CONCEPTUALIZATION OF USER ACTIVITIES IN THE SOCIAL NETWORK IN THE CONDITIONS OF DISTANCE EDUCATION

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INTRODUCTION

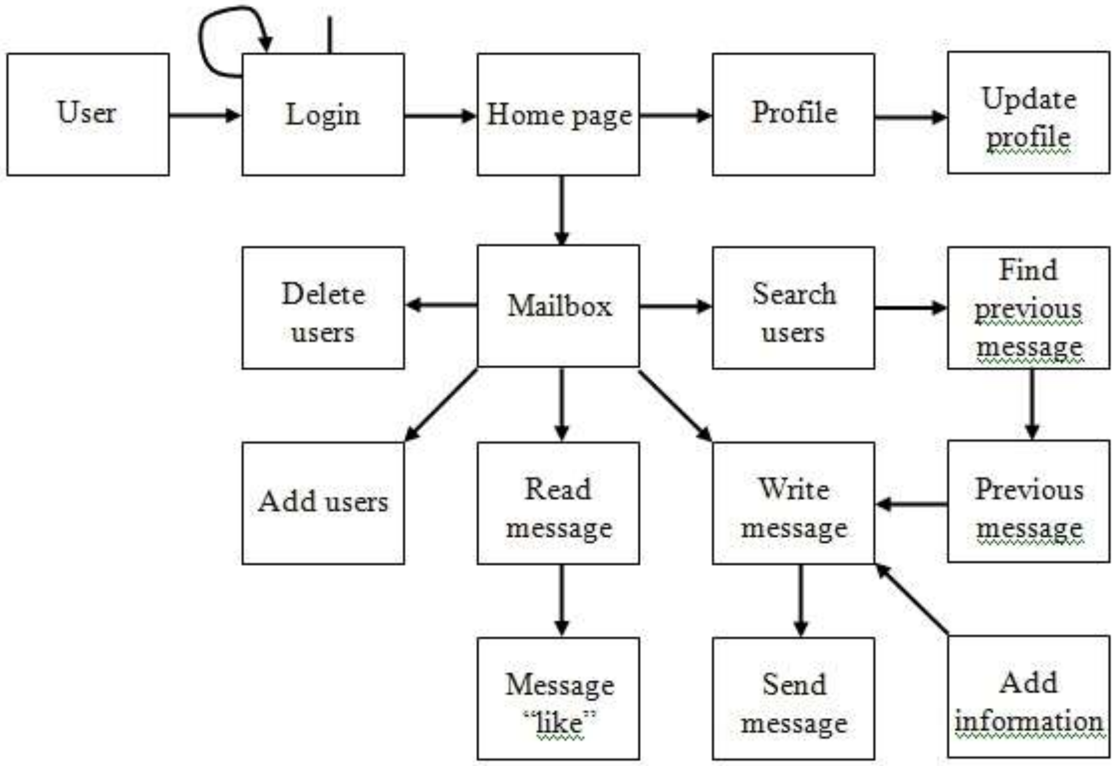
Modern telecommunication, computing and software and information technologies have made it possible to turn the Internet into a place where users of social sites actively contribute to the creation of various content (video, music, texts) and the formation of all kinds of opinions (personal, public, industrial, etc.) ... Enterprises of various levels (small, large or hypermarkets) look at social networks (SS) as a tool, a possible means to improve their performance through marketing, recommendation systems, information retrieval, etc. (JAEWON, 2015; FROLOVA et al, 2020).

The use of digital technologies requires education solutions not only economic, but social problems - the assimilation of new realities. According to foreign researchers, along with restrictions in various areas, education has become an important factor in the fight against COVID-19. And the use of digital technologies and tools has made it possible and allows to improve the educational process and not stop educational activities due to the pandemic and the imposed restrictions.

