Determination of Young Generation's Sensitivity to the Destructive Stimuli based on the Information in Social Networks

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Abstract

The paper describes the developed technique to determination of young generation's sensitivity to the destructive stimuli based on the information provided by its representatives in the social networks. The technique uses the methods of neural network processing of Internet content. The underlying approach integrates the technologies of psychological examination and artificial intelligence. It allows overcoming the challenge of manual processing of the huge amount of information. The proposed technique can be further used for detection of destructive impacts in the Internet space and monitoring of influence of these impacts on the social networks' users. The paper shows the place of the technique in this task. Implementation of the proposed technique for determination of sensitivity of social networks' users to destructive stimuli is described. The experiments that demonstrate existence of the relation between information users provide in social networks and their sensitivity to destructive stimuli are conducted and their results are analysed.

Keyworkds: social network, detection of destructive information impacts, sensitivity of young generation to destructive, stimuli, neural network, Ammon's test, user profile, psychological scales

1 Introduction

It is almost impossible to imagine the modern world without Internet space, especially, for the young generation. It is one of the most popular communication forms for them. And social networks are one of the most common Internet resources for their representatives. Information that is provided by young people in the social networks can include personal data, information about the interests, correspondence, photos, etc. We believe that this information can say a lot about the social network user.

At the same time Internet space is the main environment for the dissemination of destructive information impacts. In this research we understand the destructive information impact or stimulus as impact that can provoke aggressive actions and aggressive behavior in relation to others or yourself. In this paper we aim determining sensitivity of young generation to the destructive stimuli and we show how it can be used in the common task of detection of destructive impacts in the Internet space and monitoring of their possible influences on the younger generation.

The task under consideration is relevant as soon as timely detection of destructive stimuli for users who are sensitive to them will allow weaken or even negate their influence. The importance of this task follows from the importance of the humanistic orientation of personality development for its harmonious development.

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The initial hypothesis that formed the basis of our approach is that information on the user's pages in the social networks can serve to hypothetically determine the user's sensitivity to destructive stimulus. Therefore, we propose an approach based on the analysis of social networks data. We suggest using an artificial neural network apparatus and other methods of machine learning and data mining to implement this approach. This choice is explained by the fact that these methods show themselves well as an anomaly search tool. Currently, the specialized manual tests are used to determine the sensitivity of individuals to destructive stimulus. These tests must be carried out regularly, and expensive equipment is required, which makes the implementation of this process difficult. We argue that the proposed approach will allow analysing of the huge amount of information in the Internet space and will support the experts while determining sensitivity to destructive stimulus among young generation representatives and allowing them to focus on automatically ranked objects.

Further research of interaction of users sensitive to destructive stimulus with social networks' communities that have the destructive impacts can allow detecting of such impacts on early stages and their weaken or even negate. This idea and common approach that incorporates the technique for determination of sensitivity of the social network user's to destructive stimuli, the technique for classification of the social networks' communities considering the presence of destructive impact, and the technique for monitoring an influence of the communities in a social network on users were presented on IDC 2019 conference [8]. This paper extends the previous research in terms of the technique for determination of users' sensitivity to destructive stimuli and implementation of this technique with detailed experiments and their results. The experiment consisted in the manual determination of sensitivity of test group's representatives to destructive stimuli using the Ammon's test and further application of these data and information that the representatives provided in the social networks to train the neural network to forecast users' sensitivity to destructive stimuli. The experiments shown an existence of the relationship between the information provided in social networks and users' sensitivity to destructive stimuli.

The paper is organized as follows. Section 2 provides notations of destructiveness and related work, as well as related work in the area of application of neural networks for determination of user's character using Internet content, and for identification of destructive impacts. Section 3 describes the suggested common approach to detection of the destructive information impacts and the proposed technique to determination of sensitivity of young generation to destructive stimuli using the methods of neural networks for the Internet content processing. Section 4 describes the technique implementation, the conducted experiments and their results. Section 5 discusses the results and the future research plans.

2 Related Work

The destructive impacts provided by the people, society, informational processes are especially dangerous for the person in the period of adolescence when the person searches for his/her social "Self" [16, 17]. The destructive stimuli can highly affect the personality of a person who is in the state of frustration or crisis (the identity one, the age one, the morality one). Interaction between a person and the people, society, informational processes always has contradictory character and can be described in terms of direct impact and feedback effect [6, 29, 10, 35]. Thus the idea of searching for correlation between the informational streams that may cause negative effect on the psyche and its perception by a person appears to have potential but this scientific task is extremely complex.

To analyse aggression and destructiveness the ideas of Erich Fromm are widely used. Fromm distinguished benign aggression and malignant aggression [7]. Benign aggression is the type of aggression that is justified from the ethical point of view (like self-defense). While malignant aggression is destructive eagerness to oppress and hold under control, to frighten and to terrify, to hurt in order to get satisfaction and pleasure. Individual level of aggression is expressed in the readiness and needs of aggression, power, subordination and belonging to a certain social community that has such characteristics [34]. Rise of the malignant aggression has been stated within recent years. Thus the study aimed at detecting malignant aggression and informational streams that may cause it (or destructive stimuli), is essential. It demands the in-depth study of various pre-requisites of aggressive behavior, various types of social and cultural impact that can cause it [12, 17, 6, 9].

Informational processes that can influence consciousness, identity construction, and forming of potential destructive behavior can be unfolded in the informational streams that are shared between people and various social groups [24, 15, 34]. Hypothetically, the resulting vector of a person can be formed by constructiveness, destructiveness, and their representation in inner world of a person, his/her activity, social choices, preferences, including choices of informational streams. Talking about constructiveness and destructiveness we can't help mentioning that these phenomena are extremely complex and its simple, precise, mechanical definition can't be given. The international scientific community still has not elaborated ways of precise anticipation of destructive behavior.

Additional knowledge in understanding of aggression and destructiveness were introduced by the notion of personal identity [15, 13]. There is the point of view that destructiveness is a way of formation of personal identity with specific social community and it should be reflected in the communication system, including Internet space.

