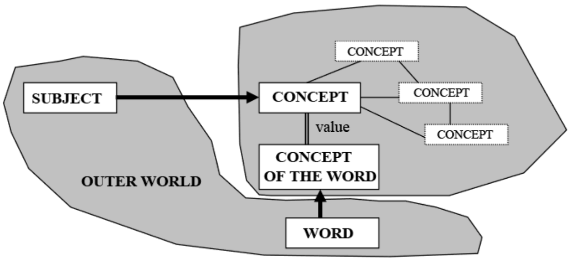


Figure 3: The relationship of various concepts in the human mind (Babkin et al., 2006).

while there are no general formal rules for recording names. There are also different types of edge sets that correspond to different types of relationships between entities in the area in question.

Many real-world phenomena can be modelling with the help of a graph. For example, we can think of various web pages as nodes and hyperlinks as directed edges to represent the World Wide Web as a graph. For instance, we can view various web-pages as nodes and hyperlinks as directed edges to represent the World Wide Web as a graph. Such a modelling can help perform various graph computations on the web. For instance, PageRank algorithm is a popular graph algorithm, which is used to rank the web-pages. Alternatively, the web-graph can be used to find clusters of web-pages, which link one another. This can help in categorizing the web-pages into various topics (Cheramangalath et al., 2020).

Graphs are best suited for explicitly expressing associations between different concepts. Thus, in the form of a semantic network, knowledge of the world is expressed. A semantic knowledge network is a marked graph in which nodes correspond to certain facts or general concepts, and edges mean relationships or associations between different facts or concepts (figure 3 (Babkin et al., 2006)).

In each academic discipline (in every science) the number of concepts reflecting the knowledge of this discipline (this science) is finite. There are a number of words that need to be conveyed to the audience. The number of these words is not infinite, because time for their transfer is limited. Textbooks establish linear links between concepts.

A normalized description of knowledge networks can be formulated as follows. The body of knowledge of the studied discipline is a system ($S$). The elementary component that is part of $S$ is a word that reflects a certain concept. With the help of words, all the concepts that make up the $S$ system are recorded. Links between the concepts are established using the grammatical rules of a particular language. With respect to each concept from $S$, there is a primary sentence that contains its definition. The totality of such definitions forms an invariant kernel $S$, which ensures the unambiguity of the perception of knowledge within a particular academic discipline. The invariant core of the discipline uses words from other areas of knowledge to determine its concepts. All concepts from $S$ are divided into main and auxiliary. The basic concepts include specific concepts of this particular discipline, which are the subject of its definition and study. Supporting concepts include concepts borrowed from other areas of knowledge that are not studied in this discipline, but are used to determine the content of basic concepts. Many of the basic concepts of a particular discipline, together with the internal relationships between them, form a hierarchically ordered network of knowledge, the nodes of which are the identifiers of the basic concepts.

Thus, the knowledge system can be represented in the form of a hierarchical directed graph – a semantic knowledge network.

The semantic knowledge network building algorithm involves several steps:

(1) Writing all the basic terms of the subject area and formulate their definitions (composing the thesaurus of the subject area).

(2) Selecting the terms from the list that appear in the definition of the other terms listed in step 1.

(3) At the lower (I) level, arranging the terms in the definition of which the terms from the list are not used.

(4) At the next (II) level, arranging the terms in the definition of which the terms of level I are used.

(5) At the III level – terms in the definition of which the terms of I and II levels are used, etc.

(6) At the last level, arranging terms that are not used in the definition of other terms.

(7) Connecting the concepts.

Visualization of data in a structural network model is the first step, but the strength of the method lies in the ability to extract important knowledge about the system through a statistical analysis of the network topology. It seems that topology bears an evolutionary imprint and functional (Barabási, 2012). A detailed analysis of the available metrics can be found, for example, in (Barabási, 2016). Consider just a few metrics often used in cognitive model research.

Let us consider in detail the network structure. A network consists of nodes and links between them, edges. Nodes are more or less stable entities that do not change over time.

Edges represent relationships, interactions, transactions, or any other temporary connections that occur between nodes over a certain period of the time.

Edges represent connections between them: friendships, proximity, transactions, exchanges and any other temporary connections between stable objects that occur with a certain frequency.

Edges are important to network analysis because they represent the connectivity basis that will be using to get insights about the complexity network. In a graph database, the relationships between the data are just as important as the data itself.

Giant component is an important notion in network analysis. It's an interconnected constellation that includes most of the nodes in a network.

Clusters are the constellations of nodes that are more densely connected together than with the rest of the nodes in the network. Clusters represent different sub networks within a network and can be used to identify various subcategories that are present within.