Today, in the digital age, there is a paradigm shift in education. Digitalization affects not only the content of education, but also its organization. Digitalization processes entail a personnel "revolution" that leads to fundamental changes not only in the labor market, but also in education. It is becoming important that in the near future there will be no specialties that we are teaching today. The challenges of today form a request for mass individualization of education, both secondary and higher, which in turn requires the possession of tools for collecting and processing a colossal amount of data.

In this article, we consider the problem of choosing an approach to determining the requirements for the analysis of a social network as an object of research. This direction is dictated by the fact that in most articles the social network is perceived rather superficially and generalized. In turn, we analyzed the logic of events of SS users, especially users of educational institutions, in particular secondary and higher education institutions (Figure 1).

Figure 1. Operations of each member of the social network (author)



Source: Search data.

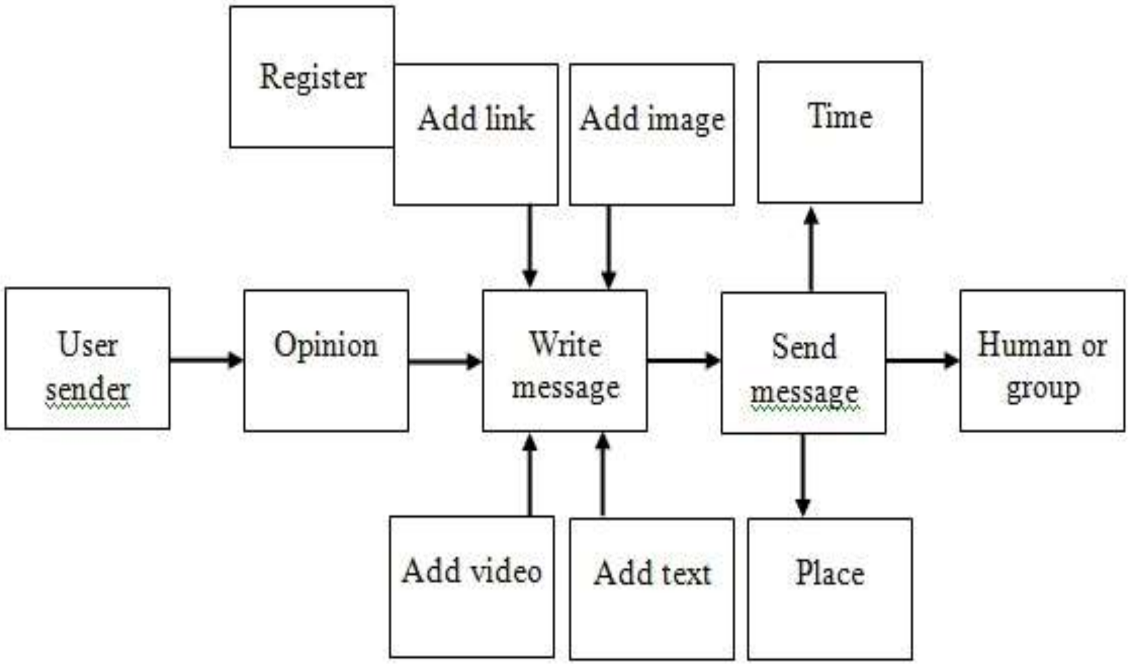
Online learning in social networks, the use of electronic platforms create opportunities for providing personalized information for students. Modern digital technologies make it possible to bring the distance learning process closer to the real interaction of participants, as well as to work in a convenient personal mode.

MATERIALS AND METHODS

To understand the processes of a social network, one need to define some terminology so that one can use it as a language for describing events. We have chosen as such a language UML (unified modeling language), which is used in the development of programs, information systems, etc. One of the elements of this language is the unit "Actor" and in our case these are ordinary people involved in the communication system, in accordance with their roles ... There can be many roles, and they are all associated with the type of information that connects an actor with other actors. An actor is also a node (vertex), as a source of receiving and transmitting information to which other actors can have relations (GUSAROVA, 2016).