The hypothesis that certain states and traits of a person can meet certain destructive influence resulting in possible displays of destructive behavior can be given. The informational streams of the Internet can act as one of the forms of consciousness handling. They can be used to form the virtual society, virtual space, indirect forms of communication. It can be accompanied by the feeling of loss of responsibility, the illusion of total freedom and impunity, occurring abilities to realize socially-troubled behavior [26, 31]. In this space there may be allocated direct destructive impacts and intermediated impacts aimed at forming destructive convictions, destructive social position and other aspects of consciousness that may have destructive character [25, 32]. There may be the following targets of this intermediated impact: destruction of meanings in value system, knowledge, activities of a person [36]. For example, formation of a nihilistic position towards medicine can lead to refusal of medical intervention and preventive treatment, thus resulting in loss of health. In its turn it can lead to destructive effect both in human and society.

Regular examinations aimed at detecting psychological disorders of the person make it possible to carry out timely prevention of a person's health state and thereby preserve his/her health. At present, specialized tests and expensive equipment are used to perform such procedures, which make the implementation of this process time-consuming. To solve this problem, we suggest using artificial neural networks. The artificial neural networks allow specifying and summarize complex processes and phenomena on the base of the available data obtained in the observation process. They are used for monitoring the psychological state of Internet users, for classification of clinical diagnoses based on medical indications, for analysis of the sentiments of Internet users, for determination of level of emotional impact produced on a person when he/she looks the content presented in digital images, etc.

In particular, in [20] the authors use convolutional neural networks to identify psychological disorders. The initial data for training and testing of the neural network model were obtained from the services of social microbloggs including text or image from a single message (tweet) and statistical attributes relating to account activity (number of tweets, number of message comments) for a given period of time. The experimental results showed the feasibility of using a four-layer neural network, in which a special kind of logistic function was used as an activation function.

The paper [21] is devoted to solving the problem of multi-class classification of clinical diagnoses based on various medical indications. The authors use a recurrent neural network designed for processing multidimensional time series of medical observations. Experimental results confirmed the high efficiency of this model.

Investigations on the analysis of the sentiments of Internet users were presented in [27, 30]. Based on the data extracted from short messages, it is proposed to build a deep neural network which is capable predict the binary sentiment (positive or negative) of the addresser. In [27] the authors use a multi-level scheme for constructing a feature vector: for analysis, information is used which is extracted from both individual character sequences and higher-level syntactic structures, namely sentences. A large amount of useful information, suitable for constructing a person's psychological profile, can be obtained from the account of the corresponding user, posted on his personal page on the social network. In particular, the authors of paper [28] consider the issue of building a system for recognizing the psychological profile and character traits of a person using his/her photos from the Facebook social network.

The study [23] discusses the approach to finding groups in social networks. The basis of the developed approach is a genetic algorithm, the optimized fitness function of which is aimed at finding tightly grouped nodes within the relation graph, and the various clusters thus formed should rarely connect with each other or have no common links at all. One of the practical purposes of this approach is to highlight common interests in the studied group of people and to construct an average psychological profile of a participant of the detected group.

Authors of [22] investigate the level of emotional impact produced on a person when looking the content presented in digital images. As the features to be processed, the luminance parameters of color schemes, the relative predominance of dark colors, the texture and composition parameters were used. To perform the tasks of automatic classification of images by the level of emotional impact, a naive Bayes classifier was used. In [11] it is proposed to consider the genetic algorithm as a heuristic tool for solving the NP-complete problem – clustering a fragment of a social network. In [14], the Bayesian approach is proposed to determine the number of clusters within a social network. In [33], the problem of predicting the reposts in the social network Twitter is solved. For the calculation of precision and recall a linear support vector machine and logistic regression are used. The issues of protecting users from malicious and unwanted information are discussed in the papers [18, 19]. One of the targeted purposes of the developed approach within the considered subject area is to reduce (or even prevent) the cases of access of the younger generation to illegitimate information.

Although the task of identifying the tendency of young generation to destructiveness is the subject of numerical research and neural networks are widely used to solve various problems of psychology including emotional coloring of texts or identification of common interests of social networks' users, the existing researches do not propose the solution for the problem of automatic determination of sensitivity to destructive stimuli using an information provided by the users in social networks. At the same time, currently there is the entire necessary scientific basis for creating such an apparatus. We argue that our approach to determination of sensitivity of young people to destructive stimuli based on the information in the social networks using the technology of artificial neural networks will become a serious auxiliary tool for psychologists. Its application area covers the activities (professions) where such detection is required and it is performed manually to this moment. Implementation of our approach will allow one not to miss the warning signals at the early stages due to the large number of subjects, the processed information and the lack of time and human resources.

3 Determination of Young Generation's Sensitivity to the Destructive Stimuli

The common approach to detection of destructive information impacts in the Internet content based on the social networks' data analysis was described in details in [8]. It incorporates:

1. Determination of sensitivity of social networks' users to the destructive stimuli.

2. Classification of the social networks' communities considering an existence of destructive impacts.

3. Detection of changes in the tendency of users to destructiveness when interacting with communities in a social network.

We developed the techniques that implement appropriate stages. In [8] we briefly described all techniques. Here we describe the first technique and related experiments in details and briefly describe other techniques.

3.1 The Technique for Determination of Sensitivity of Social Networks' Users to the Destructive Stimuli and of Destructiveness of Communities in Social Networks

These techniques are based on the data gathering from the social networks and further neural network learning to rank the web pages of social networks' users and social networks' communities. The techniques incorporate the following steps: manual determination of sensitivity of social networks' users to the destructive stimuli (or manual determination of destructiveness of communities in social networks in case of the second technique); gathering data from the profiles of social network's users (or from the community page in case of the second technique); formation of a feature vector; forecasting the sensitivity of social networks' users to the destructive stimuli based on the collected data using trained neural network (or in case of the second technique, forecasting of destructiveness of communities in social networks).

Manual determination of sensitivity to destructive stimuli. In this study we selected the Ammon's test for manual determination of users' sensitivity to destructive stimuli [1]. This test allows determining the constructive, destructive and deficient manifestations [1]. This test was selected because of its orientation on the dynamic study of personality. This means the ability to use the technique to analyse constructive, destructive and deficient aspects of the specific Ego-functions highlighted by the author of the test G. Ammon jointly. Besides, this test was adopted and validated for application using Russian sample. In Russia it is adapted by the Russian scientists, namely, Y.Y. Tupitsin, V.V. Bocharov, T.V. Alhazova, E.V. Brodskaya.