In modern network theory, the number of node connections (in the theory of graphs, nodes and nodes are edges and vertices of a graph, respectively) is called a degree. A node's degree indicates how many connections it has to the other nodes in the network. The more degree a node has, the more "connected" it is, which indicates its relative influence in the network.

The concept of degree is a local characteristic of a graph. A nonlocal, integral network structure is defined by two concepts – a path and a loop or cycle. A path is a sequential sequence of adjacent nodes and the links between these nodes when the nodes do not repeat. A loop or cycle is a path when the start and end nodes coincide. Networks without loops are trees. The number of nodes ($N$) (network size) and the number of links ($L$) are related as $N = L - 1$ (Soloviev et al., 2016).

Identifying the nodes with the highest degree (also called "hubs") is an important part of network analysis as it helps identify the most crucial parts of the network. This knowledge can then later be used both to improve network's connectivity (by linking the hubs together) and disrupt it (by removing the nodes).

Betweenness centrality is another important measure of the node's influence within the whole network. While degree simply shows the number of connections the node has, betweenness centrality shows how often the node appears on the shortest path between any two randomly chosen nodes in a network. Thus, betweenness centrality is a much better measure of influence because it takes the whole network into account, not only the local connectivity that the node belongs to.

A node may have high degree but low betweenness centrality. This indicates that it's well-connected within the cluster that it belongs to, but not so well connected to the rest of the nodes that belong to the other clusters within the network. Such nodes may have high local influence, but not globally over the whole network.

Alternatively, other nodes may have low degree but high betweenness centrality. Such nodes may have fewer connections, but the connections they do have are linking different groups and clusters together, making such nodes influential across the whole network.

In network visualization, we often range the node sizes by their degree or betweenness centrality to indicate the most influential nodes.

Network topology is an important element of network analysis. If we analyse networks on the structural basis we will discover many differences among them. A tool for studying complex networks based on graph theory is topological analysis.

When performing network analysis and visualization it is important to classify the topology of the network (Gephi, 2020a). This can be done through quantitative analysis of degree distribution among the nodes and/or through qualitative analysis using various visual graph layouts.

Degree distribution can be a good indicator of the network's topology. If most of the nodes in the network have exactly the same degree, the network is more of a regular one (it may also indicate the presence of tree-like hierarchical system within the network). If most of the nodes have an average number of connections that is the same and then some of the nodes have more and some of the nodes have less (normal bell-curve distribution of degree), we're dealing with a randomized network. Finally, if there's a small, but significant number of nodes with a high degree and then degree distribution follows a long tail towards a gradual decline (scale-free distribution), this is a small-world network, where there's a significant amount of well-connected hubs, which are surrounded by less connected satellites, which form clusters. Those clusters are connected to one another via the hubs and the nodes that belong to several communities at once.

Graph layout a qualitative measure for identifying topology of a network. A very useful type of layout is Force Atlas, where the most connected nodes with the highest degree are pushed apart from each other, while the nodes that are connected to them but have lower degree are grouped around those hubs. After several iterations this sort of layout produces a very readable representation of a network, which can be used to better understand its structural properties and identify the most influential groups, differences between them, and structural gaps within networks.

Network motifs are the different types of constellations that emerge within network graphs. They can provide a lot of useful information about the structural nature of networks.

For example, some networks may be comprised of diads or pairs of nodes (which indicates that the level of overall connectivity is quite low). Some other networks can have a high proportion of triads, which usually indicate the presence of feedback loops, which makes the resulting network formations much more stable. More complex formations include groups of four nodes that can be connected as a sequence or between each other, forming interconnected clusters that can encode certain levels of complexity that go beyond simple triad feedback constellations.

It is important to take notice of the network motifs that emerge within a network because it will provide a very good indication of the level of complexity and thus the capacity of the network.

Modularity is a quantitative measure that indicates the presence of distinct communities within a network. If the network's modularity is high, it means it has a pronounced community structure, which, in turn, means that there's a space for plurality and diversity inside. If the modularity is too high, however, it might also indicate that the network consists of many disconnected communities, which are not globally connected, making it much less efficient than an interconnected one.

Modularity works through an iterative algorithm, which identifies the nodes that are more densely connected to each other than to the rest of the nodes in the network. It will then calculate the measure of modularity for the network at large. The higher this measure is, the more distinct those communities of densely connected nodes are. If the modularity measure is 0.4 or above it means that, the community structure in the network is quite pronounced. If it's less it means that there are no big differences between the different clusters and most of the nodes are equally densely connected to each other across the whole network.

