



Selected Papers of #AoIR2017:  
The 18<sup>th</sup> Annual Conference of the  
Association of Internet Researchers  
Tartu, Estonia / 18-21 October 2017

## **FINDING AND ANALYZING JUDGEMENTS ON ETHNICITY IN THE RUSSIAN-LANGUAGE SOCIAL MEDIA**

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### **Introduction**

The ability of social media to rapidly disseminate judgements on ethnicity to wide publics and to influence offline inter-ethnic conflict (Chan et al. 2015) creates demand for the methods of monitoring of ethnicity-related online content, in particular for instruments of its automatic mining from large data collections (Burnap & Williams 2015).

In this context, Russia, a multi-ethnic country with a large migrant population, has received relatively little attention from researchers (Bodrunova et al 2017; Bodrunova et al. 2015). In this paper we seek to measure the overall volume of ethnicity-related discussion in the Russian-language social media, to compare public attention to different ethnic groups, and to develop an approach that would automatically detect various aspects of attitudes to those ethnic groups.

Suggested Citation (APA): Koltsova O., Koltcov S., Nikolenko S., Alexeeva S., Nagornyy O. (2017, October 18-21). *Finding and Analyzing Judgements on Ethnicity in the Russian-Kanguage Social Media*. Paper presented at AoIR 2017: The 18<sup>th</sup> Annual Conference of the Association of Internet Researchers. Tartu, Estonia: AoIR. Retrieved from <http://spir.aoir.org>.

## **Data**

From our previous research (Bodrunova et al 2017) we know that attention to in-Russia ethnicities is much lower than that to nations boasting of global or regional influence (first of all, to Americans, Germans, Ukrainians and Jews, but also to many European nations). We therefore limit our research to ethnic groups “indigenous” to post-Soviet space. We develop a comprehensive list of ethnonyms (nouns and bigrams referring to representatives of ethnic groups) using a large number of sources, such as Russian Census 2010, and the list of ethnophaulisms (pejorative ethnonyms). This list of more than 3,600 units embraces 100 ethnic groups all of which occur in our sample of posts from 80,000 random users of the most popular Russian SNS VKontakte. Importantly, we place 17 ethnophaulisms into separate ethnic groups (because, first, if placed together they would pull the scores of this group down, and, second, most of the time such words are not completely synonymous – thus, “khach” may include some or all Caucasian ethnic groups). Next, we acquire a dataset from a social media aggregator that includes all texts from a two-year period from all Russian-language social media in which at least one of the keywords occurs (2,850,947 texts after cleaning). Given that Russian language social media produce several million messages daily, this is a tiny fraction of the entire volume which clearly shows a low interest of the general public in this topic.

## **Volume of attention toward ethnicities**

In total, 53.3% of messages contain more than one ethnic group, with maximum being 67. Furthermore, mean length of messages with ethnonyms is much higher than that of the VKontakte random sample (354 words compared to 16.7) and 56.2% of texts contain more than 100 words. This suggests that while the vast majority of messages in social media are everyday small talk, texts related to ethnicity are often elaborated discussion pieces, often with inter-ethnic comparisons. Ten most frequent ethnic groups include Russians, Ukrainians, Jews, Slavs, Asians, Europeans, as well as two largest Muslim minorities in Russia – Tatars and Chechens. However, we find substantial regional differences. Some regions in Russia are national republics named after their “titular” ethnic groups; when ranked by the share of mentions in respective regions, such ethnic groups on average gain 60 positions compared to their positions in the general frequency list.

## **Method for automatic detection of attitudes**

We therefore make a sample where we overrepresent rare ethnic groups and obtain 7,181 texts with most ethnic groups represented by 75 texts. We get each text coded by three independent persons. Our questions include: general interpretability of a text, relevance to the topic of ethnicity and to a number of other topics, presence of an ethnonym, general positive and negative sentiment, presence of inter-ethnic conflict or positive interaction, general attitude to the ethnic group, whether the ethnic group is presented as inferior/superior, victim/aggressor, dangerous/safe, and whether the text contains a call for violence toward the group.

We then train a number of classifiers (logistic regressions) to “teach” the computer to automatically detect sentiment and other aspects of attitudes to ethnic groups. We examine only those aspects that have produced enough data for training classifiers. As the values of the predicted variables (e.g. “what is the general attitude of the author to

the given ethnic group?") are means of coders' assessments, they are often non-integer, and therefore they have been grouped into two or three categories depending on the number of values the respective variable could originally take. Next, we break the collection into a training set (90%) and a test set (10%) repeating this procedure 100 times and each time training the classifier on the larger set and testing it on the smaller set. Finally, we calculate a number of traditional quality metrics for each predicted variable (Table 1).

### Online ethnic attitudes and their prediction

We find that both general sentiments and general attitude get predicted fairly well (the latter being a three-class task). The positive end is filled in with ethnic groups that have virtually assimilated into the Russian nation (indigenous Siberian and Ural ethnicities). The negative end, apart from being dominated by various ethnofaulisms, presents a much more complicated picture. Traditionally, Caucasian groups are thought to arouse the most negative attitudes, followed by Central Asians, while Ukrainians, Belorussians and Moldovans are hardly perceived as "other" ethnic groups at all (Bessudnov 2016). However, here we see that various Central Asians take the lead in negativity. As for Caucasians, it is they who most often write for themselves – that is, produce their own discourse which is most likely to shift their scores up. Finally, Ukrainians are among most negatively represented because of the recent military conflict. Positive inter-ethnic conflict, though seemingly well-predicted, is often lost by the algorithm as a rare event. Finally, relevance of the text to the topic of ethnicity is least well predicted and in fact has caused the largest difficulties for the coders. We conclude that more hand-coding is needed for a more fine-grained analysis and prediction, and this is what is being performed at the moment.

**Table 1. Quality of automatic classification of users' texts on ethnicity**

Does the text contain:	texts	Binarization / trinarization	Avg precision	Avg recall	Avg F1	Avg accuracy
General negative sentiment	6,674	<0.3=0; =>0=1	0.75	0.75	0.75	74.67+-1.50
General positive sentiment	6,688	<0.3=0; =>0=1	0.74	0.75	0.74	75.1+-1.69
General attitude to an ethnic group	5,970	<1.3=0; [1.3;2.35]=1; >2.35=2	0.63	0.67	0.63	66.54+-1.74
Inter-ethnic conflict	6,701	<0.3=0; =>0=1	0.75	0.75	0.75	75.22+-1.60
Positive inter-ethnic interaction	6,711	<0.3=0; =>0=10.80	0.83	0.80	0.80	82.80+-1.58
Topic of ethnicity	5,970	<0.8=0; =>0.8=1	0.67	0.67	0.67	66.81+-1.82

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