Building of Directed Weighted Networks of Terms for Decision-Making Support During Information Operations Recognition

Dmytro Lande[1,2], Oleh Dmytrenko[1](✉), Oleh Andriichuk[1,2](✉), Vitaliy Tsyganok[1,2], and Yaroslava Porplenko[1]

[1] Institute for Information Recording, National Academy of Sciences of Ukraine, Kiev, Ukraine
dwlande@gmail.com, dmytrenko.o@gmail.com, {andriichuk,tsyganok}@ipri.kiev.ua, daliss@ukr.net
[2] National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kiev, Ukraine

Abstract. The study is devoted to automated processing of documents of a subject domain for formation of text corpus, construction of networks of terms and using of these networks for building of knowledge bases of decision support systems during information operations recognition. In this work, for building the undirected networks of terms the Horizontal Visibility Graph algorithm is used.

A new approach for determining the directions and the weights of links in the network of terms that correspond to certain concepts of the considered subject domain is proposed. By its application, an ontological model of the subject domain related to the information operations recognition was built.

A new approach for building the knowledge bases of decision support systems during the information operations recognition using the directed weighted networks of terms of subject domain is proposed. Using it for building of knowledge bases allows saving time and financial resources by reducing the use of expert information and make it possible to detect gaps in the knowledge bases of decision support systems.

Keywords: Information space · Text corpus · Directed weighted networks of terms · Horizontal visibility graph · Decision support system · Knowledge base · Information operation recognition

1 Introduction

The modern information space is characterized by the fast-moving development of dynamic information arrays and flows distributed in webspace.

In the information space such as the Internet, the main results of human communication activity are concentrated.

Today the totality of information, which is accessible online rapidly grows. No doubt, the impact of this information on people is also constantly growing. So, there is a problem of informational influence on people's minds and their decisions. Usually,

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this influence is an intentional (premeditated) and better known as an «information Operation».

Information operations (IO), also known as influence operations, are used in Information Warfare. IO are actions taken to affect adversary information and information systems while defending one's information and information systems. This type of modern warfare is very popular and used by many countries all over the world.

So, in the conditions of the current rapid development of information technologies and their comprehensive and deep penetration into all spheres of human life the task to recognize any manifestations of information operations is an urgent issue.

The consequence of IO is the formation of an information environment that somehow influences society, social groups and individuals within it [1]. IO make it possible to form a certain opinion and attitude in the target audience to some issue, topic, object [2, 3]. It can even provoke some negative social tension [4]. Many experimental studies confirm the presence of the effects of misinformation and gossip, and, as a consequence, the formation of belief in it inside a society [5, 6]. During information operations recognition, information contained in open sources can be used by content monitoring systems that allow building the appropriate directed weighted networks of terms based on this information [7].

On the other hand, IO belong to semi-structured subject domains [8], so it is advisable to use decision support systems (DSS) to recognize IO [9, 10]. In this case, the DSS tools build appropriate knowledge bases (KB) that describe the specifics of the object of the IO and the information environment in which it is located. For the building of the KB along with directed weighted networks of terms expert knowledge and objective information are used. The use of experts requires considerable time and financial costs, as well as the issues solution related to errors (due to human psychophysiological characteristics) and subjectivity of expert assessments. Thus, the reduction of the number of address to experts during the building of the DSS knowledge base is an urgent problem now.

2 Formation of the Corpus of Text Documents

For forming the text corpus, a tool for professionals in the field of information analysis and information warfare – the content monitoring system «Info stream» [11] was used. As a result, 135 publications that thematically related to Brexit were downloaded.

During the formation of the text corpus, it was an open question to define enough texts for complete, reliable and representative coverage of the subject area related to the subjects of the research object. In general, for this purpose, when building models of natural language within the framework of computational linguistics, the certain patterns based on the following effects are used: the appearance of new unique words with appearance new texts in the corpus [12], constancy of the ratio of the number of profile thematic publications to the number of partially profile and a total number of publications [13], constancy of the ratio of word frequency to its rank [14, 15]. The disadvantage of using these regularities is that a sufficient amount of corpus documents will be achieved with a sufficiently large number of processed texts. It, in turn, leads to significant computational costs informing and calculating of this corpus and bulding an appropriate directed weighted network of terms. In addition, a sufficient number of texts may not be achieved due to the limited presentation of some targeted themes in the media. Since the directed weighted network of terms will be used for the further processing within the framework of the building of the DSS KB during the IO recognition, then an advisable condition of a stop is a stabilization of the values of the weights of the corresponding terms during expanding the corpus of the target thematic texts.