So far we've looked at the different measures of connectivity that exist within networks and that help us identify the most influential nodes, clusters, and deduce some basic functional properties of the networks we study.

However, one of the most important aspects of network graphs is that they also let you see the gaps, empty blank spaces, between the islands. Those gaps are usually referred to as "structural gaps" and it has been shown that bridging those gaps can spur innovation, create most interesting collaborations, and give rise to new, unexpected ideas.

In other words, "structural gaps" is where creativity and potential is hidden within the network. Therefore, when visualizing a network it is important to identify those structural gaps and to devise different actions that could help bridge different nodes and clusters across those empty spaces within the graph in order to spur creativity and innovation.

## 3 RESULTS AND DISCUSSION

A study of the dynamics of the popularity of the term "network science" from 2004 to 2020 using Google Trends (Google, 2021), carried out at the time of writing this manuscript, showed a steady trend (figure 4). Of queries, which hold an average of about 80 conventional units, while the mark 100 corresponds to the largest volume of requests.

As an example of modeling semantic knowledge networks, we analyze the relationship between the concepts of academic disciplines. As you know, that discipline mastering is closely connected with the assimilation and comprehension of the course concept thesaurus. To assimilate further concepts within the framework of this discipline, it is necessary to understand the already learned, often in the framework of the already studied disciplines. Therefore, an actual task is to study the dependencies between concepts and to model them, using cognitive networks (Gephi, 2020a).

The figure 5 shows a fragment of the construction of a semantic knowledge network.

To implement the subject area model in the form of a semantic knowledge network, we propose the following algorithm:

(1) Classification of all concepts of the subject area into macro concepts (class of concepts), meta-concepts (generalized concepts) and micro-concepts (elementary concepts).

(2) The allocation of common properties, characteristics inherent in each level of concepts.

(3) Highlighting the hallmarks of each level of concepts.

(4) Establishing links between concepts related to the same level.

(5) The allocation of inter-level ties.

We have analysed 125 concepts that are necessary for the "Economic Cybernetics" discipline mastering and the relationship between them (communication means the need for one concept to master another). We conducted a similar study for 125 concepts of the