Another element of the language defines "Use Cases", which are the roles that actors play in and around the system. A "link" (relation or edge) describes a specific, well-defined relationship between two Actors. Links can be undirected, where the relationship means the same thing to both participants, or directional (unidirectional or bidirectional, etc.). "Network" is a set of actors and connections between them (FROLOV; GABYSHEVA, 2016). For example, a set of unidirectional relationships exists between users of sports club cards, hypermarkets, etc. More complex and multidirectional are bank cards, networks in which there is more than one type of communication. "Weighted connections" can also arise in networks when there are several different types of connections between actors, of different strengths or directions (Figure 1a).

Figure 1a. Operations of each member of the social network (author)



Source: Search data.

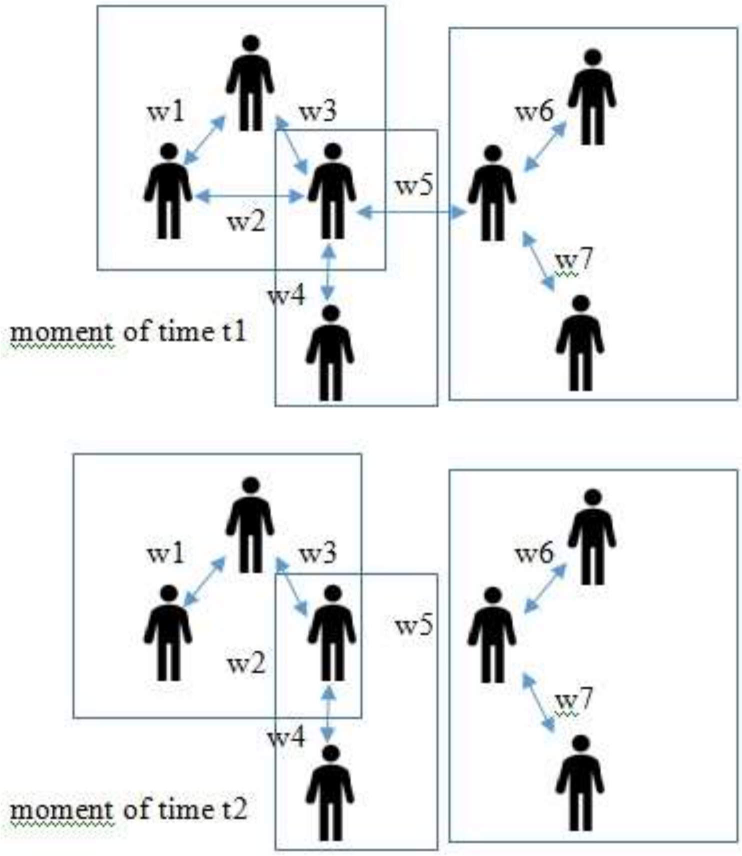
Social network structure and nodes

In a network, groups or a subset of participants can form that have certain communication characteristics, but are somewhat different from the general ones. For example, any organization can be attributed to a certain network, the employees of which in relation to the organization have a single connection, but on the other hand, a different connection that is different for each department. In the network itself, as well as in the group, one can introduce the concept of "distance", which is defined as the smallest number of links that must be overcome in order to get the relationship between any two nodes.

For example, in a network of four (A -> B-> C -> D) consecutive nodes, the distance between (AD) is 3, and the distance between nodes (AB), (BC) and (CD) is only 1 On the other hand, the node D can be connected not with the node C, but with the node B, then the distance (AD) will be 2. It turns out that the structure of the nodes can develop in the horizontal and vertical directions, forming some branched tree.

There are two main types of social media data: boundary lists and sociomatrix. Each of these data formats has its own advantages and disadvantages, mainly related to the trade-off between the ease of entering, storing and using data for subsequent analysis.

Figure 2. Development in time of a single-layer social network in time (author)



Source: Search data.