The Ego-structure Ammon's test is based on the concepts of dynamic psychiatry about personality structure. Its foundation is personality concept proposed by G. Ammon that supposes that the individual has the following Ego-functions: an aggression, an anxiety, an external I-restriction, an internal I-restriction, a narcissism, a sexuality. It allows systematically evaluating the personality structure in the complex of both healthy and pathologically changed aspects (i.e. destructive or deficient). Correct application of the technique is connected with main statements of dynamic psychiatry. The obtained experimental data should be analysed in complex for each individual. Both the ratio of indicators for the constructive, destructive and deficient components of each Ego-function, and dynamics of their interaction with the social environment (field) should be considered. Otherwise, the superficial interpretation of this test will allow adding everyone to the so-called "destructive" group because the destructive and deficient aspects are more-less characteristic for any person [5].

The results of this test are used for the neural network learning.

The technique for determination of destructiveness of communities in social networks supposes manual classification by the experts considering the features specified using pages of communities in social network.

Input data collection from social network's profiles of Internet users. To forecast the results of Ammon's test it is required to find the relation between the data provided by the users on their personal pages in the social networks and the test results. The data provided by the users on their personal pages includes messages placed on the user's personal page, his/her personal data, as well as multimedia content in the form of pictures. The results of Ammon's test include the values of eighteen scales that are the combinations of six Ego-functions (aggression, anxiety, external I-restriction, internal I-restriction, narcissism, and sexuality) and three components (constructive, destructive and deficient), and T-score (T) that is calculated for each pair. T is low if $0 \leq T \leq 39$, medium if $40 \leq T \leq 60$ and high if $61 \leq T \leq 110$.

Let us to notice that for the further neural network training we should determine the key features based on the information from the users' pages in social network.

Feature extraction. We propose to use three groups of input data as the features that describe users' profiles in social networks: (1) numerical parameters (scalars) that include month of birth, number of subscribers, friends and photos, etc., (2) sequence of words (for example, the parameters aimed at forming a set of the most common words within each psychological scale), (3) parameters calculated on the level of binary data streams (for example, the result of image classification using the neural network imagenet). The calculated parameters are provided in Table 1.

No.	Parameter	Type of input data
1	Number of subscribers	Scalar
2	Number of friends	Scalar
3	Number of group	Scalar
4	Number of photos	Scalar
5	Number of subscriptions	Scalar
6	Number of videos	Scalar
7	Gender (female/male)	Scalar
8	Number of posts	Scalar
9	Number of reposts	Scalar
10	Month of birth	Scalar
11–55	Result of application word2vec between five the most used words specific to the posts of each class, and three the most used words in the posts of the analysed profiles	Sequence of words
56–100	Result of application word2vec between five the most frequent categories of photos specific for each class, and three the most frequent categories of photos in the analysed profile	Binary sequence (image)
101	Result of application of convolutional neural network for sequence of words in posts	Sequence of words

Table 1: Parameters forming the feature vector

Table 2 contains the examples of the most popular words (it should be noticed that some words are Russian as soon as we analysed Russian social network) in the users' posts of the social network.

Determination of users' tendency to destructiveness. This step involves training the neural network classifiers to forecast the results of Ammon's test using the features outlined on the previous step. Currently we considered only destructiveness component. The multi-layer neural network (MNN) with three hidden layers of classifiers, the support vector machine (SVM) with radial basis kernel, the linear regression (LR) and the convolutional neural network (CNN) were used as neural network classifiers. The subset of features presented in Table 1 under the numbers 1–10 were used for training of the first three classifiers. As it will be shown in the subsection 4.4, the MNN demonstrates the best accuracy indicators on this feature subset, therefore, in addition to this, it was trained on feature subsets under the

Word	Frequency	Word	Frequency	Word	Frequency
Low level of destructive narcissism		Medium level of destructive narcissism		High level of destructive narcissism	
very	59	club*	106	presents	58
thank you	56	vkfeed	106	very	46
simply	32	iphone	106	the	42
even	28	very	71	can	41
always	27	thank you	64	simply	39
day	24	fear	60	come	36
cells	20	through	59	photo	35
endometrium	19	day	50	click	31
tumor	18	can	49	picture	31
people	17	life	46	guests	31

Table 2: Examples of the most popular words and categories of photos specific for different levels of destructive narcissism

numbers 1–55, 1–100, 1–101. To train the last classifier, namely CNN, the posts on the walls of profiles in a social network were used. Functionality of this classifier includes the following steps (see Figure 1):

1. *Text conversion on the distribution layer*. The text is divided into separate sentences. Each word is assigned an unique numerical identifier: the higher the frequency of occurrence of a word, the less the value of this identifier. Obtained values are placed inside a rectangle grid so that the cell (i, j) corresponds to the j-th word of the i-th sentence. Alignment is achieved by assigning zeros to the right to get the maximum length string.

2. *Applying a convolution*. Each submatrix, composed of elements of grid built in step 1, should be element-wise multiplied by the convolution kernel. Obtained compositions are summarized.

3. *Applying a max-pooling*. The matrix obtained on a step 2 is used to extract the most significant elements inside the window of the fixed size. For this purpose, the maximum operation is used.

4. *Interpretation of output results*. The signals obtained after the step 3 are represented as a vector. This vector is scalarly multiplied by the weights of the output layer. The result is value y. The low level of destructiveness corresponds to $\varphi(y) < 0.33$, the medium level of destructiveness corresponds to $0.33 \leq \varphi(y) \leq 0.66$, the high level of destructiveness corresponds to $\varphi(y) \geq 0.66$, where φ is a sigmoid activation function.

3.2 The technique for monitoring an influence of destructive impacts

As it was mentioned, determination of users' sensitivity to destructive impacts is step to monitoring such impacts in the Internet space and their influence on the users. It is required as soon as influence will depend on the initial person's sensitivity to such impacts. The technique that implements the third stage is developed to detect changes in the users' prone to destructiveness when interacting with communities in the social network. It supposes monitoring of changes of the selected for the classification features values. Besides, it supposes monitoring of changes of the composition of communities with which users with detected changes interact.

