# Ukrainian Conflict in Media: Two Approaches to Narrative Analysis

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## *ABSTRACT*

*Internet media is one of the most important tools to influence public opinion as well as reflect it. In this paper we analyze reflection of dynamics of Ukrainian conflict in BBC, RussiaToday, DayKiev and delfi.lt (main Lithuanian news portal). We apply two different approaches for the analysis: co-occurrence networks analysis to reflect change of rhetoric in four different media channels during conflict and sentiment-based storyline (syuzhet) analysis to monitor sentiment change in BBC from 2013 to 2014. We split conflict into three stages: beginning (Nov 21, 2013 – Jan 15, 2014), escalation (Jan 16, 2014 - Feb 17, 2014) and occupation of Crimea (Feb 18, 2014 – Feb 28, 2014). These approaches allow visual analysis of the conflict dynamics in media. Such application of Artificial Intelligence, Natural Language Processing and visualization techniques for big data allows better understanding of reflection of conflict dynamics and public mood on specific topics, automation of information analysis.*

## 1.0 INTRODUCTION

In narrative analysis it is essential to understand the sequence in which events occur [1, pp. 2-16]. Recent studies on narrative analysis focus on different types of events, e. g. linguistic-based narrative analysis of YouTube accounts [2]. It was used to describe common attributes of the narratives as well as to identify a list of shared thematic and linguistic characteristics. Study [3] reported how narratives were used by extremist organization. The researchers built a network of stories linked according to their semantic similarity. Moreover, it explored how narrative in social media shapes the vision of future by justification of present and explanation of past [4]. This study also showed how interconnected narratives provide intent and justification for different target audiences. Yet another study presented a case and usage of individual narrative [5]. According to this study, individual narratives help people to make sense of the world as well as shape and express their ideology, including the political functions.

Usually narratives present events in chronological order, e.g., novels, personal retelling of experiences, etc. However, in news articles narratives differ from other types of narratives as they follow a complex time structure. In producing news stories, journalists present the events in “instalments”, thus an event that was introduced in the earlier parts of a story may be described in detail later, sometimes in multiple instances [6, pp. 147-174]. Therefore, events in news stories are usually presented in a non-chronological order, i.e., in the news stories storyline or syuzhet often does not match the chronological order of the events.

In this paper we analyze reflection of dynamics of Ukrainian conflict in BBC, RussiaToday, DayKiev and delfi.lt (main Lithuanian news portal). We apply 2 different approaches for the analysis: word co-occurrence networks to reflect change of rhetoric in four different media channels during conflict as well as sentiment-based storyline (syuzhet) analysis to monitor sentiment change in BBC from 2013 to 2014.

## 2.0 DATA

We used 2 datasets for our research:

1. results of qualitative discourse analysis of media articles (BBC, RussiaToday, DayKiev and delfi.lt),

2. raw BBC articles.

The first dataset was prepared by the team of students mentored by scientists during the project “Research Meadow / Mokslo pieva”. Media articles were collected from 4 different media sources: BBC, RussiaToday, DayKiev and delfi.lt, from November 21, 2013 till February 28, 2014. This period covered 3 stages of the Ukrainian conflict, see table 2-1 for some of the more important events for each of the Ukrainian conflict.

**Table 2-1: Some of the more important events during 3 stages of Ukrainian crisis.**

| Conflict stage | Events |
|---|---|
| 1st (2013 11 21-2014 01 15) | ● V. Yanukovych postpones the signing of an association agreement with the EU.<br>● Y. Tymoshenko is prevented from leaving Ukraine.<br>● Large-scale protests begin.<br>● Over 100,000 people participate in weekly demonstrations in Kiev.<br>● First clashes with riot police and arrests occur.<br>● In early December, over 800,000 people participate in demonstrations in Kiev. |
| 2nd (2014 01 16-02 17) | January 16-23<br>● The Supreme Rada adopts anti-demonstration law.<br>● First deaths.<br>● Raid of government buildings in western Ukraine.<br>January 28-29<br>● The Prime Minister resigns.<br>● The laws directed against the protests are annulled. |
| 3rd (2014 02 18-28) | ● Clashes begin in earnest: casualties on both sides – protesters as well police.<br>● Agreement between opposition and V. Yanukovych (02 21)<br>● Y. Tymoshenko is liberated, Yanukovych leaves the country (02 22).<br>February 27-28<br>● Russian forces occupy the Crimean parliament building.<br>● Russian troops are deployed to airports and other strategic sites. |

Qualitative discourse analysis was performed for these media articles, identifying actors, qualities they were attributed to, predicates of events as well as the qualities they were attributed to. This analysis was performed for BBC, RussiaToday, DayKiev and delfi.lt articles separately. We used the dataset of these results for our narrative analysis via word co-occurrence networks.

The second dataset consists of raw BBC articles, covering the same 3 stages of Ukrainian crisis as described above. The articles were grouped according to the conflict stage they described, and no pre-processing of the texts was performed. We used this dataset for our sentiment-based storyline analysis.

# 3.0 METHODS

We used 2 methods for narrative analysis in terms of Ukrainian crisis. The first one is word co-occurrence network analysis and the second one – sentiment-based storyline analysis. We used word co-occurrence networks with dataset containing results of qualitative discourse analysis of media articles (BBC, RussiaToday, DayKiev and delfi.lt), while for sentiment-based storyline analysis we used raw BBC articles. In the following sections we describe these 2 methods in more detail.

## 3.1 Word Co-occurrence Network

Network analysis describes a group of methods that characterize relationships between units to be analysed, i.e. nodes representing units to be analyzed and edges representing connections between nodes. Network analysis is often used in the context of social networks, where nodes usually represent people, while edges refer to friendships, affiliations or other types of relationships [7], [8, p. 10]. Though network analysis is most often used in terms of relationships between people, it can also be applied to represent relationships between words, e. g. [9], [10], [11]. Word co-occurrence network analysis is text length insensitive method thus it is suitable even when dataset is made of short texts or just texts of uneven length [12]. For word co-occurrence network analysis we used *textnets*[1] package for R[2].

Word co-occurrence network analysis was performed for our first dataset, made of results of qualitative discourse analysis of media articles (BBC, RussiaToday, DayKiev and delfi.lt). The textual data was tokenized and then lemmatized i.e., each word was replaced with its most basic syntactic form [11]. Then part-of-speech tagger (integrated into *textnets*, based of language models of Universal Dependencies project[3]) was applied in order to identify nouns and noun phrases which most likely describe content of the text [12]. In the next step term frequency-inverse document frequency (TF-IDF) was characteristic was calculated for each noun and noun phrase. This characteristic was calculated for each stage of the conflict (see Table 2-1) separately. Then a bipartite word co-occurrence networks were generated for each stage of the conflict. These bipartite networks linked media sources (BBC, RussiaToday, DayKiev and delfi.lt) based on terms (nouns and noun phrases) in their messages. Finally the community detection algorithm was applied in order to detect similarities in the selected media sources in terms of reporting on the Ukrainian conflict [11], [12]. The results of word co-occurrence networks regarding Ukrainian conflict is presented in Section 4.1.