Matrix of contiguence, matrix approach

A socio-matrix (also known as an adjacency matrix) is a way of representing directed or undirected connections between network participants (in the form of the above description of a connection tree) using some kind of numerical matrix. For each node, there is one column and one row in the matrix, whose elements (0 or 1) indicate the presence of a connection between the nodes (1) or its absence (0). The advantages of this approach to storing data about the network is that it is naturally encoded and allows one to accumulate statistical indicators of the number of connections of the same nodes (FROLOV; GABYSHEVA, 2016). The list of boundaries is another form of data storage for the analysis of social networks, which takes into account information about existing connections, so it needs to be supplemented with information about the total number of network participants (even if they are not linked by messages).

Both approaches are a matrix representation of the number of nodes and the connections between them, which forces us to look for some generalizing properties to obtain statistical and analytical conclusions. One of these elements is the degree of centrality, or a measure that records the number of links with a given node. For undirected links, this is just counting the number of links for each network participant (there is no dependence on the direction of the connection), and for directed networks, participants can have an external internal direction of the links. In various social networks, users can have both external (several topics of discussion) and internal activity (selected one topic), which manifests itself in the type of selected directions of correspondence and in the number of transmitted information. Accordingly, among such users, several groups are distinguished, which are active only in the area of receiving information and are minimal in transmission, another group receives and transmits approximately equally, and the third group transmits more information and receives a response. Mathematically, activity can be roughly defined as the number of shortest paths between users that go through a particular user. This measures the degree to which information flows through a particular community member and the relative importance of each member of the network community.

RESULTS AND DISCUSSION

Types of social networks

Several generations of social networks can be distinguished. If we talk about the first generation of social networks (preceding the second generation of SS) which include blogs, Wikipedia, information exchange programs, their key goal is to facilitate the ability of people (users) to cooperate and ensure proper communication on the Internet. The first in this direction were such networks as Facebook, Instagram, YouTube, LinkedIn, Twitter, Reserch Gate, etc. At present, the requirements for social networks are expanding, and they are already becoming a field for modern enterprises, solving problems of B2C levels, or B2B and rarely B2E. Social media is a set of relationships between individual users that can grow into a more complex entity - a group with C2C or B2C functions. If we talk about the B2C level, the best examples of how this level works are a system of recommendations, as well as the so-called "viral marketing". In this context, there is no direct relationship with customers and there is only an indirect opportunity when performance evaluations or questionnaires are used. B2B programs are very rare in practice. It is important to note that at the B2E level, companies in particular position the functionality of social media as a possible means of improving their own activities through disordered cooperation, interaction that they promote among employees. We propose to group existing social networks into the following categories:

- General networks: Facebook, Google Buzz Netlog;
- Platforms for distribution and popularization of blogs and microblogs: Twitter, Jaiku, Tumblr, Xanga, Live Spaces;
- Networks for business communication: LinkedIn, Reserchgate, Xing and Viadeo;
- Platforms for distribution of video content and multimedia content: Flixster, YouTube;
- Platforms for photo distribution: Fotolog, Faces, Flickr, Sneppi;
- Platforms for music content distribution: Last.fm, MySpace, Trig, Blip.fm;
- Platforms for book distribution and reading promotion: GoodReads, weRead, Anobii, Shelfari;
- Art or creative networks: DeviantArt;
- Travel promotion networks: TripAdvisor, Tripit, Wayn.

As one can see from the above example, there are many well-known social networks with different directions (communication, music, sports, food, etc.), ego-Facebook - Links 88234, ego-Twitter Links 1768149 (MCFARLAND et al., 2015; DEVELOPERS, n.a.). The basic elements of each social network are related to communication, i.e., transfer of information from one user to another. Here is a short, summary description of the functions for each network: Support Service, Friends, Groups, Subscriptions, Profile, Contests, Messages, Guestbook, Incoming messages, Chat, Comments, Mail, Settings, Calendar, Search, Recommendations, Statistics, Events, Information Newsletters, Notifications, Downloads, Plugins, Store, Import-Export, Synchronization, Gifts, Wishlist, message support (Like), System actions, Interface, etc. Each network has a different number of basic functions, as well as a different implementation of functions that distinguish one network from another (MCFARLAND et al., 2015; METAPHYSICAL MEANING. BIG DATA, 2020; ANTONAKAKI et al., 2017).

