Comparison of Social Media in English and Russian During Emergencies and Mass Convergence Events

Fedor Vitiugin
Independent

Carlos Castillo
Universitat Pompeu Fabra

ABSTRACT

Twitter is used for spreading information during crisis events. In this paper, we first retrieve event-related information posted in English and Russian during six disasters and sports events that received wide media coverage in both languages, using an adaptive information filtering method for automating the collection of about 100 000 messages. We then compare the contents of these messages in terms of 17 informational and linguistic features using a difference in differences approach. Our results suggest that posts in each language are focused on different types of information. For instance, almost 50% of the popular people mentioned in these messages appear exclusively in either the English messages or the Russian messages, but not both. Our results also suggest differences in the adoption of platform mechanics during crises between Russian-speaking and English-speaking users. This has important implications for data collection during crises, which is almost always focused on a single language.

Keywords

Social Media, Crisis Informatics, Twitter, Information Extraction.

INTRODUCTION

Over the last decade there has been increased interest in the use of social media for disaster communication. A wide range of studies suggests that information sharing networks, such as Twitter, can be very useful in times of crisis due to quick and effective dissemination of relevant news (Yin et al. 2015). Previous works have used quantitative data collection methods and focused on strategic keyword detection (Corvey et al. 2010), a perception of false RTs (Mendoza et al. 2010), and categorization of the tweets sent during disasters (Olteanu, Vieweg, et al. 2015; Öztürk and Ayvaz 2018), among many other topics (Castillo 2016). Most previous works considered tweets in English (Reuter, Hughes, et al. 2018; Reuter, Backfried, et al. 2018), with some exceptions (Zielinski et al. 2012; Doan et al. 2011). In general, messages are collected for emergency response or research purposes in a single language.

This study aims to characterize the differences between messages posted in English and Russian in social media during the same events. Specifically, we seek to address differences in the information conveyed (e.g., mentions of persons, organizations, and locations) and in the linguistic characteristics of messages shared (e.g., parts of speech being used). We ground these differences in "background" collections done in both languages during periods without events, which allows us to use a difference-in-differences approach to quantify changes.

Intuitively, one could assume that collecting data about a crisis in multiple languages should yield more information that using a single language. In this paper, we try to quantify how much is lost by doing a single-language data collection. Our aims in this research are:

- to create a method for finding, collecting and filtering relevant data in Twitter about crises in several languages;
- to create event-driven parallel datasets of events across languages;
- to identify the most significant features for the comparison of tweets across languages;
- to compare the information and linguistic characteristics of these datasets.

LITERATURE REVIEW

Social media has become one of the main sources of communication and information during crisis situations, including disasters and mass convergence events. Using computational methods from many disciplines (Castillo 2016) helps to build systems that can help emergency managers during real crises.

Disasters in Social Media

Modern disaster management processes can use social media technologies to capture event parameters, to help effective decision making, and to share knowledge (Yates and Paquette 2010).

The information in social media during a disaster depends on different factors. For instance, during Japan's tsunami in 2011, people in directly affected areas tended to post about their unsafe and uncertain situation, while people in remote areas posted messages to let their followers know that they were safe (Acar and Muraki 2011). Systematic examinations of a diverse set of crises has uncovered substantial variability across crises, as well as patterns and consistencies across dimensions such as informativeness, information type, and source (Olteanu, Vieweg, et al. 2015).

Languages in Twitter

In most research using Twitter data, the natural tendency has been to assume that the behaviors of English users generalize to other language users (Olteanu, Castillo, et al. 2016). However, given the widespread adoption of Twitter internationally, some researchers have investigated the differences among users of different languages. Examining users of the top 10 languages and general messages (not topic-specific), cross-language differences in adoption of features such as URLs, hashtags, mentions, replies, and retweets have been described (Hong et al. 2011). Regarding news media, the linguistic properties of tweets of selected English and German daily newspapers have been analyzed to identify the structural, discursive and rhetorical goals of newspaper tweets (Tereszkiewicz 2013).

This type of cross-lingual comparison has many challenges, including detecting different nationalities (Laboreiro 2018). However, it can also be very useful to help build models and tools for detecting differences in societal priorities, people's behavioral factors, social, economic, and environmental performances (Resce and Maynard 2018).