Table 1 presents the dynamics of variation of the weight of terms when building the text corpus.

Table 1. Top 28 key words for the text corpus that thematically related to Brexit for different sizes of the corpus.

60 documents		80 documents		105 documents		121 documents		135 documents	
Label	weight	Label	weight	Label	weight	Label	weight	Label	weight
eu	0.03027	eu	0.043649	eu	0.041886	eu	0,042131	eu	0.041618
uk	0.016056	uk	0.037739	uk	0.036625	uk	0,036394	uk	0.035999
brexit	0.011355	leav	0.013201	leav	0.013856	leav	0,014264	leav	0.013976
leav	0.009713	brexit	0.012087	brexit	0.012665	brexit	0,012906	brexit	0.012657
britain	0.008863	vote	0.007993	vote	0.008576	vote	0,009134	vote	0.009089
european	0.008523	countri	0.006734	trade	0.006392	remain	0,006149	trade	0.006483
trade	0.006909	trade	0.006492	countri	0.006273	countri	0,006078	remain	0.005978
vote	0.006881	econom	0.006007	remain	0.006114	trade	0,006078	countri	0.005864
countri	0.006456	remain	0.005983	econom	0.006035	econom	0,005720	econom	0.005489
remain	0.005833	union	0.005159	referendum	0.0053	referendum	0,005684	referendum	0.005473
british	0.00555	referendum	0.005062	peopl	0.004963	campaign	0,005059	campaign	0.005115
econom	0.005324	peopl	0.004723	union	0.004764	peopl	0,004951	peopl	0.004952
europ	0.005324	polit	0.004699	campaign	0.004625	union	0,004808	union	0.004675
referendum	0.005154	market	0.00453	polit	0.004467	polit	0,004522	market	0.004528
union	0.004955	campaign	0.004384	market	0.004367	year	0,004379	year	0.004365
market	0.004701	year	0.004142	year	0.004288	market	0,004290	polit	0.004317
peopl	0.004361	immigr	0.004045	support	0.003831	support	0,003843	govern	0.003893
support	0.004191	support	0.003997	govern	0.003811	govern	0,003718	support	0.003698
member	0.004163	govern	0.003948	immigr	0.003533	immigr	0,003414	member	0.003502
polit	0.004134	member	0.003924	member	0.003474	member	0,003361	immigr	0.003258
immigr	0.004106	nation	0.003754	parti	0.003395	parti	0,003325	nation	0.003225
year	0.004049	parti	0.003488	nation	0.003275	nation	0,003182	parti	0.00303
campaign	0.004021	membership	0.003222	membership	0.003037	membership	0,003057	membership	0.003013
govern	0.003766	free	0.003004	time	0.002918	time	0,002914	time	0.002883

3 Text Corpus Processing

In this work, the tokenization, lemmatization, stop-words removal, stemming process and terms weighting are made.

The tokenization allows separating the text into the set of tokens. The lemmatization process returns the lemmas – the dictionary form of a word [16].

After the pre-procession of the textual documents in this work it is proposed to remove stop-words that informationally unimportant ones. For example, such words as 'the, a, as, are, be' etc. are commonly used in the English language and have no semantic strength. I this work the stop dictionaries [17, 18] were used. Also, we used the stop dictionary that was formed by experts within the considered subject domain.

After the stages described above, the process of stemming was made. Stemming make it possible to combine the words with a common root into a single word. The Porter's algorithm [19, 20], that was used in this work, is the most common and empirically very effective algorithm for stemming English.

The next step of the text corpus processing is an extraction of key terms. For this goal the terms weighting is made. GTF (Global Term Frequency) [21] – a modification of classic statistical weight indicator TF-IDF [22] – is used as a weight of terms to reflect the term to number.

4 Bulding a Directed Network of Terms

To build the undirected network of terms in this work a common Visibility Graph algorithm [23] that maps a time series into a network – the Horizontal Visibility Graph (HVG) algorithm is used. The process of building the Horizontal Visibility Graph consists of two steps and presented in detail in the work [24]. In the first step, the sequences of nodes are marked on a horizontal axis (x-axis) in the order it appears in the text. On a vertical axis (y-axis) the weight indicator GTF is marked. In the second step a classical Horizontal Visibility Graph is built. Two nodes t_i and t_j are connected in the HVG if and only if these nodes are in the «direct visibility». «Direct visibility» between nodes means that they can be connected with the horizontal line which does not intersect any vertical line in the resulting plot.