## 3.2 Sentiment-Based Storyline Analysis

Sentiment analysis is important task of Natural Language Technologies and Artificial Intelligence, with applications such as automated analysis of reviews and social media, monitoring of political issues, etc. [13]. Sentiment analysis assumes that emotions are important in communication among humans. Some recent work in terms of analysis of literary texts has suggested that shifts in sentiment can be used for analysis of plot development [14, pp. 73-110]. As the raw sentiment time series is very noisy, a smoothing filter is usually applied for the raw data [15]. The result is a fairly smooth curve which represents generalized trend of the sentiment development of the text. This method is based on controlled vocabulary and data compression. For sentiment-based storyline analysis we used package *syuzhet*[4] for R.

[1] https://github.com/cbail/textnets

[2] R is a software environment (free) for statistical computing and graphics, see: https://www.r-project.org/

[3] https://universaldependencies.org/

[4] https://cran.r-project.org/web/packages/syuzhet/

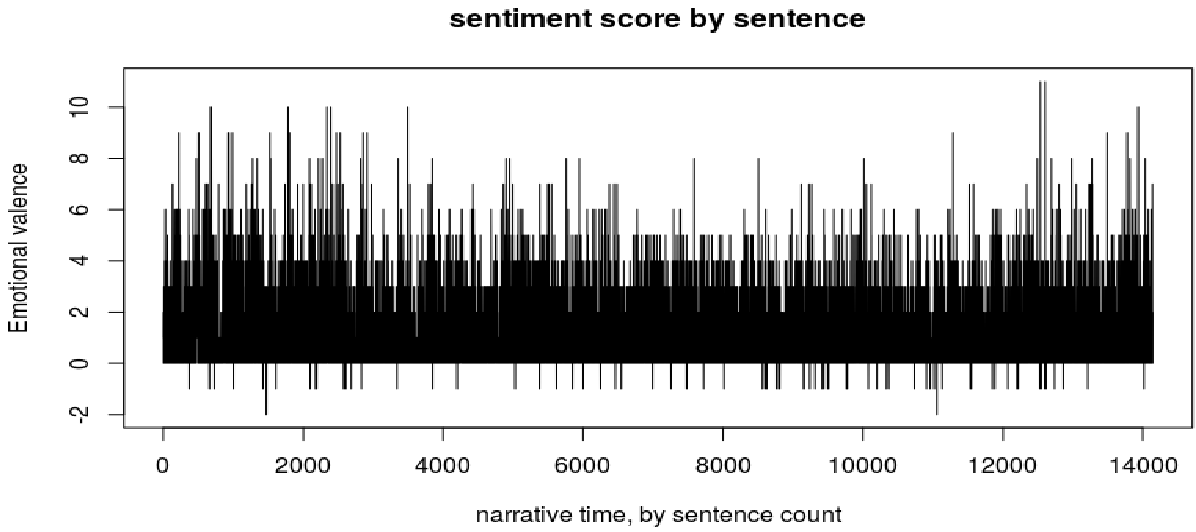


**Figure 3-1: Example of raw sentiment plot.**

Sentiment-based storyline analysis was performed for our second dataset, made of raw BBC articles, covering 3 stages (see Table 2-1) of the Ukrainian conflict. This analysis was applied for the articles grouped by the stage of the conflict they covered. Sentiment analysis was used to detect latent structure of narrative concerning reporting of Ukrainian conflict. Narrative process (development) in this analysis was marked by emotional shifts. Firstly, texts were tokenized into sentences. Then for each sentence sentiment value was calculated. For these calculations NRC Emotion Lexicon[5] [16], integrated into R package *syuzhet*, was used. The words in each sentence are assigned a sentiment value according to their emotional intensity and polarity. When a sentiment value is absent, the word is assigned a value of zero (neutral). Then emotional score of each sentence is estimated by aggregating the word-sentiment values.

As we calculate sentiment values for every sentiment, the cumulative results of all sentences belonging to certain Ukrainian conflict stage is “noisy” and non-interpretable for human eyes (see Figure 3-1). For generalized sentiment trajectory Discrete Cosine Transformation (DCT) was applied [17]. After that, the sentiment trajectory was sub-sampled to have 100 elements so that sentiment arcs of BBC news coverage for each stage of Ukrainian conflict could be represented from 0% (beginning of the textual data belonging to certain stage of Ukrainian conflict) to 100% (end of the movie of the textual data belonging to certain stage of Ukrainian conflict). This transformation was used to extract sentiment and sentiment-derived plot arcs from text. Finally, as NRC Emotion Lexicon allows dataset evaluation not only according to polarity scale (positive-neutral-negative), but also according to prevalence of 8 emotions (anger, fear, anticipation, trust, surprise, sadness, joy, disgust), we generated emotional “profiles” for BBC coverage of 3 stages of Ukrainian conflict. The results of sentiment-based storyline analysis of Ukrainian conflict are presented in Section 4.2.

# 4.0 RESULTS

In this section we present results of 2 approaches to narrative analysis. In Section 4.1 we present results of word co-occurrence networks for news coverage of 3 stages of Ukrainian conflict by 4 media sources – BBC, RussiaToday, DayKiev and delfi.lt. In this approach narrative of the conflict was analyzed based on relations (co-occurrences) of nouns and noun phrases in the messages of these 4 media sources for each stage of the conflict separately. In Section 4.2 we present results of sentiment-based storyline analysis of news coverage of the same 3 stages of Ukrainian conflict by BBC. In this approach narrative of the conflict was

[5] http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

analyzed based on emotional shifts in the textual data and generation of plot trajectories as well as emotional "profiles".

## 4.1 Results of Word Co-occurrence Network Analysis

Figure 4-1 presents word co-occurrence network made of nous and noun phrases for the 1st stage of Ukrainian conflict (2013 11 21-2014 01 15). As it was presented in Table 2-1, some more important events during the 1st stage of Ukrainian conflict were V. Yanukovych's postponement to sign an association agreement with the EU, Y. Tymoshenko's prevention from leaving Ukraine, the beginnings of large-scale protests and demonstrations.