In scope of the technique we propose the descriptive scale of trends in the occurrence of destructive manifestations. This scale allows describing different possible manifestations of possible destructive

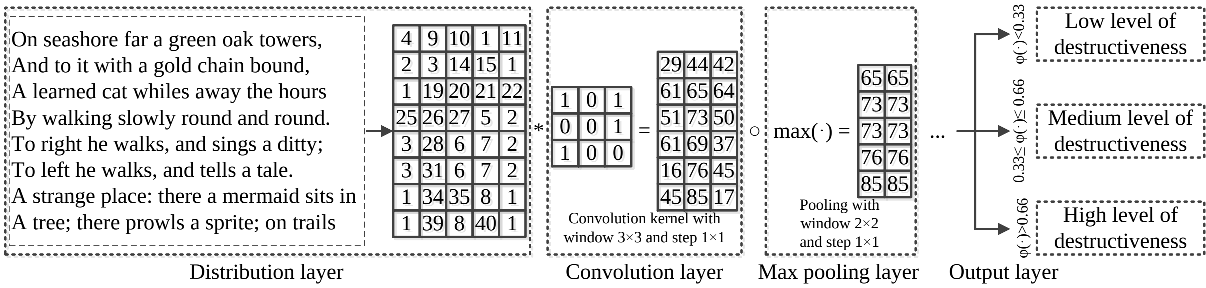

Figure 1: Operation of CNN trained on the basis of the posts in a social network (application of normalization on the distribution layer and of activation function on the convolution layer are omitted)

state. Suggested steps are considered relating to the complex and multidimensional phenomenon of destructiveness (i.e. we doesn't suppose that individual should pass the previous step to move to the next step of the destructive behavior).

Step 1: "Frustration". Person suffers from negative emotions and translate his/her state to the social network using reposts and liking the appropriate posts that represent (in the figures or slogans) negative emotions, with a hint of profanity.

Step 2: "Aggressive protest". Person uploads his/her own photos expressing the protest through gestures, facial expressions, clothes, makeup, etc. This virtual action doesn't have continuation. It is a short-term reflection of the subject's state.

Step 3: "Demonstrative aggression". Person wears an element or elements of signs and symbols of protest on himself(herself). It can be tattoo, piercing, haircut, etc. This image element is stable and demonstrative. He/she does not conduct aggressive propaganda of destructive actions, but clearly establishes his belonging to some destructive group. It should be noticed that not all youth subcultures are destructive. Some external manifestations (tattoos, piercings, etc.) are currently entering the field of mass culture and often become "fashion-following". Therefore, the deep content analysis of such signs should be conducted.

Step 4: "Non-verbal appeal for general protest". Screaming holistic appearance of a person: clothes, shoes, piercings, tattoos, image reflects the role - paying attention to himself/herself. On this step interpretation of the protest is given to the observer. But the observer's interest and emotions are guaranteed. It should be noticed, that representatives of creative environment can have the goal to attract attention in this way. Besides, it can be the consequences of personal neurotic experiences. That is, such an appearance does not necessarily indicate a call to protest. This shows a need for deep analysis of such behavior in dynamics.

Step 5: "Search for everyone who has the same feelings". This step is characterized by imposing, provocative intimidation, union on the basis of negative motivation in order to search for like-minded people. Impact by the word appears: text calls, thoughts, attracting an attention and joining.

Step 6: "Do like me in a virtual world". It supposes offering behavior and lifestyle with a negative context, specific recipes for games with consciousness, propaganda of "the elite of dissent", the value of provocative or destructive behavior.

Step 7: "Do like me in reality". It supposes a call for protests with specification of place and time, the conviction of joining the ranks of radical groups, as well as a call for attending squats, taking drugs, and collective suicides.

Features of any of this step show the necessity of preventive psychological and pedagogical work with young people as soon as they indicate that a person is in the state of frustration, and is searching for discharge of negative experiences. Properly conducted psychological and pedagogical work in this case will lead to the formation of patterns of constructive behavior.

4 Implementation, Experiments and Discussion

This section describes the experiments related to the technique for determination of sensitivity to destructive stimuli. They included manual testing of users using the Ammon's test, collection of the input data (information on the web pages of users in social networks) for the further automated analysis of the web pages of users in social networks on the subject of tendency to destructiveness, and neural network training for forecasting test results.

4.1 The test sample

The test was conducted among the first-year medical students. Young people are the part of population characterized by a craving for a new one, a desire for self-identification, a search for the meaning of life, and, at the same time, a rather labile consciousness [17]. At the same time, young people do not have enough life experience. They have traits such as the pursuit of justice, romanticism. Thus, young people can absorb information, including destructive one, uncritically. They also can become its propagators sincerely believing that they are acting for the good of society.

It should be noticed that the medical students are specific category of studying young people. The specifics of the future profession lead to a number of characteristics that distinguish them from the youth and, in particular, the student population as a whole. In the process of studying, starting from the first year, the students deal with suffering and death (for example, in the process of studying they interact with dead tissue, study a variety of pathological processes in such disciplines as histology, anatomy, pathological anatomy, pathophysiology).

The choice of such profession, from the one hand, may be due to certain predispositions of personality, including aggression (since any medical interventions can be interpreted as aggressive actions, albeit aimed at the benefit). On the other hand, a number of students choose the profession of a doctor from romantic and altruistic motives. But these students are affected by the content of vocational training and the rather rigid educational environment of a medical university. Thus, the medical students of a medical university in many ways, including the level of aggressiveness, may differ from, for example, philological students or architectural students. At the same time an aggression of such students is socially oriented since the essence of the doctor's work is to provide medical care, and thereby benefit society.

Anxiety among students of medical universities can also differ from indicators of anxiety in general among the youth, and, in particular, among the student population. High level of uncertainty arising in the process of medical work (where a specialist deals with a wide variety of factors), high risks and responsibility of a doctor's work, learning difficulty, the need to assimilate a huge amount of information in a short time, leads to the increased level of anxiety and decreased emotional background.

4.2 Manual determination of sensitivity to destructive stimuli

We developed the social network application that implements the Ammon's test to simplify the test passing procedure. Its architecture is represented in Figure 2. It incorporates HTTPS hosting with MySQL database and web-application that works with VK API (contains JavaScript, PHP and HTML files) and VK application, created and customized in social network.

Our application type is community application, so it's connected to our community on vk.com[1]. This community is the start point for any social network user.