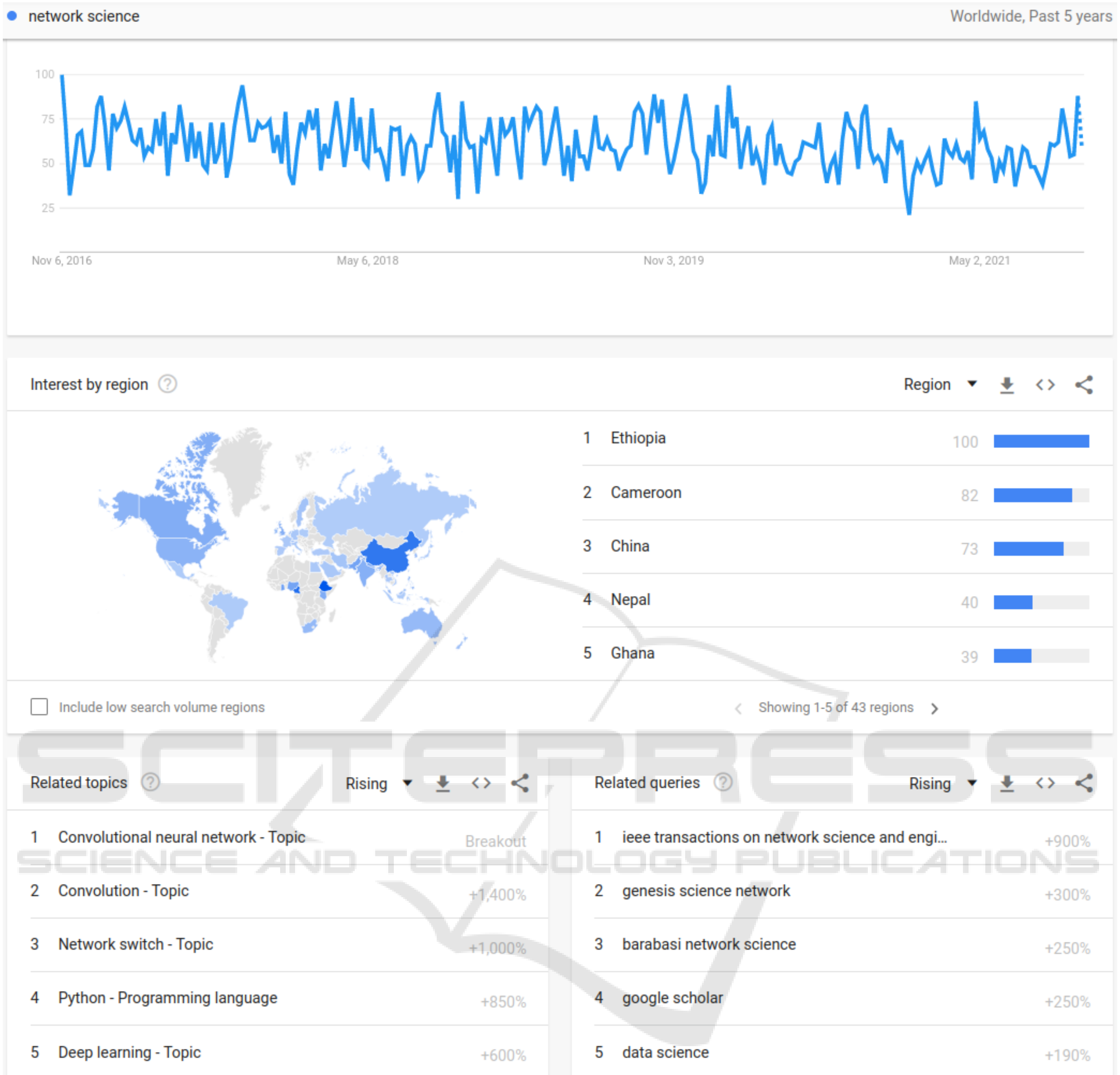



Figure 4: Dynamics of the popularity of the query "network science" in Google Trends (Google, 2021).

"Algorithmization and Programming" and 125 concepts of the "Mathematical Analysis" discipline.

There are many systems used by analysts (mainly researchers), both for visualizing network structures and for performing computations. At the time of this writing on Wikipedia (Wikipedia, 2021), we have counted 89 links to various programs for analyzing complex networks. To select the most popular programs, we turned to the analysis of software tools that are used by the world's leading universities (Gephi, 2020b; iGraph, 2021; NetworkX, 2021; SNAP, 2021). These can be ready-made products with a user interface and a set of implemented functions, as well as libraries of computational methods. Some systems developed for scientific research are briefly described in the table. All considered systems, except Gephi, do not have a user interface and are simply libraries of computational functions for analyzing and visualizing graphs (table 2).

After a comparative analysis, the results of which are presented in the table, the obtained graphs were visualized using the Gephi software product (Yevin, 2010). Gephi is free open-source, leading visualization and exploration software for all kinds of networks and runs on Windows, macOS, and Linux. It is highly interactive and user can easily edit the node/edge shapes and colors to reveal hidden patterns. The aim of the Gephi is to assist user in pattern discovery and

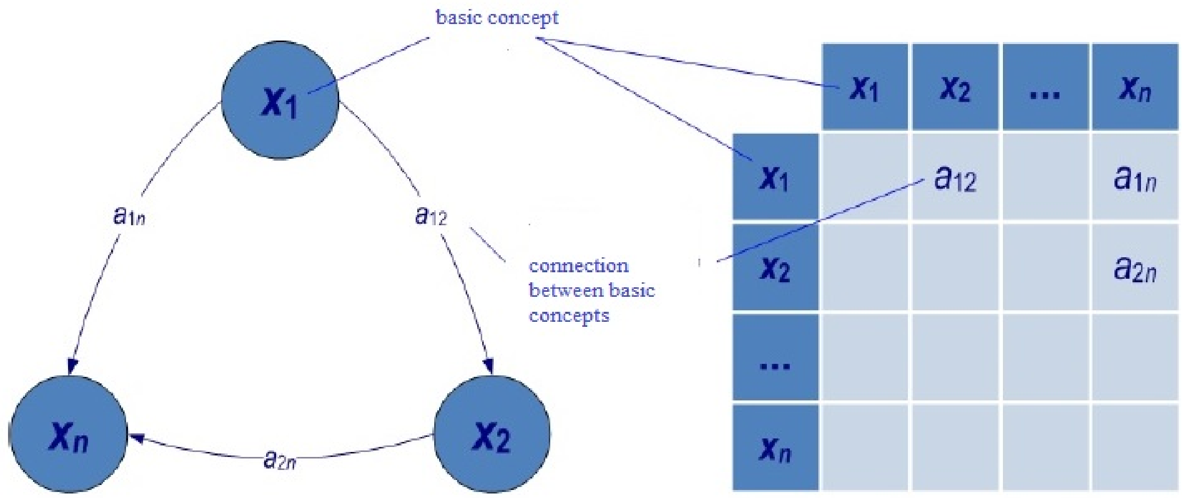


Figure 5: The semantic knowledge network diagram.

hypothesis making through efficient dynamic filtering and iterative visualization routines.