Thus, the HVG algorithm allows building an undirected network of terms in case, when the numerical values are assigned to separated words or phrases of a thematic text corpus.

In the work [25] the approach for determining the directions of links in undirected networks of terms that correspond to certain concepts of the considered subject domain is proposed. We will use this approach to build a directed network of terms. It is supposed that a causal link exists in the direction from the node t_i to the node t_j in the undirected network if, within the sentence, the term to which the node t_i corresponds precedes the term to which the node t_j corresponds.

As a result of applying a described above approaches, the directed network of terms of a thematic text corpus is built.

5 Determining the Weights of Links

This work proposes a new approach for determining the weights of links between nodes in the directed network of terms based on a thematic text corpus. Using the method described above the directed network of terms is built.

At the graph level, the general principle is described as follows: the nodes corresponding to the same terms of the directed network built at the previous stage are merged. Since any graph is defined by an adjacency matrix, the task of determining the weighted values of the links is reduced to the concatenation of columns and corresponding rows. In other words, it is a weighted compactification of the Horizontal Visibility graph [24].

More formally, the process of determining the weights of links in the network of terms is as follows. Let D be the directed network of terms that built according to the described above rule: $D:= (V,E)$ where V is the set of nodes, E is the set of the ordered pairs of nodes from the set V that correspond to the causal links between the nodes. Let A is a square matrix of size n in which the value of the element a_{ij} is 1 if there is an edge (arc) from vertex i to vertex j else a_{ij} is 0. Let $T = \{t_1, .., t_m\}$ is the set of nodes that corresponds to the same terms of text (where $1 \leq m \leq n$). It is obvious that each node t_k ($1 \leq k \leq m$) in the set T has a column a_{ik} and row a_{kj} in the matrix A. Therefore, the corresponding column (row) elements of all same nodes are summarized and written to a new column (row, respectively) – w_{ik} (w_{kj} respectively), and a new matrix W is formed. As a result of the concatenation process described above, in the resulting matrix W the value of the element w_{ij} is equal to the number of edges from vertex i to vertex j.

Also, the above-mentioned process of the concatenation of columns (rows) uses the so-called hash table of similar or synonymous terms that correspond to the same concepts. This table is formed by experts within the considered subject domain. This table makes it possible to further merge nodes that correspond to the same terms in the text.

The resulting matrix W defines an oriented weighted graph formed of nodes that correspond to the unique terms within the considered text. The weight of the edge connecting the vertex i to the vertex j is defined by the number of appearances of the term to which the node t_i corresponds before the term to which the node t_j corresponds (the number of occurrences of an element t_i of the time series before the element t_j) in the considered text.

6 Building of Knowledge Bases of Decision Support Systems During Information Operations Recognition

The building of the KB of DSS is carried out within the framework of the method of hierarchical decomposition and complex target-oriented dynamic evaluation of alternatives [26]. At first, decomposition of the main goal into elementary sub-goals (factors, criteria) that are its constituents and directly influenced by it is performed. Then there is a decomposition of each component into respective sub-goals and so on. The decomposition process of goals stops when direct actions (projects) are received as sub-goals within the next decomposition [10]. In addition to expert knowledge, decomposition can also use objective information (for example, the values of certain target indicators). After the decomposition process of goals is completed, each decomposition calculates the partial impact coefficients (PIC) of the sub-goals on the respective goal. To do this, the expert estimation with the software tools of DSS is used. In the area of IO recognition, we have as projects specific themes of publications related to the object of IO. Thus, using DSS tools it is possible to calculate recommendations in the form of ranking of information impact of publications themes on the object of IO.

It is supposed that there is a sufficiently high quality directed weighted network of terms (of sufficient volume, representative, without errors, without redundancy and with a sufficient level of stability of weights) that is built using the content monitoring system of the IO subject domain. It is the initial network of terms, which will be used later.