[1]https://vk.com/psyneuralnet

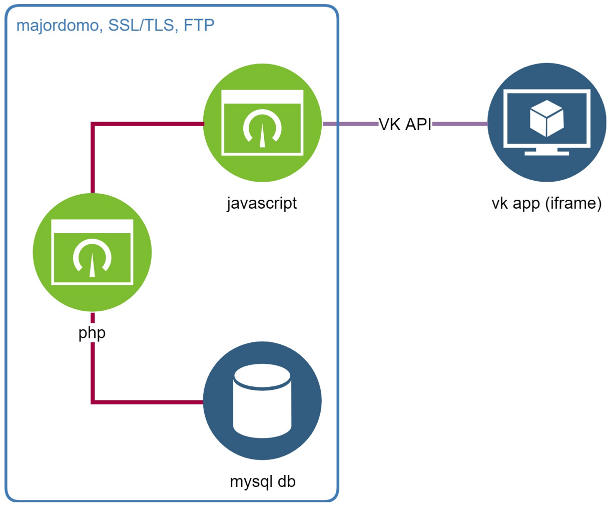

Figure 2: Architecture of the application that implements the Ammon's test

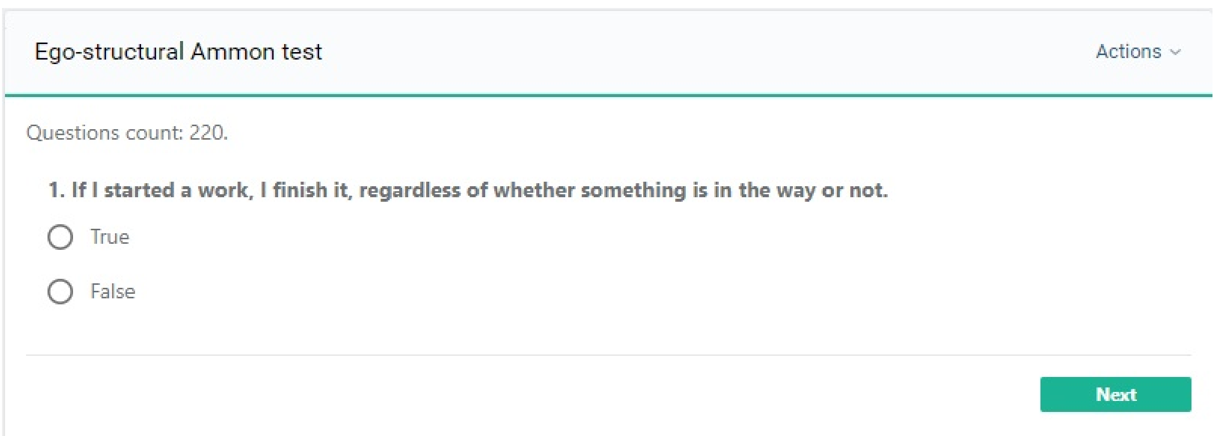

Figure 3: Interface of the Ammon's test application

Community application on vk.com is that type of application that is running on external resource (remote server, hosting and etc.) and viable on social network application page as IFrame with help of JavaScript SDK [4]. The implementation of Ammon's test is based on SurveyJS [3] and Bootstrap [2] JavaScript libraries. Interface of the Ammon's test application is represented in Figure 3.

After the Ammon's test is completed its results are provided to the user (see Figure 4). There are three progress bars (constructive, destructive and deficient) for each of six ego-functions (aggression, anxiety, external I-restriction, internal I-restriction, narcissism and sexuality). The shown numbers are depending on the number of "agree" answers on questions that are related to the appropriate progress bar. After normalization (T score) the resulting values can be from 0 to 110, where from 0 to 39 is less than normal (yellow progress bar), from 40 to 60 is equal to normal (green progress bar) and from 61 to 110 is more than normal (red progress bar).

With help of JavaScript SDK we collect data on test results in JSON format, anonymize and transfer it to MySQL database. Each info part of any table in database contains appropriate JSON string that can be extracted from the table with SQL SELECT and transformed to JSON object for further analysis.

Currently we have 1092 sessions from 671 unique users in our database. During these sessions we'd

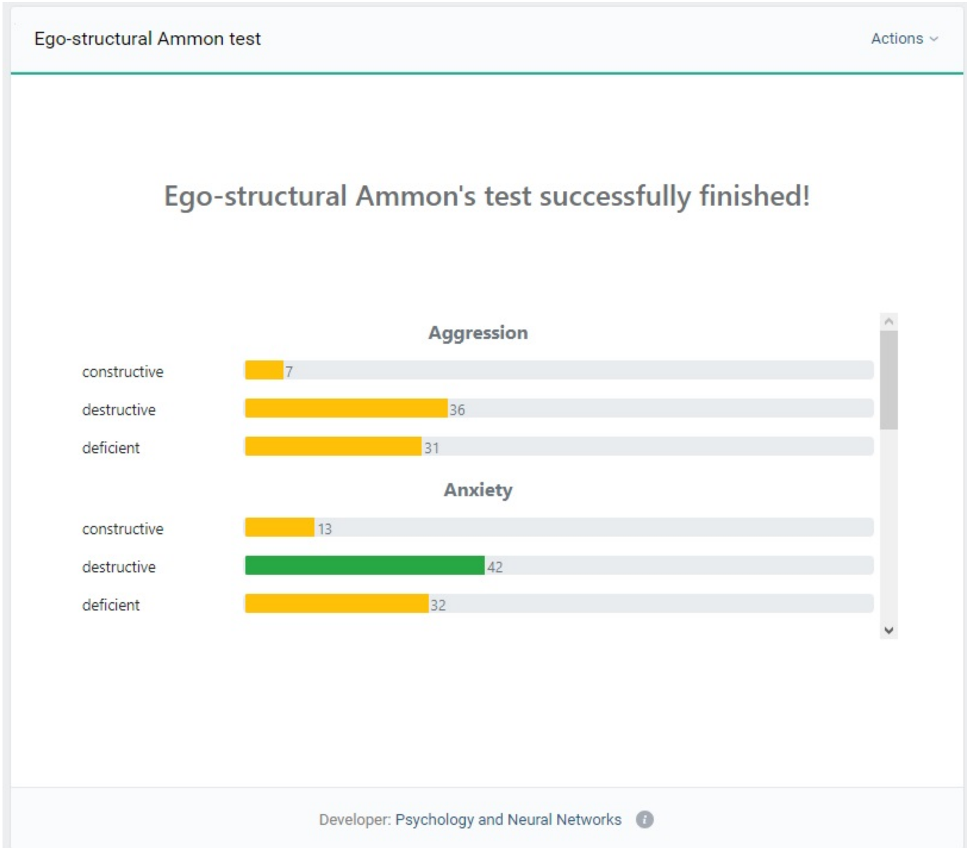

Figure 4: Results of Ammon's test

collected 605 answers to Ammon's test with their results from 588 unique users. It means that several users completed Ammon's test more than once: 1 user completed test 3 times and 15 users completed test 2 times. Among the 1092 sessions there are 788 from female (72.16 %) and 304 from male (27.84 %) users. Average time of the Ammon's test completion is 23 mins and 44 secs, while minimum time is 2 mins 32 secs and maximum time is 2 hours 25 mins 43 secs.