Multilingual users are very prevalent in Twitter (Hale 2014), indeed, there is a large interest within the research community on multilingual texts in Twitter and the interaction of multilingual users in the network (Papalexakis and Doğruöz 2015).

In addition to language, a further axes for comparative social media analysis are location and platform. Distance and related variables (language, country, and the number of flights) all have an effect on Twitter ties despite the substantial ease with which long-range ties can be formed (Takhteyev et al. 2012) There are also significant differences across platforms, e.g., in the microblogging behavior on Sina Weibo and Twitter. These provide valuable insights for multilingual and culture-aware user modeling based on user's behavior, microblogging syntactic, semantic and sentiment data (Gao et al. 2012).

In contrast to the previous works, our contribution is that we focus on changes during crisis events, which can be very varied but almost invariably leave a large footprint in social media communities. We compare multiple events in two languages: English and Russian, and our proposed research methodology includes not only an analysis of the linguistics characteristics of messages, but also of the informativeness of messages and their sources, and virality.

DATA COLLECTION AND FILTERING

In this section, we discuss our approach for collecting data: an Adaptive Information Filtering approach based on locations, which helps in the detecting new keywords and collect relevant data. After that, we briefly describe the classification model that helps us automate dataset creation for further analysis.

Overview

For data collection, we build a processing pipeline (Figure 1) that starts with a seed set of location-based keywords (place names) for real-time filtering of tweets and captures messages about an event that happens in the specified location(s). Public tweets were collected and stored independently by language using Twitter's public API. Next, we use an algorithm based on TF-IDF (Ramos et al. 2003) for gathering new keywords for searching and continuing collecting messages. All tweets with keywords mentions were filtered by an automated classifier (Aggarwal and Zhai 2012) based on hand-labeled samples of data to obtain the final lists of tweets for analysis.

We used standard text data preprocessing and extracted informational and linguistic features. The final stage of the analysis was the difference in differences comparison (Abadie 2005) that shows similarities and differences of short-text messages between "normal" and crisis situations in Russian and English.

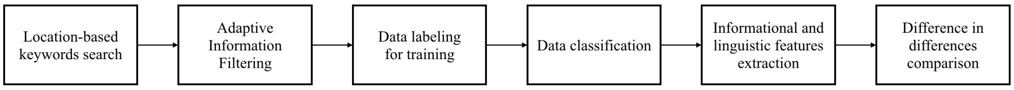

Figure 1. Pipeline of research system

The main challenge for collecting data that we faced is availability large events receiving wide media coverage in both languages, which already hints that information in Twitter in both languages might be quite different. Many large events were discussed quite prominently through tweets in English but were much less talked about in Russian tweets, and vice-versa.

Adaptive Information Filtering

The primary task of Adaptive Information Filtering is to reduce a user's information load with respect to his or her interest described by a request. The filter is supposed to correctly filter an incoming stream, such that relevant keywords are added to adapt the request described by the user. Thus, adaptive information filtering can be described as a type of unsupervised classification problem which must detect new topics in the incoming stream. The objective of our task is similar to the task of topic detection and tracking (TDT) (Allan et al. 1998). TDT is defined as an unsupervised learning problem. There are no relevance classes with respect to a particular user interest. The primary interest is to detect the occurrence of changes as early as possible. Once new topics have been detected, the tracking of new topics must be corrected.

In our implementation, the initial user's query contains only location keywords (district, city, country) which are related to the event. Through the Twitter API we perform a request for collecting public tweets in the stream which contain these keywords. When the number of messages collected surpasses a threshold, all collected documents processed by the Adaptive Information Filtering (AIF) model.

The first stage of our AIF implementation is a pre-processing stage, which starts with language detection. We use the standard Twitter API language parameter for this. After this stage, we had two datasets in different languages — Russian and English. All documents in every message are preprocessed — texts tokenization, deleting special symbols which are used in Twitter for mentions, hashtags, etc., and lemmatization because of in Russian language stemming shows lower efficiency for pre-processing texts (Jivani et al. 2011). Then, every document becomes a bag of words represented using the Vector Space model (Salton and McGill 1986). The vectors are built during the initial phase from the corpus created based on the request from the user.