The process of building the DSS KB using the directed weighted networks of terms during IO recognition is proposed:

1. The preliminary building of the DSS KB is carried out with the use the content monitoring and expert information [27, 28], a number of decompositions are defined, within which the appropriate PIC must be determined.
2. An analysis of the initial directed weighted network of terms in order to define the completeness of coverage of the subject domain is performed. Also, the pre-built DSS KB and the selected decomposition is taken into account. A situation might arise, for example, when not all decompositions are sufficiently covered by the network of terms. For such decompositions, other available approaches to determining the PIC [28, 29] or even consult experts are used.
3. For each "covered" decomposition, the necessary level of abstraction and stratification and corresponding terms of the initial network that correspond to each of the objects of the selected decomposition are determined.
4. A new network of terms is formed by merging certain nodes of the initial network according to each of the objects of the selected decomposition (goals and sub-goals).
5. The values of the impact of sub-goals on the target by the method of the optimal impact are determined [7]. The obtained values of the impacts are normalized and entered in the DSS KB as the appropriate PCI.
6. Next move on to step 3 until we go over all "covered" decompositions.

The advantages of the proposed approach are as follows: saving time and financial resources by reducing the use of expert information; the possibility of detecting gaps in the DSS KB during the analysis of the initial directed weighted network of terms; objectification of the PCI definition.

The disadvantages of the proposed approach are the complexity and, sometimes, the ambiguity of finding the conformity between some rather complex and broad goals and the terms of the network; the lack of the ability to apply the approach to other areas other than IO recognition.

7 Practical Example

Described above approaches are illustrated by the example of Brexit. Currently, Brexit is a topical issue that is widely researched by the scientific community [30]. Applying the stages of the computerized processing of text corpus described above, the key links between the nodes were extracted. The Python programming language and its module NLTK (Natural Language Toolkit open-source library) [31] are used to build the software realization of the proposed and considered approaches and methods.

Table 2 shows the list of the most influential and significant links between the corresponding nodes in the network of terms that, in turn, correspond to certain concepts of the considered subject domain.

Table 2. Top 17 significant links for the corpora «Brexit».

№	Source	Target	Weight
1	uk	eu	889
2	leav	eu	404
3	eu	uk	319
4	brexit	uk	213
5	vote	leav	211
6	eu	union	174
7	uk	leav	145
8	remain	eu	120
9	brexit	eu	102
10	leav	uk	95
11	trade	eu	88
12	eu	leav	77
13	eu	countri	73
14	eu	membership	72
15	uk	vote	69
16	leav	campaign	66

Using the software for modeling and visualization of graphs – Gephi [32, 33], the directed weighted network of terms was built and visualized (Fig. 1). Figure 1 depicts the key words of the considered subject domain.

Also, using the Gephi software tools, the following parameters of the built network were obtained: the number of nodes is 28; the number of links is 640; the net-work density is 0.847; the number of connected components is 1; the average path length is 1,153; the average clustering coefficient is 0.856.

After analyzing the obtained results, it was established that the most significant links between the corresponding nodes in the network of terms built for the subject domain Brexit are: «uk → eu», «leav → eu», «eu → uk», «brexit → uk» and «vote → leav» (Fig. 2).

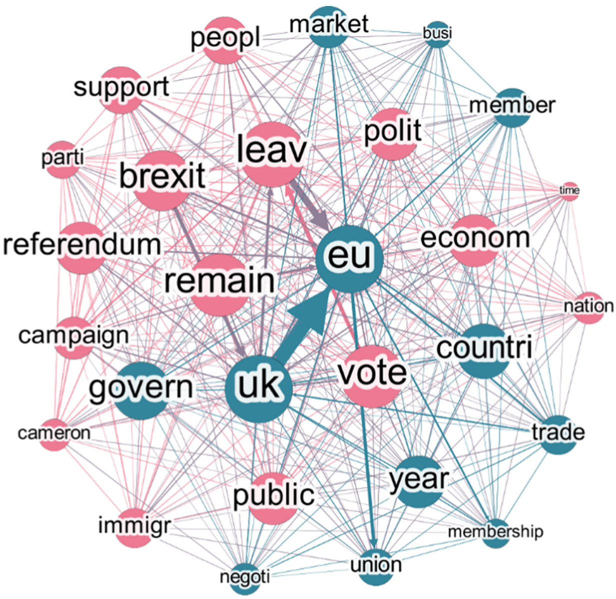

Fig. 1. The directed weighted network of terms for Brexit.