Minimum, maximum and average T score on each type of ego-function among students are presented in Table 3. It should be noticed that Table 3 represents average values for the limited group. In each case, it is necessary to consider a person in all the variety of his/her personal manifestations: each person has his/her own unique picture of the relationship between the constructive, destructive and deficient aspects of ego-functions, and their manifestations in behavior are due to both the education and the system of personal values, and the dynamics of interaction with the complex social field.

4.3 Data collecting

For the selected 455 profiles with test results we have collected the data from the social network analysis.

The architecture of the system for collecting and processing data received from social profiles of Internet users consists of three components: a profile scanner, an HTML-parser and neural network classifiers. Profile scanner is a software tool which can automatically follow links. To retrieve the data, the HTML-parser is intended. The role of classifiers is to identify the type of personal destructiveness, whose social profile was scanned. Currently we collect the following data from social network: profile of the user; friends list and their short profiles; groups list and short info about them; followers list and

Ego-Function	Type	Average	Minimum	Maximum
Aggression	constructive	45	7	65
	destructive	56	36	82
	deficient	54	31	89
Anxiety	constructive	49	13	67
	destructive	59	42	97
	deficient	53	32	96
External I-restriction	constructive	44	11	61
	destructive	53	25	91
	deficient	56	34	83
Internal I-restriction	constructive	46	2	61
	destructive	55	27	100
	deficient	60	31	83
Narcissism constructive	constructive	48	7	65
	destructive	54	32	93
	deficient	53	38	102
Sexuality constructive	constructive	48	20	66
	destructive	50	33	80
	deficient	52	36	88

Table 3: Statistics of the Ammon's test results

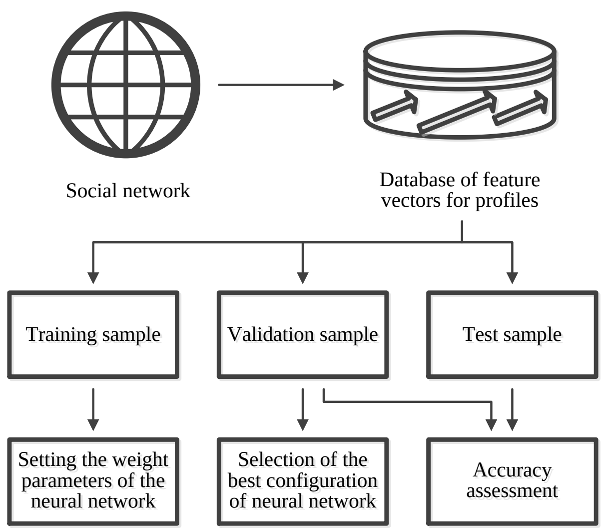

Figure 5: The common scheme of the experiment

their short profiles; subscriptions list and short info about them; wall posts, info about them and their statistics; photos from the user page, info about them and its statistics; videos from the user page, info about them and its statistics. These data are used to generate features for the neural network training.

4.4 Forecasting of the test results using neural network

The common scheme of the experiment is represented in Figure 5.

In the experiments we used 10-fold cross-validation. Initial set of the feature data was divided into

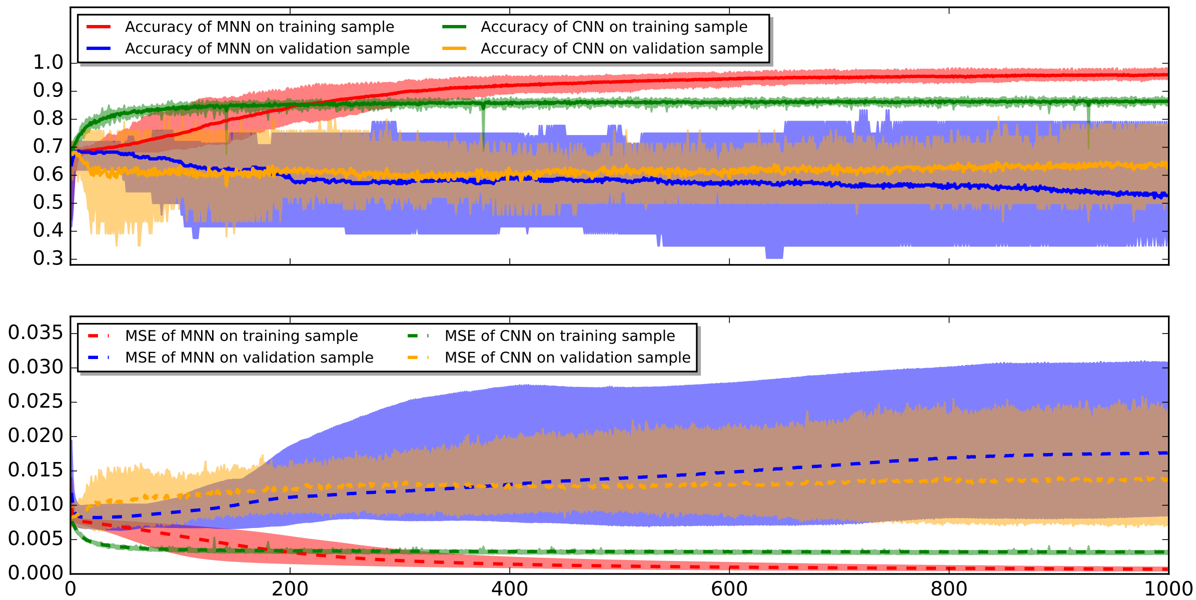

Figure 6: Dependence of accuracy and MSE of MNN and CNN from the epoch number for the psychological scale of destructive aggression

10 parts so that each part contains roughly equal sized subsamples with the elements of the same class. 9 parts were used for training. The rest part was used for testing. The half of this part was validation set.