Let's take a quick look at a few services. Facebook was launched in 2004 and has reached 2.5 billion active users, some of whom access Facebook via mobile devices and others via desktop computers (DEVELOPERS, n.a.). The average Facebook user has at least 150 friends and is connected to various groups and events. Users use over 70 languages for correspondence, which is provided by this site. Twitter launched in July 2006 and allows users to send text notes up to 280 characters using the web interface, SMS, instant messaging, or third-party client programs. Twitter has approximately 350 million users. Messages created on this social network are called tweets, and a follower, a person who follows the messages of a certain resource user, is called a follower. A user's post can be used by another user, which is called a retweet, which is a way to express your positive opinion, and if there are many retweets, this message is popular. The world-famous social network YouTube began its work in February 2005, as a resource on which users, in addition to watching informative and inspiring video content of various topics, had the opportunity to share them. Today, according to various estimates, the active users of this social network are more than two billion users. As a platform for the distribution of YouTube videos, not only authors who produce narrowly or widely specialized content, but also advertisers themselves are actively used. An equally popular feature of the resource is the ability for users to share their impressions and impressions (feedback) about previously watched movies, music videos, political talk shows, etc. Another social network that also focuses on promoting knowledge and positions in various fields is LinkedIn. The latter was created in May 2003 and already unites more than six hundred million Internet users (DEVELOPERS, n.a.; SNAP. STANFORD, 2020).

On LinkedIn, a user provides their profile information that other users and companies can view, allowing them to share information and find jobs. Vkontakte, which was launched in October 2006, was initially targeted at schoolchildren and university students, but with its development it became a full-fledged product that allows one to create groups and communicate on the network. The site has about 500 million users. Odnoklassniki is another social network that launched in March 2006 and has about 500 million users. A user of this site can send messages personally or in a group, upload and rate photos, leave comments in forums and visit other users' pages, as well as use other functions (NETWORKREPOSITORY, 2020).

Social media data analysis

Given the diversity and number of social media users, a huge variety of post content types as well as the number of posts are generated, resulting in huge amounts of data. To analyze this data set, in order to maintain the functionality of the site, telecommunications services, content analysis, marketing, etc. mathematical approaches of various classes are being developed. These approaches can be conditionally divided into two groups of methods: quantitative and qualitative research methods.

Quantitative approaches allow one to analyze the frequency of discrete signals with which you can approximate each message, which allows one to get a wide range of information about information in datasets. Here are several groups of methods for analyzing message content:

1) Volumetric is the easiest way to view the volumes of data generated by messages and search for their correlation with certain factors: age, group direction, a certain keyword, time period, etc. In fact, the task of this direction of analysis is to find out the factors that caused a particular data flow exceeding a certain threshold.
2) Analysis of the links that appear in the detected message flow found in the first approach. Interactions between users that are not isolated and based on fixed relationships (for example, Facebook friends, Instagram followers, etc.) are considered. This can be the number of responses to the post (for example, Twitter retweets, YouTube comments, etc.). This allows one to obtain an analysis of the involvement of social network users in a process launched by a user or a group of users.
3) Correlation is designed to compare one social media dataset with another dataset by post type or variable (e.g. location, age, gender, etc.), and how the characteristics of that dataset change over time. The analysis of the development of a dataset over time forms the basis of an approach for using social media data as a forecast.
4) Regression is designed to build models that can be used to analyze weights and choose independent variables or predict values, depending on the change in the value of a variable. This approach allows one to build a tool to inform about changes in the characteristics of the dataset, and therefore about changes in the structure of user messages or the intervention of another group.