After lemmatization, every text document is transformed into a list of words without functional words (also known as a stoplist). The words are weighed by the standard $TF - IDF$ product, with TF is the term frequency in the document, and $IDF = log(n/DF(i))$ with n the number of documents in the collection and $DF(i)$ the number of documents in the collection who contain the word i (Marinilli et al. 1999). Then we chose the L most popular terms in the collection, where L is set heuristically to 4 terms based on initial experiments. The new query contains terms which were chosen in the previous step. After the number of messages in the new query becomes the same as the threshold parameter, all new documents are again processed by our AIF-model. All documents in all queries are collected into one dataset which contains filtered tweets connected with the specified event.

The AIF-model approach allows capturing the data variability and collecting more informative data by adding new keywords and new threads which connected with the event.

Classification model

The messages we capture using the procedure described above include many messages that are not related to any specific event of our interest. Hence, the next step for creating the datasets is building a classification model for filtering tweets that are contain information about an event, excluding other information that is not related to an event but is nevertheless captured by the data collection process. This task can be described as an supervised, binary classification problem.

We compared several learning schemes (Support vector machine, Stochastic gradient descent, Extremely randomized trees), based on word embeddings (similarly to (Wijeratne et al. 2016)). We first create words embeddings for every social media message with the help of the doc2vec embeddings model (Le and Mikolov 2014), which is well suited for short length text and outperforms the word2vec model and probabilistic latent semantic analysis model approach, as discussed in (Gupta, Abhinav, et al. 2013; Nguyen et al. 2016; Khosla et al. 2017). Now, each of the word embedding combines another feature vector which was formed using the frequency of each term available in a tweet. After preprocessing, we have one entire embedding vector of length 300 which will be the final representative of the respective class.

Social media tweets in our collections are transformed into vectors (each of length 300) in which the absence of most similar tweets are ensured. These embeddings will be the input for training models.

Training data includes two labeled collections of sport events containing 6 000 tweets and 3 000 tweets respectively, with 20% of tweets for testing and 80% for training. We use a batch-based online learning method with batch size equals 300.

During the training of the Random Forest model, entire training embedding vectors were cross-validated with K-folds (k=10), and showed maximum precision and recall in comparison with Support vector machine, Stochastic gradient descent, Extremely randomized trees, including F-Score (Table 1).

Table 1. Results of learning schemes comparison

	Precision	*Recall*	*F1*
RandomForest	**0.9022**	0.7339	**0.8079**
LinearSVM	0.8747	**0.7407**	0.8019
SGD	0.8819	0.6679	0.7550
ExtraTrees	0.8393	0.6372	0.7243

For our research we considered six events from September to December 2018 that were widely covered in both English and Russian in Twitter. Four of these events are disasters, while the remaining two are worldwide sports events with a significant footprint in social media in both languages. The amount of data collected, before filtering and after filtering using the AIF approach above and for each event is listed on Table 2.

Table 2. Collected data

		Number of tweets before filtering		Number of tweets after filtering	
Events	*Dates*	*English*	*Russian*	*English*	*Russian*
Anchorage Earthquake	01.12.18 — 03.12.18	36,865	1,263	26,691	1,082
Ebeko Volcano Activities	02.11.18 — 06.11.18	67,000	1,500	2,595	258
Kerch Poly Massacre	18.10.18 — 20.10.18	1,850	3,350	1,267	1,358
Paris Fuel Riot	24.11.18 — 26.11.18	163,345	2,344	64,385	676
F1 Race in Sochi	30.09.18 — 04.10.18	333	1,650	102	189
UFC229 Khabib vs Connor	05.10.18 — 07.10.18	650	600	267	190

EXTRACTION OF CONTENT FEATURES

Primarily, the motivation for this paper is to compare the informativeness of crisis tweets across languages. To quantify the extent to which information in each language is unique, we focus on Named Entities, which include:

- persons — these features consider mentions of people by users in their messages. Empirically they are typically politicians, celebrities or people directly affected by an event;
- locations — this feature considers mentions of places in their messages e.i. city, district, state etc.;

- organizations — this feature considers mentions of government or non-governmental organizations, for-profit companies, or other organizations or associations;
- time references — this feature considers time and time interval mentions.