Iterative setting of weight coefficients of neural network was made using the elements of training sample. Validation sample was used to calculate mean squared error (MSE) after each training epoch and further selection of neural network configuration with minimum MSE. Test sample was used to calculate an accuracy of forecasting results. Figure 6 represents the dependence of accuracy and MSE of MNN and CNN from the epoch number on the training and validation samples for the psychological scale of destructive aggression.

MNN is characterized by the fast convergence of the learning algorithm compared to the CNN. At the same time, for the MNN with an increase in the number of training epochs, there is a noticeable decrease in forecasting accuracy of psychological scale level on the validation sample. It is explained by the detailed representation of the features and overfitting effect. Figure 7 represents an influence of dimension of feature vector processing using MNN on accuracy and MSE of forecasting of training and validation samples elements. An increase in the number of features can significantly reduce the MSE calculated on the training set. But as the number of epochs of training increases, as in the case of Figure 6, there is also a decrease in the generalizing ability of the MNN on the validation sample.

Correlation of the features with a label of predicted levels of destructive narcissism is provided in Figure 8. The maximum absolute value of correlation is given by the last feature, namely the output value of CNN previously trained on the posts. In Figure 9 the first two principal components of features are represented. The areas containing the objects from different levels overlap each other. Therefore, a narrowing of the dimension of the analysed feature vectors for training neural networks can lead to an increase in prediction errors for the results of the Ammon's test.

In Table 4 the accuracy values calculated on the test sample for four classifiers: MNN, SVM, LR, CNN, are represented. The values presented in this table were averaged over 10 cross-validation folds. To train SVM and LR only 10 scalar parameters from the table 1 were used. For the MNN the training was performed also using the parameters of the second and third groups of source data.

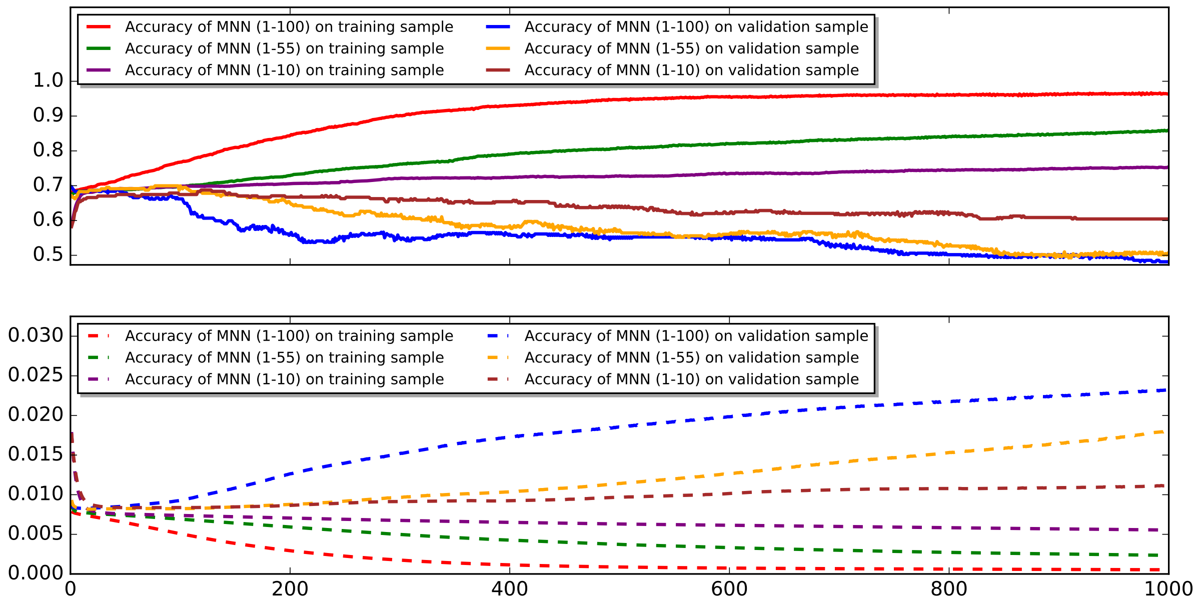

Figure 7: Dependence of accuracy and MSE of MNN rom the epoch number for the psychological scale of destructive aggression

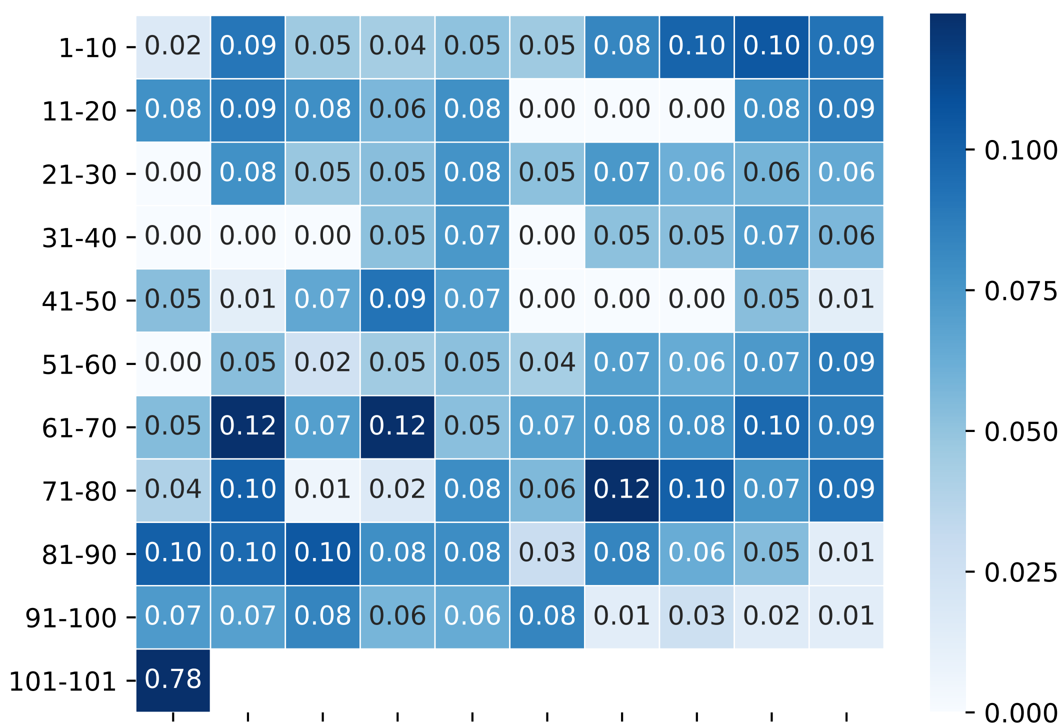

Figure 8: Correlation of features with label of the forecasted levels of destructive narcissism