5) Clustering allows you to split a set of messages into some areas that are homogeneous in some characteristics, clusters, where all elements have similar characteristics, according to some criteria. For example, this is useful when looking at age, gender, and message topics discussed.

Qualitative approaches are needed to obtain characteristics such as:

1) User activity in different time periods, topics discussed, etc.
2) Segmentation of the message type and understanding what is a user group or subgroup in an existing group.
3) Thematic analysis is associated with the definition of the emotional, informational nature of the content, etc.
4) Graphical analysis is associated with the construction of various images that allow assessing the state of a group of users, the process of interaction, etc. (for example, social graph, histogram, correlation matrix, etc.).

With the spread of social networks, the number of their type and the number of users, the tasks of analyzing the data flows arising in them arise. The complexity of solving the problems of analysis is associated with the uneven distribution of users' connections in space, time and types of groups; a small degree of separation of the characteristics of the message flows of one user, associated with the choice of several groups at the same time; time-delayed form of message flows (message -> reply) and many other options.

The analysis of data arising in the course of the functioning of a social network (SS or social network SN) began to be supported by various branches of computer science, psychology, economics, etc. The main characteristic of SN is that they consist of many layers corresponding to different types of relationships. Relationships are determined by the type of message direction (scientific, nutritional, sports, etc.). Extracting and analyzing the relationships of user groups in social networks is not a new scientific direction and has been investigated, by now, by many scientists (GEREKE et al., 2018; KOLOMEYCHENK et al., 2015). However, nevertheless, the tasks of temporal analysis of a newly emerging group or an already existing one, as well as a disintegrating group, remain unresolved. Analysis of the literature did not identify studies that address this issue for social media.

Many approaches to the analysis of groups (communities) in social networks, which consist of a homogeneous flow of messages (according to a certain criterion), are carried out by approaches based on graph theory, probability theory, cluster analysis, as well as data mining methods (method of neural networks, support vectors, and etc.). The main direction of application of the methods is the concept of a group and the rules for formalizing it according to the general properties of the homogeneity of the community of participants and finding some rules; the assessment of this function determines whether a group of these participants can be considered as a community or not. To solve this problem, a lot of techniques have been developed based on complete reciprocity, reachability, diameter and nodal degree of proximity (BAZENKOV; GUBANOV, 2016; LINDEN et al., 2017); there are methods based on fuzzy clustering approaches, etc. The central problem, which has not been resolved at the moment and is under discussion, is related to the fact that it is a community based on the example of temporary events that occur once and do not repeat again.

There are two general approaches to extracting the activity of user groups in a multi-layer social network: 1) extracting groups in each layer separately, and then combining communities throughout the layers 2) first transforming the social network into one layer, and then searching for different groups within.

The most common representation of social network connections is a structure such as a graph. Graph theory is widely used to analyze social networks (ASN). In our opinion, the best way to determine the graph of a social network is through the following expression: SN = (V, E), in which V - should be understood as a finite set of nodes (or rather users of social networks), and E - we propose to denote a set of arcs (relations between users of social networks) that unite them. Such a graph SN, depending on the nature of the connections, can be either undirected or directed. A directed graph is a digraph that does not have symmetric pairs of directed edges, i.e., arcs of the form (u, v) and (v, u). Graphs can also be weighted or unweighted. In a weighted graph, the weight of each arc will be equal to some real number, defined as a function of parameters that take into account a set of factors. In social network analysis, relationships within an unweighted graph are called binary, and they only indicate the existence of a symmetric relationship between two nodes. In a weighted graph, the weights indicate the strength or importance of the links (relationship) between two nodes (SN users).