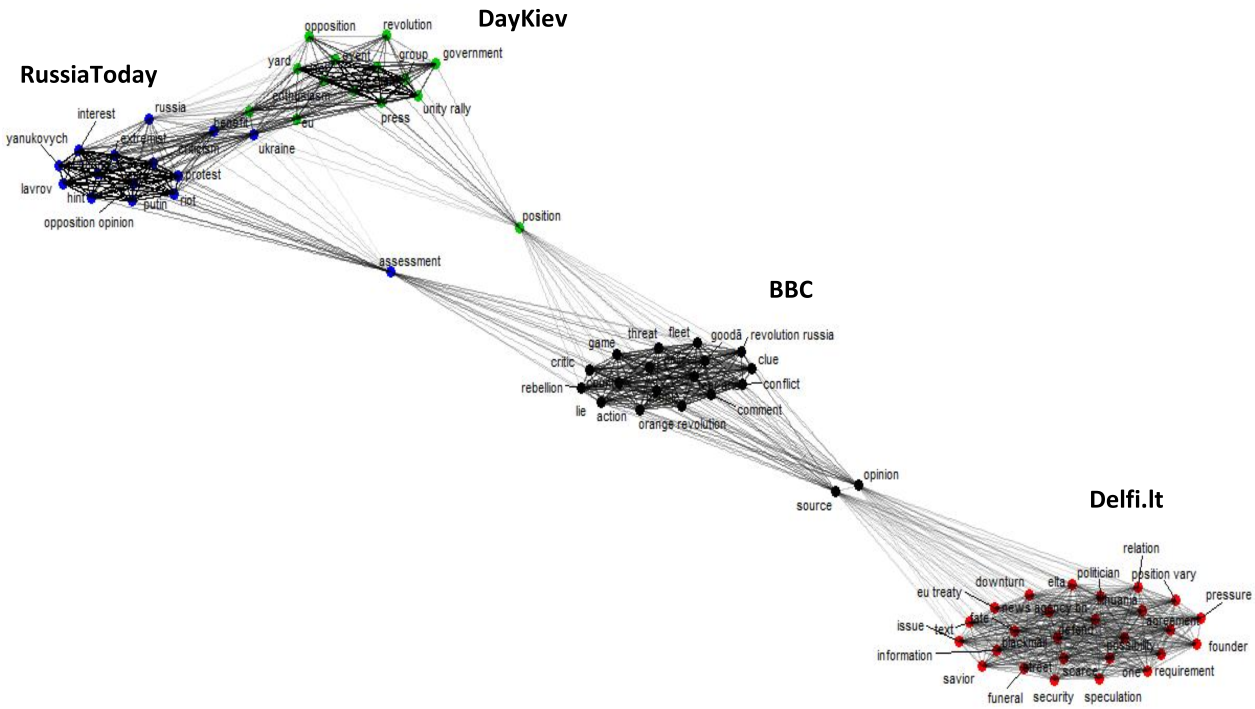


**Figure 4-1: Word co-occurrence network: 1st stage of Ukrainian conflict (alpha=0.5).**

As Figure 4-1 shows, in RussiaToday messages Nov 21, 2013 – Jan 15, 2014 names of politicians as important actors in the conflict are distinguished ('yanukovych', 'lavrov', 'putin'). Naturally, names of the countries involved in the conflict are frequent as well ('russia', 'ukraine'). Events during beginning stage of 'Euromaidan' by RussiaToday was described as 'protest', 'riot', 'criticism', 'extremist', 'interest', 'benefit', 'opposition opinion'. DayKiev spread messages about 'eu', 'enthusiasm', 'press', 'unity rally', 'government', 'group', 'revolution', 'event', 'opposition', 'yard'. Although these 2 media sources were supposed to be on the opposite sides of the reporting, word clusters that represent the most frequent topics in reporting are close to each other indicating similarities in news coverage. Words 'ukraine' (blue color; belongs to RussiaToday cluster) and 'benefit' (green color; belongs to DayKiev cluster) could be treated as so called "cultural bridges" [11] that link RussiaToday and DayKiev messages about 1st stage of Ukrainian conflict. "Cultural bridges" are terms (nouns and noun phrases in our case) that lie between clusters and act as bridges by linking disjoint discourses [12].

BBC reporting was distinguished by describing events as 'rebellion', 'conflict', 'game', 'threat', 'lie', 'action', 'orange revolution', 'revolution russia'. Words 'comment', 'clue', fleet', 'critic' were important in BBC messages as well. BBC and DayKiev messages on the conflict were linked by word 'position', while

BBC and RussiaToday messages were linked by ‘assessment’ acting as “cultural bridge”. Finally, delfi.lt messages contain words ‘eu treaty’, ‘downturn’, ‘elta’, ‘politician’, ‘lithuania’, ‘position vary’, ‘relation’, ‘pressure’, ‘agreement’, ‘founder’, ‘requirement’, ‘possibility’, ‘defend’, ‘security’, ‘speculation’, ‘scarce’, ‘street’, ‘funeral’, ‘blackmail’, ‘savior’, ‘information’, ‘issue’, ‘fate’, etc. Words ‘source’ and ‘opinion’ as “cultural bridges” link delfi.lt and BBC messages together.