Gephi allows to calculate the topological characteristics of the graph, as:

- Nodes and edges (what networks are made of).
- Clusters (groups of nodes that are connected).
- Degree (the number of connections that the node has).
- Centrality between (how influential a node is).
- Modularity (community structure).

Gephi comes with a very fast rendering engine and sophisticated data structures for object handling, thus making it one of the most suitable tools for large-scale network visualization. It offers very highly appealing visualizations and, in a typical computer, it can easily render networks up to 300 000 nodes and 1 000 000 edges. Compared to other tools, it comes with a very efficient multithreading scheme, and thus users can perform multiple analyses simultaneously without suffering from panel "freezing" issues.

In large-scale network analysis, fast layout is a bottleneck as most sophisticated layout algorithms become CPU and memory greedy by requiring long running time to be completed. While Gephi comes with a great variety of layout algorithms, OpenOrd (Martin et al., 2011) and Yifan-Hu (Hu, 2005) force-directed algorithms are mostly recommended for large-scale network visualization. OpenOrd, for example, can scale up to over a million nodes in less than half an hour while Yifan-Hu is an ideal option to apply after the OpenOrd layout. Notably, Yifan-Hu layout can give aesthetically comparable views to the ones produced by the widely used but conservative and time-consuming (Fruchterman and Reingold, 1991). Other algorithms offered by Gephi are the circular, contraction, dual circle, random, MDS, Geo, Isometric, GraphViz, and Force atlas layouts. While most of them can run in an affordable running time, the combination of OpenOrd and Yifan-Hu seems to give the most appealing visualizations. Descent visualization is also offered by OpenOrd layout algorithm if a user stops the process when 50–60% of the progress has been completed. Of course, efficient parameterization of any chosen layout algorithm will affect both the running time and the visual result.

The constructed graphs (figures 6–8) can be used to identify the most important concepts that have the highest degree of apex, as well as concepts that are in the way of studying other important course concepts. In figures 6, 7 and 8 the size of the nodes-concepts of semantic knowledge networks characterizes the degree of importance and fundamentality of the corresponding terms of the academic discipline.

The table 3 shows various metrics and methods for calculating them. For the obtained graphs, their topological characteristics were calculated and analysed. The results of the study are shown in table 4.

Let us analyse the found values of measures (table 4). The Network Density measure is a measure of the density of edges, calculated as the ratio of the number of edges of a graph to the corresponding number of vertices and determines the maximum number of edges in a given graph. Thus, the values 0.17 – for the graph of discipline "Economic cybernetics" and 0.2 – for the "Mathematical Analysis" means that the edges are filled with about 17.3% and 19.5% of the maximum possible respectively. The density of the

Table 2: Comparative characteristics of systems for analyzing network structures.

| | **Gephi** | **Igraph** | **NetworkX** | **SNAP** |
|---|---|---|---|---|
| Website | gephi.org | igraph.sourceforge.net | networkx.lanl.gov | snap.stanford.edu |
| Users | Scientific, Educational Organizations | | | |
| Data Volumes | Up to 1 million nodes and edges | Up to several million nodes and edges | | |
| Data Collection | None | | | |
| Data Sources | None | | | |
| Analysis Mode | Retrospective Analysis | | | |
| Methods | Visual Analysis, Basic Statistical Methods, Basic Methods of Graph Theory | A wide range of graph theory methods | | |
| Objects Considered | Network structure (nodes, directional and non-directional links) | | | |
| Distribution Terms | OpenSource (CDDL 1.0, GPL 3.0) | OpenSource (GPL 2.0+) | OpenSource (BSD License) | |
| Language support | English | | | |
| Developer | Gephi Consortium (more than 10 organizations). USA, France, Germany, etc. | Gábor Csárdi (Harvard University, USA), Tamás Nepusz (Eötvös University, Hungary) | AricHagberg, Dan Schult, Pieter Swart and others | Stanford University |
| Clients | Used in research projects, data visualization and educational programs. | Used in research projects | Scientific organizations | Used in research projects, in particular by Stanford University |

graph of concepts of the discipline “Programming” is less: 11%, which can be explained by a smaller number of connections between concepts on average in the graph.

The maximum degree of 121 vertices was demonstrated by the concept graph in the “Programming”. The maximum value of the degree of the vertex in the column “Economic cybernetics” – 111. The minimum degree of vertices in the graphs “Economic Cybernetics” and “Programming” are 3 and 1, respectively, which are almost the same. For “Mathematical Analysis”, the number of weakly connected nodes is higher – 7, and strongly connected – 113, which is less than in “Programming”, but more than in “Cybernetics”.