For a better understanding of the analysis of a social network, several concepts must be introduced, for example, a route is a sequence of nodes and connections between them, which begins and ends with a node. A closed route is one that starts and ends with the same node. An open route is when there is only one connection between two users (however, one of the nodes (user) can have connections with other users. The length of an open route is equal to the number of connections it contains. Two routes are independent if they have no common users and only the first and last users of the actor can be the same These concepts represent a variant of calculating the features of the manifestation of the structure of the graph, and hence the social network (RAYGORODSKIY, 2010; LESKOVEC et al., 2009).

Another option for analyzing a social network is the calculation of an element of graph theory, an adjacency matrix, which is called a socio-matrix, where each row and column corresponds to a node from the SN graph. The nodes are taken in the same order for both rows (i) and columns (j). The matrix element denotes the fact that there is a connection between two nodes and contains the strength of the relationship. For example, an unweighted and directed graph can be represented by a matrix whose elements can have two values: "1" if there is a relationship from i to j, and "0" if such a relationship does not exist. Sociomatrix can be symmetric, if it is an undirected graph, and asymmetric, when it describes a directed graph. Moreover, it will only contain the values 1 and 0 if the social network is unweighted (GEREKE et al., 2018; SABATINI; SARRACINO, 2020).

It should be noted that initially a social network is a probabilistic model, when each user has a random (in fact) visit to the site, the time of the visit, the size and type of message, the choice of emotional content, etc. Therefore, all the assumptions made and the existing models are in fact random and built on a large sample of time. Since the statistically determined sample is the basis for constructing the model, the results obtained can be taken as some analytical basis. On the other hand, the presence of functions on the site allows the user to use this variety to achieve the goal of their messages and on the one hand it separates one site from another, on the other hand it makes it difficult to build a statistical model, it becomes complex (HAMM et al. 2019; SILVA et al., 2018).

Based on the analysis of different social networks through the prism of their connections and their dynamics, it can be used to track and understand different types of user behavior (users) in the context of active dissemination of distance learning and education in the face of the spread of pandemic COVID-19. You can analyze the work of a social network in four stages. The latter include: first, the collection of various data; secondly, the selection of indicators for analytical calculations; third, direct, practical use of the method of analysis; fourth, summarizing specific conclusions. Next, in order to identify and study the patterns that may occur in the work of social networks, it is first necessary to divide users into groups of different thematic specifics. It should be borne in mind that the prospect of analyzing a network node (especially for large and heterogeneous networks) has its limitations, dictated by existing computing resources and as a result at the basic stage it is necessary to select a purely representative group of users for future analysis. At the stage, the following methods are key: 1) Methods based on the collection and research of data from across the network; 2) methods such as "snowball", which focus on the fact that the work begins with one user or a limited sample of persons (users).

It is worth noting that for one or all network users, their relationships must be clearly identified and systematized. As a result, the process ends. Thus, the conditions for the completion of this process are either the absence of new links to systematize or reduce the number of defined iterations of the algorithm. This approach is best used to analyze the behavior of members of a highly connected group of users in large enough networks. At the same time, this method has vulnerabilities, namely the selection of an isolated group member according to certain parameters (duration of communication, number of messages, etc.), which cannot be positioned as passive and eliminated in the second stage of the analytical process. Another weakness of this method is the need to find the most active contacts by users (or group) (PYTLIK ZILLIG et al. 2017; MCFARLAND, et al., 2015).

Second, if the first actor was not chosen properly, the method may allow an incorrect result; 3) egocentric method provides an opportunity to study a single user and the flow of communication with his community. The value of this method is to provide useful information exclusively for the local network and how it affects the user.

CONCLUSION

Thus, we have made an attempt to consider the logic of events that make up the activity of users of social networks. Analysis of the variety of behavior of users of social networks leads to the conclusion that a huge amount of data appears as a result. For the analysis of this data array, various types of mathematical approaches are being developed. The result of the above was, first, the formation of operational schemes in which participants of social networks participate; secondly, the development of both single-layer and multi-layer social network in real time.