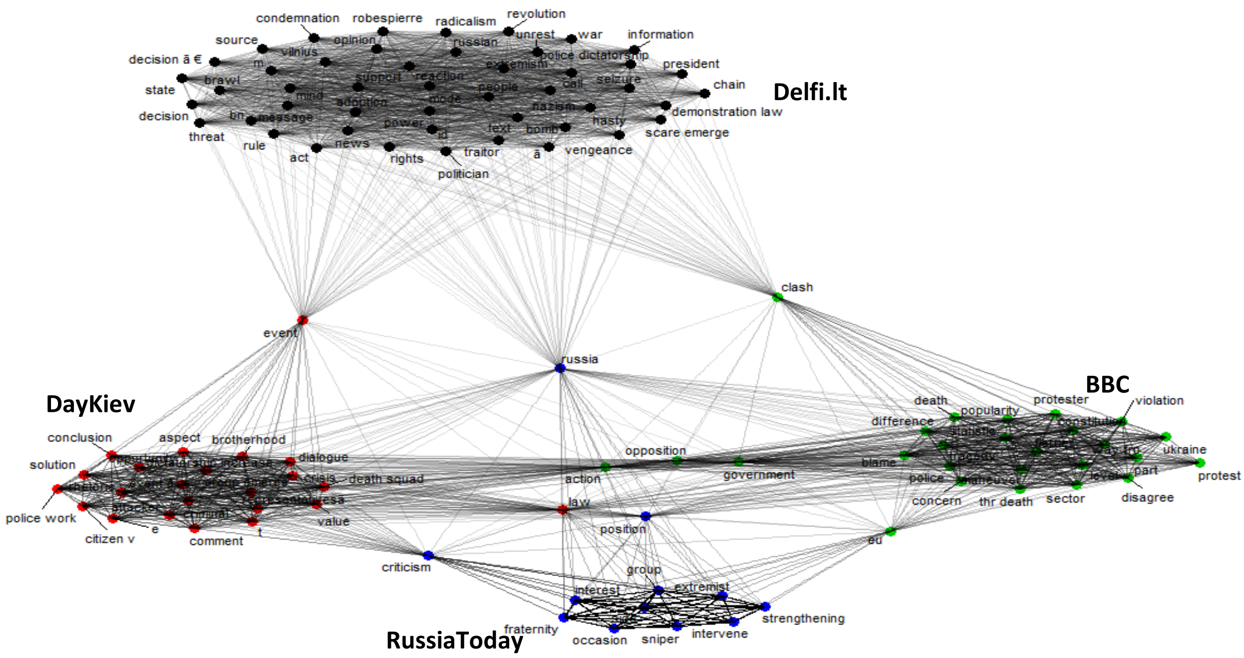


**Figure 4-2: Word co-occurrence network: 2nd stage of Ukrainian conflict (alpha=0.6).**

2nd stage of Ukrainian conflict (Jan 16, 2014 - Feb 17, 2014) can be described as *escalation* because during this period first deaths occurred, raiding government buildings in western Ukraine took place, etc. (see Table 2-1). As Figure 4-2 shows, RussiaToday during this period spread messages about ‘fraternity’, ‘occasion’, ‘sniper’, ‘intervene’[6], ‘strengthening’, ‘extremist’, ‘group’, ‘occasion’, ‘interest’, etc. Meanwhile, DayKiev focused on ‘police work’, comment’, solution’, ‘conclusion’, ‘rhetoric’, ‘opportunity’, ‘attacker’, ‘criminal’, ‘value’, ‘crisis’, ‘death squad’, ‘dialogue’, ‘brotherhood’, etc. Word ‘criticism’ links DayKiev and RussiaToday as “cultural bridge”, i. e., discursive theme that is seldom discussed but have a potential to attract feedback and opinion from public [11]. BBC reporting on *escalation* of Ukrainian conflict focused on ‘difference’, ‘blame’, ‘death’, ‘popularity’, ‘tragedy’, ‘maneuver’, statistic’, ‘constitution’, ‘violation’, ‘police’, ‘concern’, ‘disagree’, ‘protest’, ‘protester’, ukraine’, ‘sector’, etc. BBC and RussiaToday narratives are connected by ‘eu’ (green; belongs to BBC). 3 words – ‘event’ (red – DayKiev) , ‘russia’ (blue – RussiaToday) and ‘clash’ (green – BBC) link narratives of all 4 news sources (see Figure 4-2). Narratives of RussiaToday, DayKiev and BBC were linked by ‘law’ (red – DayKiev) and ‘position’ (blue – RussiaToday). DayKiev and BBC narratives had 3 “cultural bridges”: ‘action’, ‘opposition’, ‘government’ (all green, belong to BBC word cluster). Finally, delfi.lt narrative told about ‘state’, ‘decision’, ‘rule’, ‘condemnation’, ‘opinion’, ‘robespierre’, ‘radicalism’, ‘revolution’, ‘unrest’, ‘war’, ‘dictatorship’, ‘rights’, ‘president’, ‘demonstration law’, ‘vengeance’, ‘politician’, ‘traitor’, ‘reaction’, ‘support’, ‘power’, ‘people’, ‘seizure’, etc. Based on Figure 4-2, it might be assumed that delfi.lt narrative was the most diverse while RussiaToday – the least diverse in terms of discursive themes (size of cluster).

[6] Part-of-speech tagger was not always successful in correctly recognizing nouns.

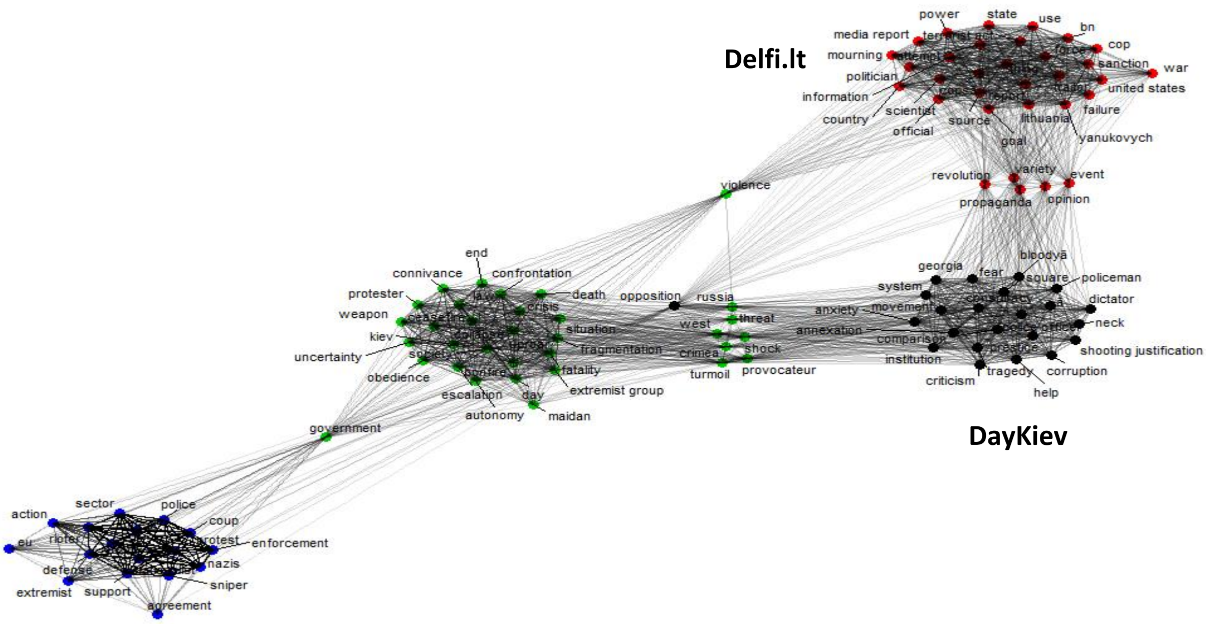


**Figure 4-3: Word co-occurrence network: 3rd stage of Ukrainian conflict (alpha=0.4).**

3rd stage of Ukrainian conflict (Feb 18 – 28, 2014) is exceptional due to casualties on both sides – protesters as well police, – and agreement between opposition and Yanukovych, liberation of Tymoshenko, Yanukovych 's escape from Ukraine and its final event was occupation of Crimea (see Table 2-1).

As Figure 4-3 shows, reporting of RussiaToday featured 'eu', 'extremist', 'police', 'coup', 'protest', 'enforcement', 'rioter', 'defence', 'support', 'protest', 'nazis', 'agreement', 'sniper', 'action', 'sector' discursive themes. BBC coverage of the 3rd stage of Ukrainian conflict spread messages about 'uncertainty', 'obedience', 'kiev', 'weapon', 'protester', 'end', 'confrontation', 'death', 'situation', 'fragmentation', 'extremist group', 'fatality', 'connivance', 'law', 'ceasefire', 'collapse', 'uproar', 'autonomy', 'maidan', 'crisis', 'escalation', etc. Word 'government' (green, belongs to BBC cluster) lies between RussiaToday and BBS cluster, acting as a bridge between narratives of these media channels. Furthermore, delfi.lt reported about 'mourning', 'information', 'media report', 'terrorist act', 'country', 'scientist', 'power', 'state', 'use', 'war', 'failure', 'cop', 'sanction', 'united states', 'lithuania', 'goal', 'force', 'yanukovych', etc. Finally, DayKiev featured 'georgia', 'fear', 'bloody'[7], 'square', 'policeman', 'conspiracy', 'dictator', 'neck', 'police officer', 'shooting justification', 'prestige', 'corruption', 'help', 'tragedy', 'criticism', 'comparison', 'institution', 'anxiety', 'annexation', 'movement', 'system'. Words 'russia', 'threat', 'west', 'shock', 'crimea', 'turmoil' and 'provocateur' (all green, belong to BBC) link narratives of BBC and DayKiev together. BBC and delfi.lt narratives were bridged by discursive theme of 'violence' (green dot between BBC and DayKiev clusters). Finally, words 'revolution', 'propaganda', 'variety', 'opinion' and 'event' (red dots between delfi.lt and DayKiev clusters) act as bridges for delfi.lt and DayKiev narratives.