It also confirms a greater connection between the concepts of the “Economic cybernetics” and “Programming” than the concepts of the “Mathematical Analysis”.

Mean average node degree for the “Economic Cybernetics” graph is 21.45, and for the “Programming” graph – it is 13.66 and for the “Mathematical Analysis” – 24.18. This is confirms the presence of more connections in the last graph.

The global clustering coefficient (clustering) for a graph is the ratio of the number of vertically connected triples of vertices to the number of triangles (cyclically connected triples of vertices). For the “Economic Cybernetics” graph, the clustering coefficient is 0.4, for the “Programming” graph – it is 0.33, and for the “Mathematical Analysis” – 0.59. This means that the concepts of the “Mathematical Analysis” course are more often on the path to mastering other important concepts.

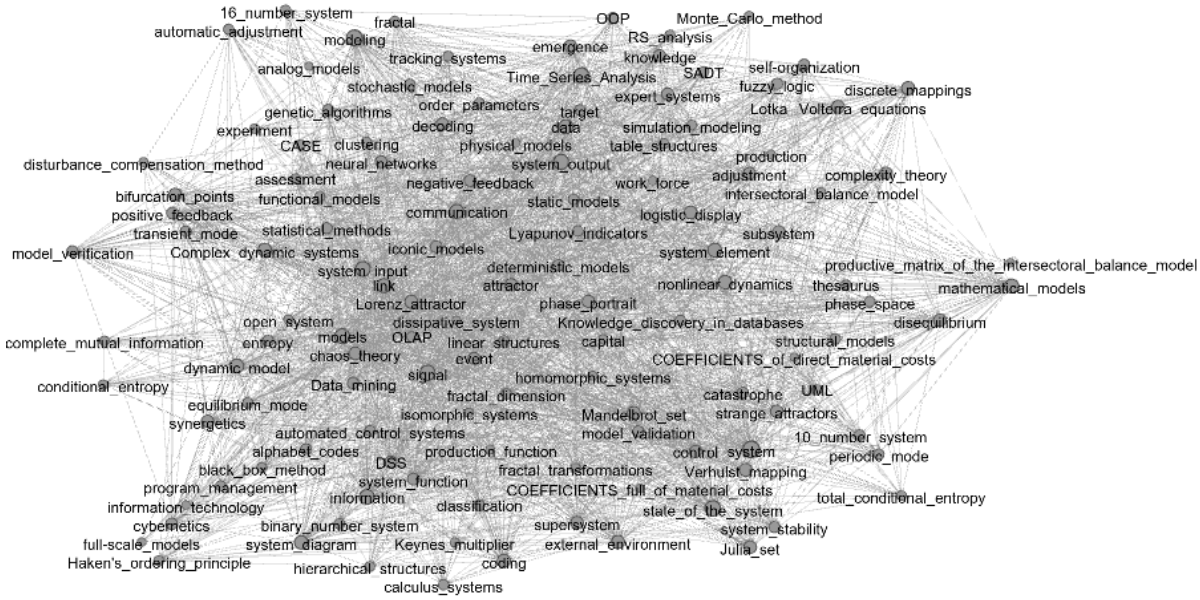


Figure 6: The semantic knowledge network of the course concepts “Economic Cybernetics”.