In addition to named entities, we considered other features which are stylistic or refer to platform mechanics:

- type of account — it shows relation between regular users and verified i.e. accounts of politics, celebrities, media or another organizations;
- usage of links in texts — shows if the message is full or is it just a teaser of another material or petition;
- usage of numbers — this feature shows how much facts the message contains because digits/numbers are the main feature of fact in text;
- usage of quotes — this feature shows how much times users cite another person, direct participant of event or expert in disaster;
- dialogues (or @mentions) — it shows how much times Twitter users entered into a dialogue with another user;
- number of retweets — this shows how many times the message was re-posted in Twitter and is related to the relevance of the message for Twitter's community;
- usage of hashtags — exposure desire of an author come into trend connected with event.

The last group of features which were analyzed during this paper are part-of-speech elements, including:

- verbs — typically indicates actions described by users in their tweets;
- nouns — typically describes a variety of elements and objects that participate in those actions.

While extracting these features we were faced several complexities connected with language differences. For each of the two languages we created a separate analytics pipeline included linguistic resources (dictionary of stopwords, special symbols), morphological parser for POS-detection (Russian — pymorphy2[1] Python library, English — Python NLTK[2] pos-parser), Named Entities parsers (Russian — natasha[3] Python library, English — SpaCy[4] Python library).

RESULTS

Based on datasets we evaluated tweets for the purpose of detecting differences. The filtered datasets were used for comparison against the control group (regular Russian and English tweets collected while no large event was happening; 10 000 in both cases) and get the difference in differences (DD) index.

For calculating average DD for feature (example — persons in English tweets) at first we calculate feature values for every event. Then we calculate DD index for every event by the difference between the values during the event and during the general stream: $DD_{event} = value_{event} - value_{general}$. After that we calculate average value of DD for feature: $DD_{avarage} = (DD_{event}1 + DD_{event}2 + \ldots + DD_{event}n)/n$.

For calculating median DD for feature we also use DD indexes for every event: DD_{median} equals mean of the two middle values in the ordered row of DD_{event}. DD_{median} helps us to get "typical" value if some of DD_{event} values are extremely large or small.

In the tables we mark with an "*" in the English column cases where the $DD_{average}$ in English is larger than the $DD_{average}$ in Russian by more than one standard deviation among the different events as captured in Russian. Conversely, we mark with an "*" in the Russian column cases where $DD_{average}$ in Russian is larger than $DD_{average}$ in English by more that one standard deviation among the different events as captured in English.

[1]https://pymorphy2.readthedocs.io/
[2]https://www.nltk.org/
[3]https://github.com/natasha/natasha
[4]https://spacy.io/

Entities

During analysis of named entities we get interesting results that illustrate differences in Russian and English tweets published during disasters (Table 3). Both languages mention a similar number of person entities in the background collection, but during events these numbers similarly increase/decrease, depending on the types of event. During sport events and human-made crises we see more person entities, but during natural disasters this number decreases.

Table 3. Named entities analysis results. The "*" marks statistics for the Russian messages that differ by more than one standard deviation from the English messages.

	DD Average	*DD Median*
Av. persons in English tweet	0.0941	-0.0473
Av. persons in Russian tweet	**0.1133**	**0.0599**
Av. locations in English tweet	0.6708	0.6859
Av. locations in Russian tweet	**0.9021**	**0.8418**
Av. organizations in English tweet	**0.2549***	**0.1649***
Av. organizations in Russian tweet	0.0204	0.0148
Av. unique persons in English tweet	-0.0559	-0.0999
Av. unique persons in Russian tweet	**-0.0394**	**-0.0714**
Av. unique locations in English tweet	-0.0148	**-0.0122**
Av. unique locations in Russian tweet	**-0.0131**	-0.0332
Av. unique organizations in English tweet	-0.0868	-0.0659
Av. unique organizations in Russian tweet	**-0.0118**	**-0.0286**

During the analysis of the most mentioned persons (Table 4) we find that more than half (52,5%) of top-5 named entities in both languages are the same (Figure 2).

Table 4. Exclusive entities in top-5 distribution

	Exclusive English	*English and Russian*	*Exclusive Russian*
Persons	55%	42%	62%
Locations	43%	50%	50%
Organizations	86%	9%	76%

Texts in Russian language contain more location entities and this variable also increases during all types of events. We obtain opposite results for the number of organizations entities — their number in Russian tweets is lower in the background collection and remains lower during all types of events. These observations can be connected with Russian-speaking users who prefer to know more about where something happens but not interested in who made it happen.