Beside analysis of the whole networks representing narratives of media coverage of 3 stages of Ukrainian conflict, we also identified communities, i.e., grouped media channels according similarity of their narratives. For this task Louvain community detection algorithm [18] was applied. Thus, for the 1st stage of Ukrainian conflict 2 groups were discerned: 1) DayKiev and delfi.lt, 2) RussiaToday and BBC. Top nouns and noun phrases that distinguish narratives of these two groups are presented in Table 4-1.

[7] Again part-of-speech tagger did recognize some nouns correctly.

Table 4-1: Similarity of narratives: 1st stage of Ukrainian conflict.

| DayKiev & delfi.lt | RussiaToday & BBC |
|---|---|
| action | benefit |
| clue | criticism |
| comment | enthusiasm |
| conflict | event |
| country | government |
| critic | group |
| fear arise | hesitant |
| fleet | lack |
| game | press |
| lie | unity rally |
| orange revolution | yard |

Interestingly enough, for the 2nd stage of the Ukrainian conflict all 4 media channels fell into the same group. This leads to the assumption that for this stage of the conflict narratives of BBC, DayKiev, delfi.lt and RussiaToday were not that different, or discussions were wide enough to include different options. Another possibility, which slightly complicates things, is application of terms, as extremist to opposing sides by different media channels. Top nouns and noun phrases of collective narrative of 4 media channels are presented in Table 4-2.

Table 4-2: Collective narrative of the 2nd stage of Ukrainian conflict.

| DayKiev & delfi.lt & RussiaToday & BBC |
|---|
| protester |
| extremist |
| fraternity |
| group |
| interest |
| intervene |
| occasion |
| side |
| sniper |
| strengthening |

Table 4-3: Similarity of narratives: 3rd stage of Ukrainian conflict.

| DayKiev & delfi.lt | RussiaToday & BBC |
|---|---|
| dictator | action |
| georgia | appear |
| attempt | coup |
| cop | defence |
| country | enforcement |
| failure | group |
| force | nationalist |
| goal | nazis |
| yanukovych | police |

| | |
|---|---|
| information | protester |
| media report | rioter |
| mourning | sniper |

For the 3rd stage of the Ukrainian conflict we again discerned the same 2 communities as for the 1st stage of the conflict: 1) DayKiev and delfi.lt, 2) RussiaToday and BBC. Top nouns and noun phrases that distinguish narratives of these two groups are presented in Table 4-3. Comparing top terms (nouns and noun phrases) of the 1st and the 3rd stages of Ukrainian conflict, it was observed that word ‘country’ remains for the both cases for the group DayKiev + delfi.lt, while the same goes for the group BBC + RussiaToday in terms of word ‘group’. Top nouns of the 2nd stage of Ukrainian conflict did not have matches for the group DayKiev + delfi.lt neither in the 1st, nor in the 2nd stage of the conflict. However, 3 of the top nouns of the 2nd stage of Ukrainian conflict matched the ones for the group BBC + RussiaToday: ‘protester’ and ‘sniper’ – 3rd stage of the Ukrainian conflict, ‘group’ – 1st as well as 3rd stage of the conflict.

## 4.2 Results of Sentiment-Based Storyline Analysis

In this section we present results of sentiment-based storyline analysis in terms of BBC narrative regarding 3 stages of Ukrainian conflict (see Table 2-1). Firstly, we discuss emotional shifts representing narrative development in BBC reporting (Section 4.2.1). After that we discuss emotional “profiles” of BBC narratives in terms of 3 stages of Ukrainian conflict (Section 4.2.2).

### 4.2.1 Sentiment-Based Plot “Arcs”: Emotional shifts as Narrative Development in BBC Coverage of Ukrainian Conflict

In this section we present results of sentiment-based storyline analysis of BBC coverage of Ukrainian conflict. Generalized sentiment values allow generation of plot trajectory curves (or arcs) in terms of polarity scale (positive-neutral-negative). These plot arcs represent emotional shifts in the reporting on 3 stages of Ukrainian conflict (see Table 2-1) separately. Emotional shifts in our study was used to evaluate narrative development in BBC coverage of the conflict.