To obtain practical results for this article, we used a number of scientific approaches, the purpose of which was to remove the activities of different groups of Internet users in multi-layered social networks: 1) extracting groups in each layer separately, and then combining communities throughout the layers; 2) first transforming the social network into one layer, and then searching for different groups within. As a result, several generations of social networks with different directions (communication, music, sports, food, etc.) were identified, the main elements of each social network are connected by the transfer of information from one user to another. In addition, a statistically determined sample is the basis for constructing a model, the results obtained can be taken as some analytical basis.

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Conceptualization of user activities in the social network in the conditions of distance education

Conceituação das atividades do usuário na rede social nas condições da educação a distância

Conceptualización de las actividades de los usuarios en la red social en las condiciones de la educación a distancia

Resumo

No artigo, as mídias sociais são analisadas através do foco de entender este último como um espaço virtual da mídia, o que reflete indicadores identificados dos usuários como: interesse, desejo, entusiasmo e direção dos processos de integração. A relevância do estudo é determinada pelo desenvolvimento insuficiente e inconsistência dos conceitos e resultados empíricos da pesquisa sobre os processos de diferenciação da comunidade das redes sociais e seu papel nas condições da educação a distância. Foram utilizados os métodos filosóficos, de análise e hermenêutica: interpretação, conceituação, análise comparativa. Como base teórica e metodológica, utilizamos o aparato categórico da filosofia social, matemática, teoria da prática, pragmatismo, epistemologia social. Utilizamos abordagens para extrair a atividade de grupos de usuários em uma rede social de várias camadas: 1) extrair grupos em cada camada separadamente e, em seguida, combinar comunidades em todas as camadas; 2) primeiro transformar a rede social em uma camada e, em seguida, procurar diferentes grupos dentro.

Palavras-chave: Educação a distância. Redes sociais. Gráfico. Estrutura de nó. Rede social multicamadas de regressão.

Abstract

In the article, social media is analyzed through the focus of understanding the latter as a virtual space of the media, which reflects such identifying indicators of users as: interest, desire, enthusiasm and direction of integration processes. The relevance of the study is determined by the insufficient development and inconsistency of the concepts and empirical results of research on the processes of differentiation of the community of social networks and their role in the conditions of distance education. The methods of philosophical, analysis and hermeneutics were used: interpretation, conceptualization, comparative analysis. As a theoretical and methodological base, we used the categorical apparatus of social philosophy, mathematics, theory of practice, pragmatism, social epistemology. We used approaches to extracting the activity of user groups in a multi-layer social network: 1) extracting groups in each layer separately, and then combining communities throughout the layers; 2) first transforming the social network into one layer, and then searching for different groups within.

Keywords: Distance education. Social networks. Graph. Node structure. Regression multilayer social network.

Resumen

En el artículo, se analizan las redes sociales a través del enfoque de entender estas últimas como un espacio virtual de los medios, lo que refleja indicadores identificativos de los usuarios como: interés, deseo, entusiasmo y dirección de los procesos de integración. La relevancia del estudio está determinada por el insuficiente desarrollo e inconsistencia de los conceptos y resultados empíricos de la investigación sobre los procesos de diferenciación de la comunidad de redes sociales y su papel en las condiciones de educación a distancia. Se utilizaron los métodos filosóficos, de análisis y hermenéuticos: interpretación, conceptualización, análisis comparativo. Como base teórica y metodológica, utilizamos el aparato categórico de la filosofía social, las matemáticas, la teoría de la práctica, el pragmatismo, la epistemología social. Utilizamos enfoques para extraer la actividad de los grupos de usuarios en una red social de múltiples capas: 1) extraer grupos en cada capa por separado y luego combinar comunidades en todas las capas; 2) primero transformando la red social en una capa, y luego buscando diferentes grupos dentro.

Palabras-clave: Educación a distancia. Redes sociales. Gráfico. Estructura del nodo. Regresión multicapa de red social.