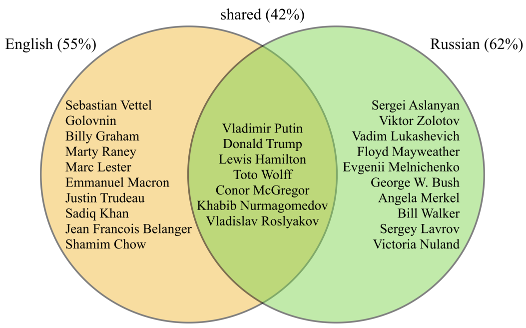

Figure 2. Persons entities distribution

Links and citations

In regular periods (background collection) tweets in Russian contain more links compared with tweets in English. But analysis of events shows this is reversed — Russian-speaking users prefer to share their own impressions, not to spread links (which come mostly from news and similar sites), while the number of links in English tweets usually increases. Tweets in both languages contain a lower number of citations during events than in regular time (Table 5).

Table 5. Links and citations analysis results

	DD Average	*DD Median*
Usage of links (number) in English	**0.4569**	**0.4747**
Usage of links (number) in Russian	0.2194	0.2649
Usage of citations in English	-0.0174	-0.0312
Usage of citations in Russian	**-0.0053**	**-0.0053**

Part of speech

For analysis we choose just nouns and verbs as informative parts of speech for our purposes (Langacker 1987). Part of speech analysis revealed that Russian-speaking users more often use verbs in regular tweets, but during disasters the number of verbs decreases. Actions in crises for Russian-speaking community are less often included in messages. On the other hand, the number of nouns in Russian tweets during events increases (Table 6).

Table 6. Part of speech analysis results. The "*" means a different of more than one standard deviation.

	DD Average	*DD Median*
POS-parsing (verbs) in English	-0.2891	-0.3262
POS-parsing (verbs) in Russian	**-0.0790***	**-0.2899**
POS-parsing (nouns) in English	-0.2247	0.0433
POS-parsing (nouns) in Russian	**0.8731***	**0.8810**

Platform mechanisms

Analysis of platform mechanics including as mentions, retweets, hashtags, and account verification shows that English-speaking users are more familiar with them than Russian-speaking users (Table 7). During events, verified accounts become more active. This is due to the activation of media — more news, analysis, and expert opinions about what happened. This is clear during the Kerch Poly massacre, where the amount of English-speaking verified accounts is much bigger than Russian-speaking while the amount of mentions in English decreases (see Appendix Table 9). This confirms decreasing numbers of mentions and retweets in both languages because users prefer to share their own impressions.

Table 7. Platform mechanics analysis results. The "*" means a different of more than one standard deviation.

	DD Average	*DD Median*
Type of account (name, verification) in English	**0.0328**	0,0157
Type of account (name, verification) in Russian	0.0175	**0.0164**
Dialogue (usage of mentions) in English	-0.4657	**-0.4011**
Dialogue (usage of mentions) in Russian	**-0.3458**	-0.4484
Spreading information (usage of RT) in English	-0.3701	-0.5167
Spreading information (usage of RT) in Russian	**-0.1377**	**-0.4068**
Want to trend (usage of hashtags) in English	**0.2430***	**0.1821**
Want to trend (usage of hashtags) in Russian	-0.0017	-0.0146

Times, numbers

Tweets in Russian contains less temporal references and during events this number further decreases. It shows that Russian-speaking users use Twitter as a real-time platform, to speak about what is happening now. The number of numerical facts (tweets including numbers) is similar in both languages in background collection and during events is similarly increased or decreased, depending on the type of event (Table 8).

Table 8. Times and numbers analysis results. The "*" means a different of more than one standard deviation.

	DD Average	*DD Median*
Av. time reference in English tweet	**0.0160***	-0.0417
Av. time reference in Russian tweet	-0.0100	**-0.0048**
Av. unique time reference in English tweet	-0.0178	-0.0400
Av. unique time reference in Russian tweet	**-0.0053**	**-0.0065**
Usage of numbers (check of using numbers) in English	**0.3284**	**0.0855**
Usage of numbers (check of using numbers) in Russian	0.0660	0.0372

CONCLUSION, LIMITATIONS, AND FUTURE WORK

We have made the first step for comparison of informativeness in social media in English and Russian languages. We found that analyzing tweets about an event in two languages simultaneous can yield substantially more information than in only one language.