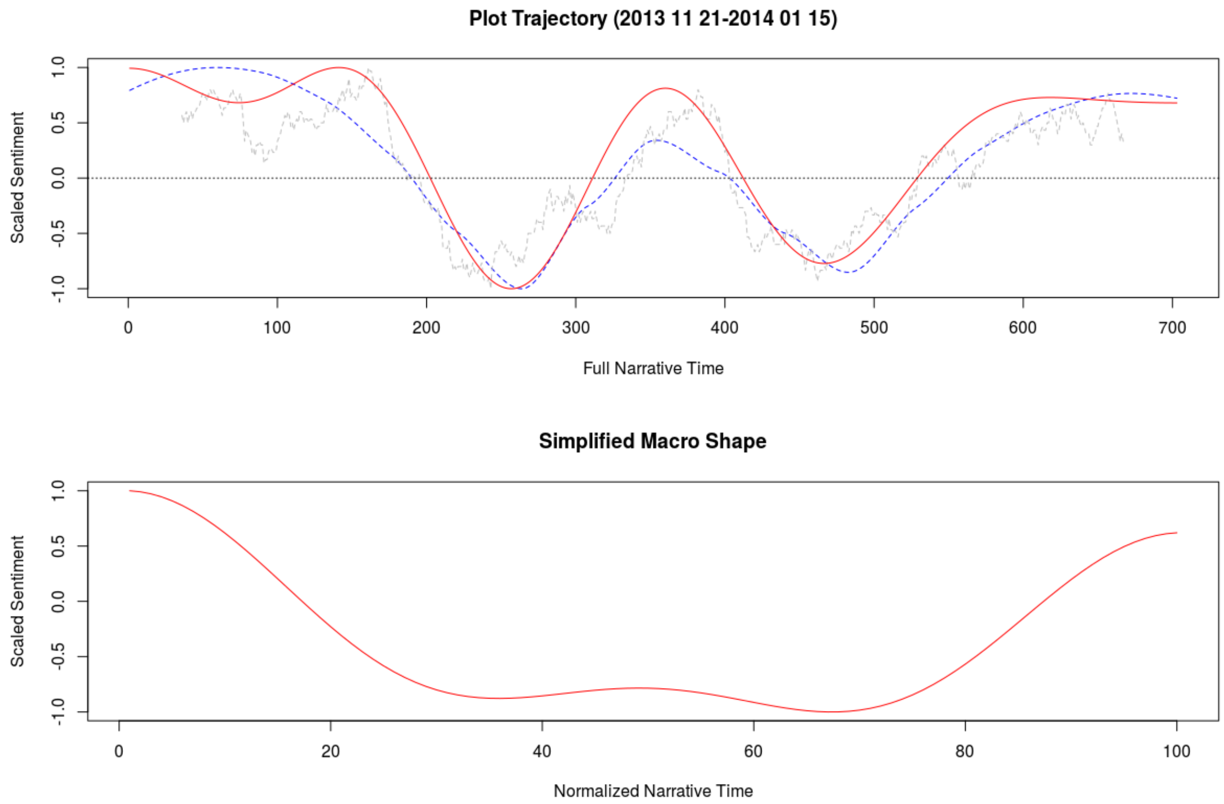


**Figure 4-4: Sentiment-based Narrative Trajectory: 1st stage of Ukrainian conflict.**

Figure 4-4 shows sentiment-based narrative trajectory for the 1st stage of Ukrainian conflict (Nov 21, 2013 – Jan 15, 2014), Figure 4-5 represents sentiment-based narrative trajectory for the 2nd stage of Ukrainian conflict (Jan 01 – Feb 17, 2014) and Figure 4-6 – narrative trajectory for the 3rd stage of Ukrainian conflict (Feb 18-28, 2014). Upper diagrams represent full narrative time (measured in number of sentences that comprise our dataset for this stage of Ukrainian conflict), while the lower ones depict simplified macro shapes of the narrative, expressed as emotional ups and downs. Both graphs in the Figures 4-4, 4-5 and 4-6 evaluate sentiments across narrative of separate stages of Ukrainian conflict as reported by BBC. Sentiments range between -1 and 1, thus the closer to 1 sentiment value is, the more positive it is.

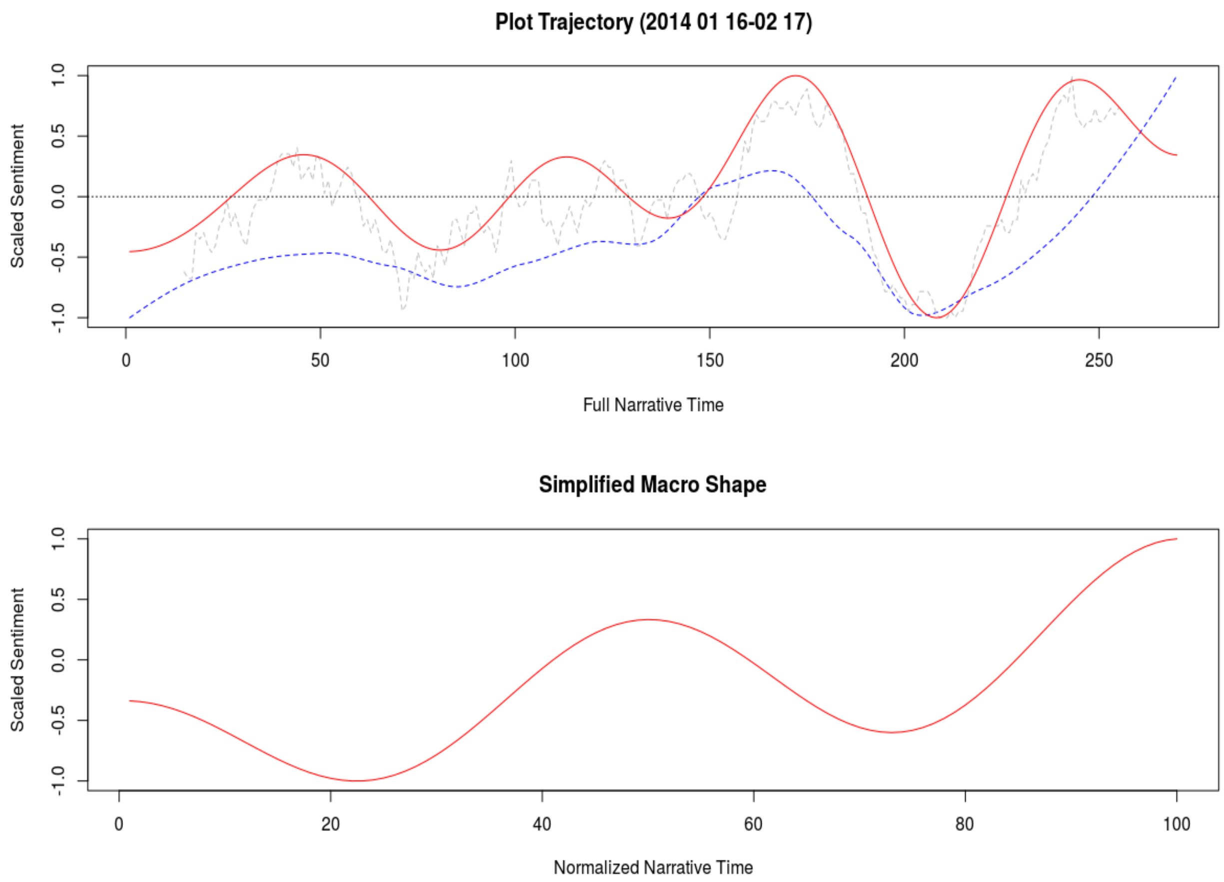


**Figure 4-5: Sentiment-based Narrative Trajectory: 2nd stage of Ukrainian conflict.**

The narrative time is measured in number of sentences. Plot trajectory (upper diagram) is composed of 3 plots, each of them representing a smoothing method applied on the data. The red line indicates the Discrete Cosine Transformation (DCT) of the narrative, which was used to extract sentiment and sentiment-derived plot arcs from text (for more detail, see Section 3.2). This transformation made it possible to evaluate the overall emotional trends through narrative arcs of BBC reporting about different stages of Ukrainian conflict. The grey dashed line shows the results of applying a moving-average filter on the narrative in order to smooth the short-term fluctuations of sentiments detected in the sentences of textual data. It features extended emotional sense of the stories being told by BBC coverage of separate stages of Ukrainian conflict. Finally, the blue dashed line shows another smooth pattern of the sentiments created using Loess regression [19].

The simplified macro shape plot (lower diagram) is a flattened representation of data previously depicted by 3 curves mentioned above. This macro shape plot was generated by adopting a combination of discrete cosine transformation (DCT) and a low pass filter [20], where the emotional trajectory bears the analogy to functions fluctuating at different frequencies. Simplified macro computed with DCT retained fewer low frequency components, that is, minimized the noise. Also, it used the reverse transform process to normalize the x-axis to 100 units, i.e., the sentiment trajectory was sub-sampled to have 100 elements so that sentiment arcs of BBC news coverage for each stage of Ukrainian conflict could be represented from 0% (beginning of the textual data belonging to certain stage of Ukrainian conflict) to 100% (end of the movie of the textual data belonging to certain stage of Ukrainian conflict).