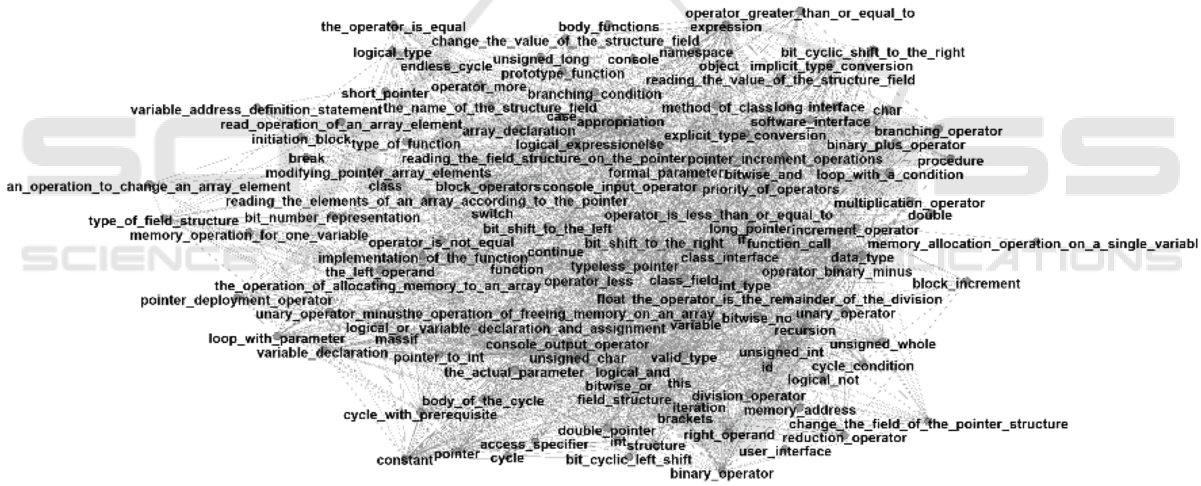


Figure 7: The semantic knowledge network of the course concepts “Algorithmization and Programming”.

As for the diameters of the graphs – for the “Economic Cybernetics” concept graph the diameter value is 5, for the “Programming” graph – 9 and for “Mathematical Analysis” – 3. The same relationships are observed for average shortest path-lengths. Which may mean the existence of longer paths in the connections between the “Programming” discipline concepts.

The modularity index is less than 0.4, which means that the structure of communities in all three networks is not sufficiently expressed.

In the field of education, there is always a problem of the contradiction between increasing the amount of scientific information and limiting the time allotted for its assimilation. Teaching academic disciplines in higher education requires constant work on educational information in order to move from extensive to intensive teaching methods. One of the ways to intensify the educational process can be the optimal “packaging” of educational information.

The solution to this problem is the construction of a semantic network. An important condition for the successful mastering of educational material is the ability of the teacher to highlight the key issues of the program. Nodal issues of the program are the basis for studying the whole topic. Their significance can be determined using a graph or adjacency matrix.

For example, let a topic contain 6 questions and the logical connections between them are presented

Table 3: Metrics used for network analysis in Gephi.

| Metric | How calculated |
|---|---|
| Nodes | Nodes contain discipline concepts. Simple count. |
| Weakly Connected | Number of maximally sized clusters in which each node is reachable from every other node along undirected edges. |
| Strongly Connected | Number of maximally sized clusters in which each node is reachable from every other node along directed edges. |
| Diameter | Longest finite optimal path between nodes using undirected edges. |
| Average Shortest Path Length | Average Shortest Path Length (along undirected edges) between all connected nodes. |
| Network Density | Fraction of all possible undirected edges present. |
| Average Degree | Average number of undirected, unweighted edges per node. |
| Modularity | Calculated using Gephi algorithm. |
| Clustering Coefficient | A node's clustering coefficient is the ratio of the number of actual connections between the node's neighbours, to the number of the maximum potential connections between those neighbours. The network's clustering coefficient is the average of the clustering coefficients for all the nodes. |

Table 4: Comparison topological characteristics of the graphs of the relationship between the concepts of the disciplines: "Economic Cybernetics" (E), "Algorithmization and Programming" (P) and "Mathematical Analysis" (M).

| Parameters | E | P | M |
|---|---|---|---|
| Nodes | 125 | 125 | 125 |
| Weakly Connected | 3 | 1 | 7 |
| Strongly Connected | 111 | 121 | 113 |
| Diameter | 5 | 9 | 3 |
| Average Shortest Path | | | |
| Length | 2.21 | 3.416 | 1.806 |
| Network Density | 0.17 | 0.11 | 0.20 |
| Average Degree | 21.45 | 13.66 | 24.18 |
| Modularity | 0.25 | 0.30 | 0.23 |
| Clustering Coefficient | 0.40 | 0.33 | 0.59 |

in the form of an adjacency matrix (table 5).

The significance of the question can be characterized by the weight coefficient determined by the formula:

$$\alpha_\beta = S_i/k,$$

where $S_i$ is the number of references to the $i$-th question when studying the others contained in this topic, $k$ is the total number of questions in this section.

Table 5: Example topic adjacency matrix.

| | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | $\alpha_B$ |
|---|---|---|---|---|---|---|---|
| $P_1$ | 0 | 1 | 1 | 0 | 0 | 1 | 3/6 |
| $P_2$ | 0 | 0 | 1 | 1 | 1 | 1 | 4/6 |
| $P_3$ | 0 | 0 | 0 | 1 | 1 | 0 | 2/6 |
| $P_4$ | 0 | 0 | 0 | 0 | 1 | 0 | 1/6 |
| $P_5$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $P_6$ | 0 | 0 | 0 | 1 | 0 | 0 | 1/6 |

The larger the coefficient leads to the greater the significance of the issue. Thus, it is possible to determine the importance of the discipline (section) in the study of all disciplines of the curriculum. A similar technique can be used in the formation of the content of academic subjects on the basis of discipline standards, in the development of curricula and tests, in the selection and organization of educational information for training.