Our analysis of named entities allows to capture a larger number of locations (in Russian) and organizations (in English), as well as learning about more people associated with an event (almost 50% of popular people are exclusive to each language). The analysis of messages in Russian indicates an increase in the information content through a decrease in the use of links and quotations, a simultaneous decrease in the number of verbs and an increase in the number of nouns. In future work, we plan to analyze the impact of these parameters on subjectivity in tweets. An analysis of messages in English language revealed the activation of verified accounts, as well as the use of numbers and time references.

Hence, the analysis of only English (or only Russian) tweets would miss a substantial amount of valuable data that can describe the effects of a crisis — detailed names of locations or new names of relevant persons. We will consider the size of the impact of this data in future work.

The main implication from this work is that collecting data in one language during a crisis means losing significant and relevant information. This can only be avoided by collecting information in several languages. While we have not analyzed the location of the users, we assume that users who write messages in the local language have more relevant information about a crisis, from relatives or local media, than users who write messages in other languages.

In the next steps of our research we will add more languages and concentrate in specific classes of disaster. We also plan to use more sophisticated classification models including convolutional neural networks (including LSTM) for filtering tweets that are relevant for an event.

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APPENDIX

Table 9 includes all the statistics we have presented in a single view.

Table 9. Full analysis results of all events

	Regular	*Anchorage*	*DD Anchorage*	*Ebeko*	*DD Ebeko*	*Kerch*	*DD Kerch*	*Paris*	*DD Paris*	*F1*	*DD F1*	*UFC*	*DD UFC*
Av. persons in English tweet	0.2507	0.1664	-0.0843	0.1642	-0.0865	0.2032	-0.0475	0.2037	-0.047	0.7921	0.5414	0.5393	0.2886
Av. persons in Russian tweet	0.2617	0.2190	-0.0427	0.004	-0.2578	0.2380	-0.0239	0.4050	0.1436	0.4160	0.1540	0.9680	0.7067
Av. locations in English tweet	0.3736	0.3054	-0.0682	0.6876	0.3140	1.3347	0.9611	0.5601	0.1865	0.3663	-0.0073	0.5169	0.1433
Av. locations in Russian tweet	0.0700	0.002	-0.0681	0.0120	-0.0584	0.166	0.0957	0.0030	-0.0671	0.2020	0.1322	0.1580	0.0879
Av. organizations in English tweet	0.1890	0.1662	-0.0228	0.5832	0.3942	0.1283	-0.0607	0.2395	0.0505	0.0792	-0.1098	0.0337	-0.1553
Av. organizations in Russian tweet	0.0325	0.0320	-0.0002	0.0310	-0.0015	0.0300	-0.0023	0.0250	-0.0074	0.0110	-0.0213	0.0050	-0.0272
Av. time reference in English tweet	0.1890	0.1662	-0.0228	0.5832	0.3942	0.1283	-0.0607	0.2395	0.0505	0.0792	-0.1098	0.0337	-0.1553
Av. time reference in Russian tweet	0.0325	0.0320	-0.0002	0.0310	-0.0015	0.0300	-0.0023	0.0250	-0.0074	0.0110	-0.0213	0.0059	-0.0272
Av. unique persons in English tweet	0.1724	0.0418	-0.1306	0.0573	-0.1151	0.0876	-0.0848	0.0099	-0.1625	0.2178	0.0454	0.2846	0.1122