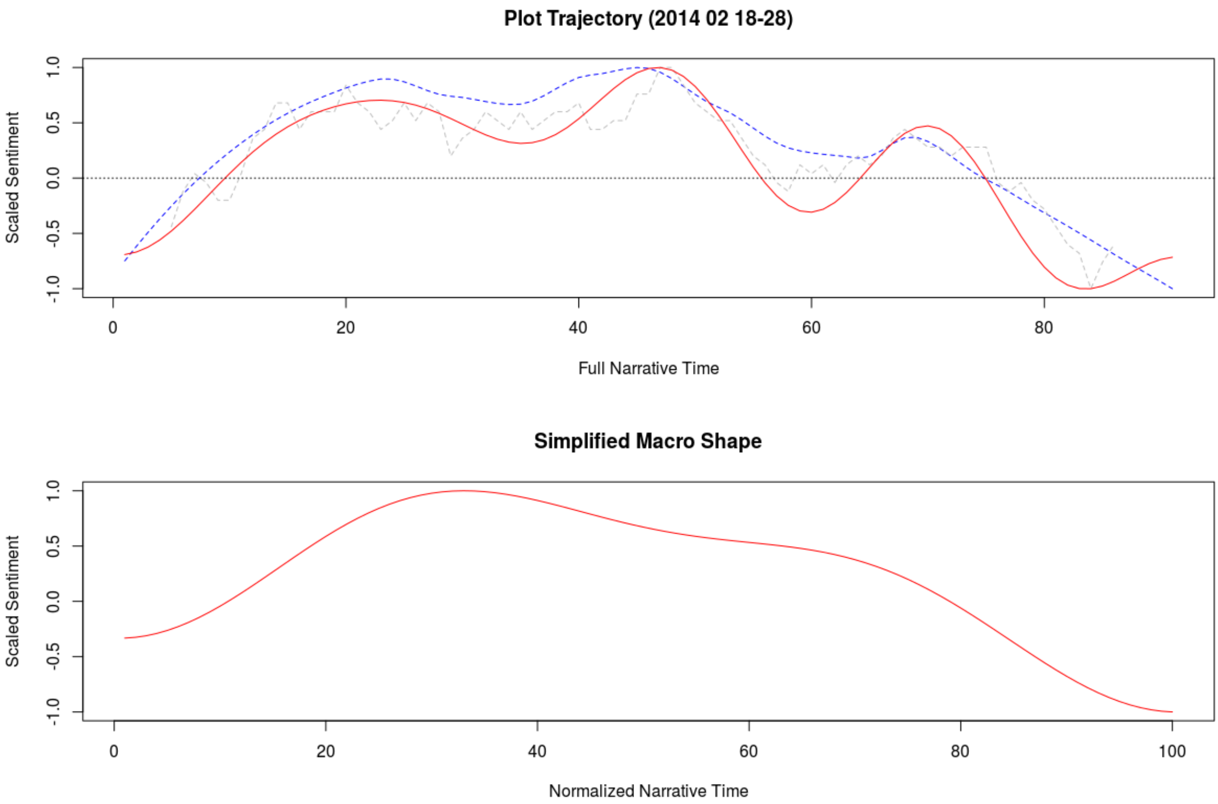


**Figure 4-6: Sentiment-based Narrative Trajectory: 3rd stage of Ukrainian conflict.**

In Figure 4-4, representing the 1st stage of Ukrainian conflict, macro shape indicates that narrative trajectory starts on the high positive note, then rapidly descends down into negativity and at the end we see the rise of positive sentiment again. In Figure 4-5, which shows the 2nd stage of Ukrainian conflict, macro shape reveals that there several “ups and downs”, the beginning is marked by moderately negative sentiment value, however, the narrative trajectory ends very positively. Finally, in Figure 4-6, representing the 3rd stage of Ukrainian conflict, macro shape shows that narrative trajectory again starts with moderately negative sentiment, then we can see a “peak” of positive sentiment, which gradually deteriorates, and thus narrative trajectory ends with extremely negative sentiment.

Explanations of the narrative trajectories above can be the following ones:

1. 1st stage of Ukrainian conflict: starts with Ukraine being “courted by East and West” (positive sentiment), then Yanukovych postponed the signing of an association agreement with the EU and large-scale protests began (sentiment rapidly descends down into negativity), and this stage of the conflict ended with Maidan “rally” (the rise of positive sentiment).
2. 2nd stage of Ukrainian conflict: starts with adoption of anti-demonstration law (moderately negative sentiment), then first deaths occurred (extremely negative sentiment), after that – some attempts to solve crisis peacefully (positive “peak”), clashes with police (moderately negative descend of sentiment) and the 2nd stage of Ukrainian conflict ended with nullification of the laws directed against the protests (narrative trajectory ends very positively).
3. 3rd stage of Ukrainian conflict: beginnings of the clashes (moderately negative sentiment), then Yanukovych signed peace agreement with opposition, liberation of Tymoshenko (“peak” of positive sentiment) and the finale of this stage of the conflict – occupation of Crimea (sentiment deteriorates, and narrative trajectory ends with extremely negatively).

### 4.2.2 Emotional "Profiles" of BBC Coverage of Ukrainian Conflict

Package *syuzhet* and NRC Emotion Lexicon allowed to evaluate BBC coverage of 3 stages of Ukrainian conflict in terms of prevalence of 8 emotions – anger, fear, anticipation, trust, surprise, sadness, joy and disgust). Thus we generated emotional "profiles" for each Ukrainian conflict stage we analysed. These emotional "profiles" are presented in Figures 4-7, 4-8 and 4-9.

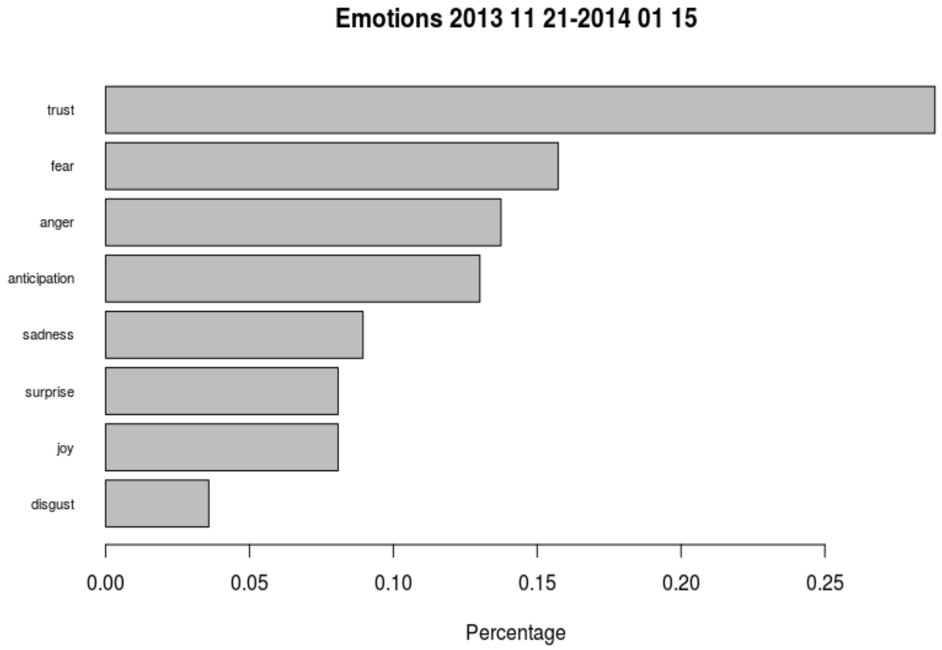


**Figure 4-7: Emotional "profile": 1st stage of Ukrainian conflict.**

Figure 4-7 shows emotional "profile" of BBC reporting on the 1st stage of Ukrainian conflict. The most prevalent emotion is 'trust', other emotions were less expressed. However, Figure 4-8 reveals that although 'trust' is still the most expressed emotion in BBC coverage of 2nd stage of Ukrainian conflict, 'fear' is much closer to it than in 1st stage of the conflict. Other emotion, such as 'anger', 'sadness' and 'disgust' was also expressed more than in the 1st stage, while 'anticipation' and 'joy' – less than in the 1st stage of conflict.