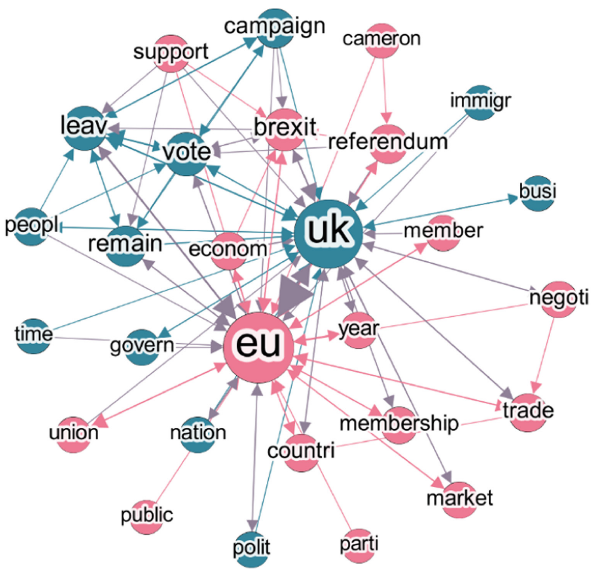

Fig. 2. The directed weighted network of terms for Brexit with the strongest links.

Within the framework of this practical example, let consider the fragment of the building of the DSS KB during IO recognition using the directed weighted network of terms. Let consider the decomposition of the “Brexit” goal, which has the following sub-goals: “Economic factors of Brexit”, “Social factors of Brexit” and “Partial loss of sovereignty of UK”. As a result of the analysis, the terms of a directed weighted network (Fig. 3) that cover these decompositions are determined. The following network terms as “brexit”, “uk” and “eu” correspond to the goal “Brexit”. The following network terms as “econom”, “market”, “busi” and “trade” correspond to the sub-goals “ Economic factors of Brexit”. The following network terms as “immigr” and “peopl” correspond to the sub-goals “Social factors of Brexit”. The following network terms as “nation”, “countri” and “govern” correspond to the sub-goals “Partial loss of sovereignty of UK”. By merging the mentioned above nodes of the initial network in accordance with the main goal and sub-goals of the decomposition, the new network of terms is built (Fig. 3).

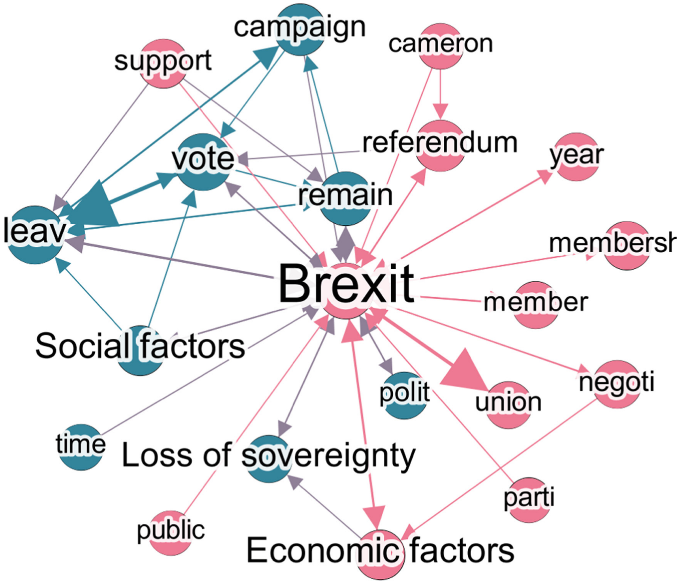

Fig. 3. The directed weighted network of terms after decomposition.

The value of the impact of these sub-goals on the goal is determined by using the method for searching the optimal impact [7]. Then we normalize these values and get the corresponding PICs for the decomposition in the KB of DSS. As a result of these calculations and after rounding the following values of the PIC were obtained. So, the PIC of the sub-goal “Economic factors of Brexit” is 0.5, the PIC of the sub-goal”Social factors of Brexit” is 0.29 and the PIC of the sub-goal “Partial loss of sovereignty of UK” is 0.21.

8 Conclusion

In this work, the approach for determining the weights of links in the network of terms was proposed. The directed weighted network of terms was built for the thematically targed subject domain.

The approach was suggested for building of knowledge bases of decision support systems during information operations recognition which allows to provide the decomposition of the topics of the information operations and assess rating of the effectiveness of these topics.

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