Av. unique persons in Russian tweet	0.1237	0.0150	-0.1089	0.0040	-0.1198	0.0900	-0.0339	0.0120	-0.1119	0,1910	0,0673	0.1950	0.0710
Av. unique locations in English tweet	0.0689	0.0223	-0.0466	0.0704	0.0015	0.0430	-0.0259	0.0048	-0.0641	0.1089	0.0400	0.0749	0.0060
Av. unique locations in Russian tweet	0.1140	0.0280	-0.0863	0.0500	-0.0636	0.1110	-0.0028	0.0330	-0.0815	0.1570	0.0433	0.2260	0.1123
Av. unique organizations in English tweet	0.2498	0.0777	-0.1721	0.1566	-0.0932	0.2112	-0.0386	0.0232	-0.2266	0.2772	0.0274	0.2322	-0.0176
Av. unique organizations in Russian tweet	0.0404	0.0020	-0.0386	0.0080	-0.0326	0.0760	0.0354	0.0030	-0.0374	0.0670	0.0270	0.0160	-0.0246
Av. unique time reference in English tweet	0.0777	0.0266	-0.0511	0.1825	0.1048	0.0454	-0.0323	0.0054	-0.0723	0.0693	-0.0084	0.0300	-0.0477
Av. unique time reference in Russian tweet	0.0124	0.0030	-0.0096	0.0160	0.0031	0.0070	-0.0058	0.0010	-0.0109	0.0110	-0.0012	0.0050	-0.0071
Type of account (name, verification) in English	0.0102	0.0145	0.0043	0.0255	0.0153	0.1131	0.1029	0.0094	-0.0008	0.0693	0.0591	0.0262	0.0160
Type of account (name, verification) in Russian	0.0059	0.0037	-0.0022	0.0166	0.0107	0.0279	0.0221	0	-0.0059	0.0449	0.0390	0.0474	0.0415
Usage of links (number) in English	0.4021	0.5114	0.1093	1.0120	0.6099	1.0629	0.6608	0.5986	0.1965	1.2277	0.8256	0.7416	0.3395
Usage of links (number) in Russian	0.4487	0.4778	0.0291	1.0581	0.6094	0.9065	0.4578	0.1391	-0.3096	0.7640	0.3153	0.6632	0.2145
Usage of numbers (check of using numbers) in English	0.2283	0.6648	0.4365	1.8880	1.6597	0.4988	0.2705	0.0849	-0.1434	0.1287	-0.0996	0.0749	-0.1534
Usage of numbers (check of using numbers) in Russian	0.2425	0.7348	0.4923	0.4884	0.2459	0.2224	-0.0201	0.0369	-0.2055	0.3371	0.0946	0.0316	-0.2109
Usage of citations in English	0.0447	0.0158	-0.0289	0.0073	-0.0374	0.0924	0.0477	0.0373	-0.0074	0	-0.0447	0.0112	-0.0335
Usage of citations in Russian	0.0053	0	-0.0053	0	-0.0053	0	-0.0053	0	-0.0053	0	-0.0053	0	-0.0053
Dialogue (usage of mentions) in English	1.0965	0.8548	-0.2417	0.4442	-0.6523	0.1514	-0.9451	0.9434	-0.1531	0.5743	-0.5222	0.8165	-0.2800
Dialogue (usage of mentions) in Russian	0.7876	0.8531	0.0655	0.0039	-0.7837	0.3152	-0.4724	0.9246	0.1369	0.1910	-0.5966	0.3632	-0.4244
Spreading information (usage of RT) in English	0.6933	0.6833	-0.0100	0.3029	-0.3904	0.0502	-0.6431	0.8894	0.1961	0.0099	-0.6834	0.0037	-0.6896
Spreading information (usage of RT) in Russian	0.4337	0.8226	0.3889	0	-0.4337	0.0538	-0.3799	0.8994	0.4657	0	-0.4337	0	-0.4337
Want to trend (usage of hashtags) in English	0.2724	0.4557	0.1833	0.9529	0.6805	0.5394	0.2670	0.4140	0.1416	0.2772	0.0048	0.4532	0.1808
Want to trend (usage of hashtags) in Russian	0.1429	0.0702	-0.0727	0.0349	-0.1080	0.2298	0.0869	0.2559	0.1130	0.1461	0.0032	0.1105	-0.0324
POS-parsing (verbs) in English	0.7929	0.5075	-0.2854	0.4259	-0.3670	0.2948	-0.4981	0.8573	0.0644	0.3267	-0.4662	0.6105	-0.1824
POS-parsing (verbs) in Russian	1.4528	1.0887	-0.3641	0.9651	-0.4877	1.1797	-0.2731	2.3210	0.8682	1.1461	-0.3067	1.5421	0.0893
POS-parsing (nouns) in English	5.4366	6.1311	0.6945	5.3423	-0.0943	5.6175	0.1809	5.8024	0.3658	3.3069	-2.1297	5.0712	-0.3654
POS-parsing (nouns) in Russian	4.2638	5.1580	0.8942	5.3423	1.0785	4.8004	0.5366	5.6361	1.3723	4.7528	0.4890	5.1316	0.8678