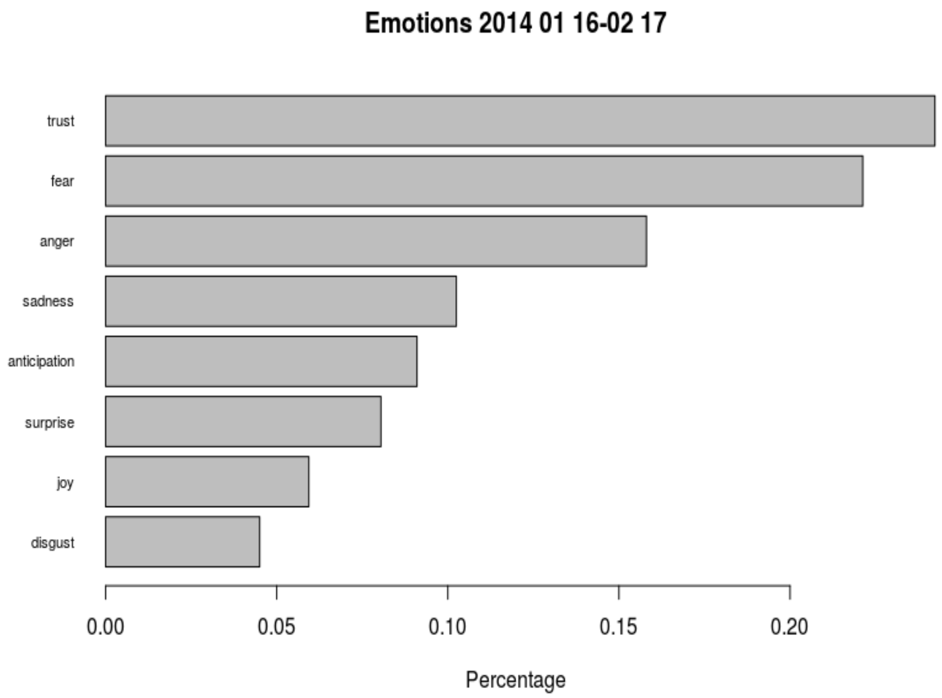


**Figure 4-8: Emotional "profile": 2nd stage of Ukrainian conflict.**

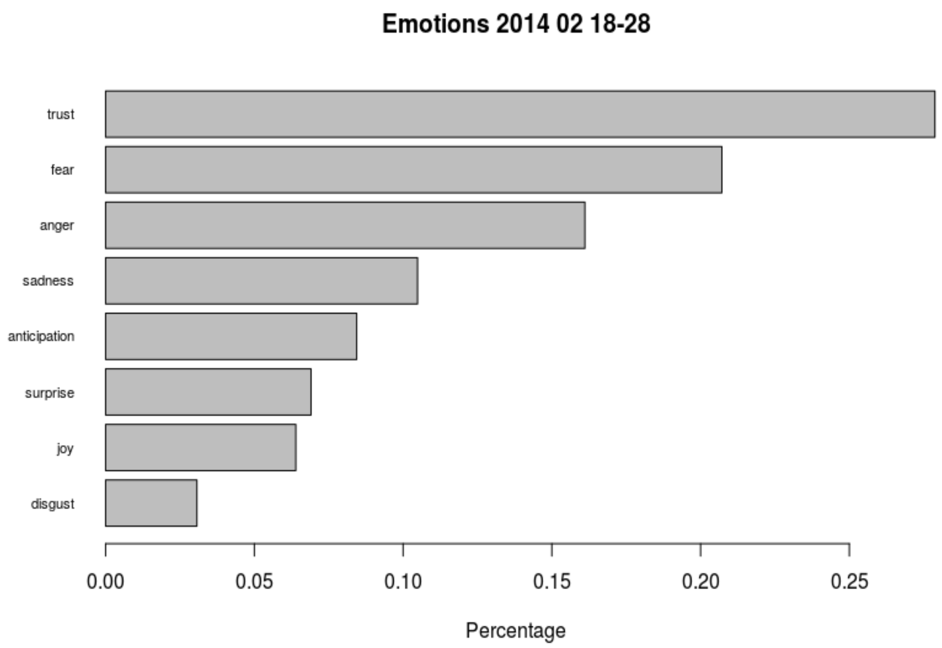


**Figure 4-9: Emotional "profile": 3rd stage of Ukrainian conflict.**

During the 3rd stage of Ukrainian conflict BBC reporting still expressed 'trust' the most and more than during 2nd stage (it might be assumed that 'trust' level more or less returned to the level of reporting about the 1st stage of Ukrainian conflict). The same tendency was observed for 'disgust' and 'joy' – the former decreased, the latter – increased. 'Fear' was expressed on moderately lesser degree, although it did not shrink to the same level as during coverage of the 1st stage of the conflict. 'Anger' and 'sadness' levels remained almost the same as during reporting on 2nd stage of Ukrainian conflict and ‘anticipation’ might be considered as expressed the least in comparison to reporting on all 3 stages of Ukrainian conflict.

## 5.0 CONCLUSIONS

The goal of the research was two-fold: to evaluate possibility to analyse media – population interaction during conflict, and to evaluate possibility to automate the process.

Research results show that it is comparatively easy to track opinion and rhetoric change using Natural Language Processing Tools. Events in the conflict are well reflected in media, and media partially reflects population mood.

While automation was not investigated in details, in most of the cases separate tools that could work with minimal human interference. Of course, several aspects still should be chosen by analysts, namely the conflict itself, media sources (in full-fledged tool just ticking corresponding checkboxes), and, events. We did not investigate automatic or even semi-automatic choice of events. Of course, to make visualizations nicer, human help is valuable as well.

**Results:**

1. Description of two media rhetoric analysis processes: cooccurrence networks and syuzhet based.
2. Experimental evaluation of cooccurrence networks approach on Ukrainian conflict reflection in 4 media channels: BBC, RussiaToday, DayKiev and Delfi.lt.
3. Experimental evaluation of syuzhet-based approach for Ukrainian conflict dynamics in BBC.

**Conclusions:**

1. Cooccurrence networks approach reflects change of rhetoric in different media channels. Spatial visualisation of networks shows rhetoric differences and similarities between channels.
2. Suyzhet-based analysis reflects change of opinion over time in media channel. However, sentence-wise analysis does not reflect sufficiently well change over time due to sampling, hence representation can be badly distributed.
3. Both approaches are suitable for automation.

**Based on the results, the following future developments are proposed:**

1. Automation of both processes (except selection of events and topic).
2. Research of automatic events detection (which is quite popular research area with some interesting results).
3. Detection of narrative itself (it is quite well explored research area as well).
4. Modification of syuzhet-based model, i.e. time-normalization, to better reflect change over time, instead of simple sampling, some kind of weighted aggregation.
5. More advanced sentiment analysis methods could improve precision of syuzhet as well.

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