# 4 CONCLUSIONS

Algorithms for the formation of a semantic knowledge network are developed. The knowledge network is the basic concept of knowledge management. In fact we introduce a new discipline that implements the principles of sustainable development of education. The method of constructing a semantic knowledge network of terms allows forming a so called adjacency matrix that reflects the correlation of terms from a terminological dictionary. This matrix allows to evaluate the quality of the terminology in the particular discipline, as well as to determine quantify the semantic connectivity of the whole tutorial. According to obtained results, we can conclude that the concept system in the "Economic Cybernetics" is connected and complex. This means that in this case when studying any concepts, it is necessary to repeat the meaning of those already studied. The concept system in the "Programming" contains fewer dependencies and less connectivity in comparison with graphs. However, the experience of studying these disciplines indicates that also the "Programming" is not easy to learn. Further the problem of planning the learning process based on semantic networks of knowledge will be studied. Namely, the distribution of lectures, practical and laboratory exercises will be determined to achieve successfully the learning objectives.

We can continue to analyse the network structure of the curriculum. The curriculum is a complex system with nodes representing courses and links between nodes, course prerequisites. The latter is easy to obtain from the course catalogue. The resulting

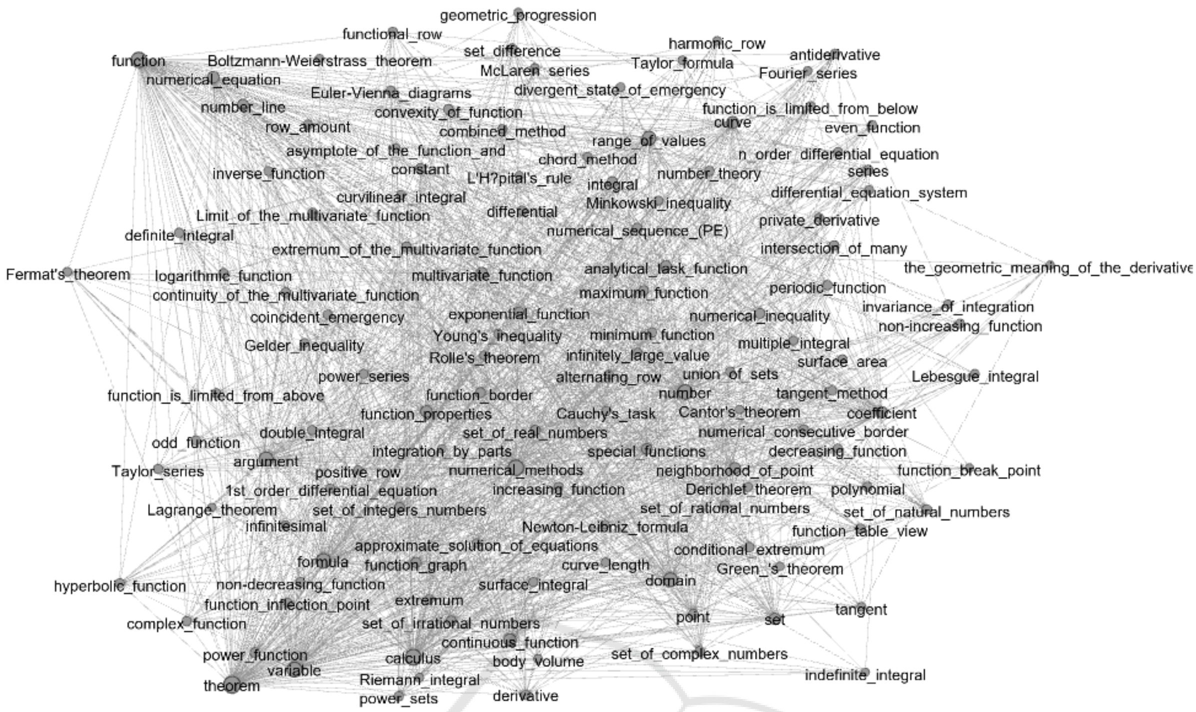


Figure 8: The semantic knowledge network of the course concepts "Mathematical Analysis".

network of curriculum prerequisites is in the form of a directed acyclic graph. This graph has certain analytical characteristics. In future work, we will to calculate spectral characteristics of graphs for the studied disciplines, as it was done in (Soloviev et al., 2020).

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