MNN demonstrates the maximum accuracy value obtained by averaging via six psychological scales of destructiveness. Accuracy of MNN is 61.34% when training using 101-dimensional feature vector. LR possesses the minimum accuracy value. It approves the necessity of introduction of nonlinearity

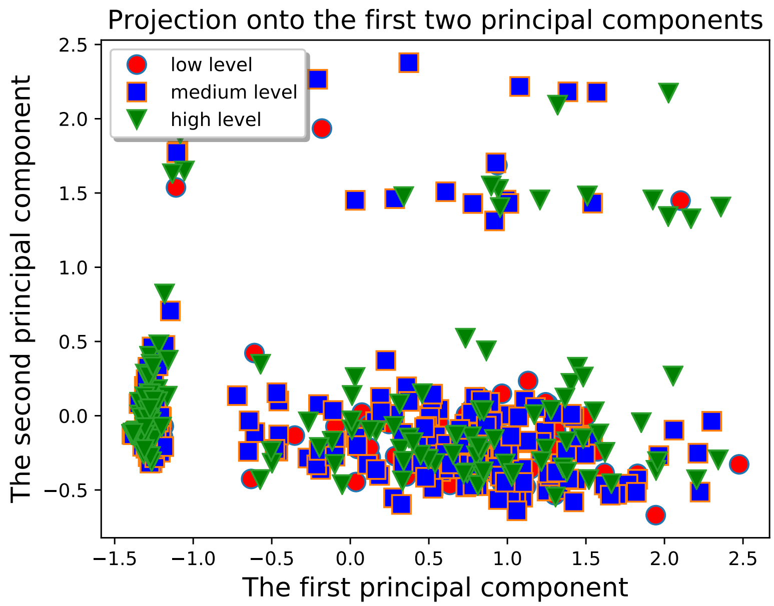

Figure 9: The first two principal components of features for the psychological scale of destructive narcissism

	Classifier						
	MNN (1-10)	MNN (1-55)	MNN (1-100)	MNN (1-101)	SVM (1-10)	LR (1-10)	CNN
Destructive component of the first Ego-function							
Accuracy	68.74%	69.62%	70.1%	70.15%	68.49%	30.89%	64.48%
Destructive component of the second Ego-function							
Accuracy	57.87%	62.18%	59.36%	59.76%	55.4%	41.84%	46.94%
Destructive component of the third Ego-function							
Accuracy	48.96%	49.89%	52.32%	52.82%	48.35%	39.21%	44.51%
Destructive component of the fourth Ego-function							
Accuracy	66.23%	66.47%	66.65%	66.12%	65.07%	30.41%	58.99%
Destructive component of the fifth Ego-function							
Accuracy	50.43%	48.51%	51.39%	51.59%	48.57%	41.12%	43.85%
Destructive component of the six Ego-function							
Accuracy	67.39%	67.62%	67.8%	67.6%	67.79%	47.74%	59.06%
Average value							
Accuracy	59.94%	60.71%	61.27%	61.34%	58.95%	38.54%	52.97%

Table 4: The accuracy values for forecasting the Ammon's test results for four types of classifiers on the test sample

layer for the correct isolation of objects from different classes.

4.5 Discussion

The experiments shown the correlation among the test results and an information on the users' web pages in social networks. At the same time it should be noticed that currently the experiment were conducted only for the limited specific group of the young people. Thus, some additional analysis of their personality traits and environment should be conducted. In its turn, to get the personality traits of persons that can hypothetically lead to some forms of destructive behavior and appropriate features on the web pages of persons in the social networks we need to conduct more deep analysis of the obtained data. To get features on the web pages of persons in the social networks the expert can visually analyse them, for example, it relates to the photos and reposts of the images. In the photo, the experts pay attention to the appearance, posture, gestures, the environment, the scale of the image in the photo and other signs. A repost of photos, memes, slogans and signs can also allow one to detect the text content of personal pages, the number of friends, the composition and approximate orientation of the communities the user is subscribed to. This requires a detailed semiotic analysis of these components.

For further application of these results in scope of the common approach for detection of destructive impacts and their influence an analysis of communities the user is subscribed to is required as well as application of the suggested technique for monitoring of user changes while interacting with these communities.

When analysing groups, the title, cover, avatar and content of two or three dozen recent posts (the number of viewed posts can be increased) should be taken into account, including text, images, animation, video. In addition to the content, the method of material presentation, the frequency of publications with signs of destructiveness, and comments should be also investigated. This also requires a detailed semiotic analysis of these components that will be performed in the future work.

5 Conclusion

The paper described the developed approach to detection of the young people sensitivity to destructive impacts on the basis of information presented by them in the social networks. The main elements of the proposed approach were provided including the techniques that implement it.

The conducted manual testing of the young people using Ammon's test provided the data for neural network learning to forecast the users' sensitivity to destructive stimuli. The conducted experiments shown the relationship between the information provided by the users in the social networks and their psychological profile and their sensitivity to destructive stimuli though the accuracy is not very high yet.

The main challenge while detecting the destructive impacts in the Internet space is connected with a huge amount of information that should be analysed. The proposed approach reduces the amount of the analysed information for the experts and allows them to focus on automatically ranked objects.

Further deep analysis of data that users provide in social networks for the features that represent the personality traits of persons will allow enhancing current results. Besides, in future work we plan to implement two other techniques of the common approach and to use the results of the presented study to detect destructive impacts and their influence in the social networks.

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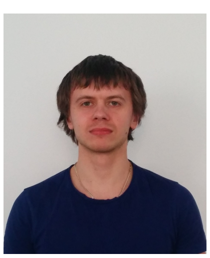

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