АНАЛИЗ ТОНАЛЬНОСТИ ТВИТОВ О ТЕЛЕКОММУНИКАЦИЯХ И БАНКАХ НА ОСНОВЕ МЕТОДА МАШИННОГО ОБУЧЕНИЯ В РАМКАХ SENTIRUEVAL

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A SUPERVISED APPROACH FOR SENTIRUEVAL TASK ON SENTIMENT ANALYSIS OF TWEETS ABOUT TELECOM AND FINANCIAL COMPANIES

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This paper describes a supervised approach for solving a task on sentiment analysis of tweets about banks and telecom operators. The task was articulated as a separate track in the Sentiment Evaluation for Russian (SentiRuEval-2015) initiative. The approach we proposed and evaluated is based on a Support

Vector Machine model that classifies sentiment polarities of tweets. The set of features includes term frequency features, twitter-specific features and lexicon-based features. Given a domain, two types of sentiment lexicons were generated for feature extraction: (i) manually created lexicons, constructed from *Pros* and *Cons* reviews; (ii) automatically generated lexicons, based on pointwise mutual information between unigrams in a training set.

In the paper we provide results of our method and compare them to results of other teams participated in the track. We achieved 35.2% of macro-averaged F-measure for banks and 44.77% for tweets about telecom operators. The method described in the paper is ranked second and fourth among 7 and 9 teams, respectively. The best SVM setting after tuning parameters of the classifier and error analysis with common types of errors are also presented in this paper.

Key words: sentiment analysis, sentirueval, twitter, social media, tweet sentiment classification

1. Introduction

Sentiment analysis has received much attention in recent years due to its capability to identify people's opinions about products, named entities, facts (or events), and companies. This field of study has become important, especially due to the rapid growth of microblogging services such as Twitter, in which people talk about their personal experiences.

The goal of this task is to determine whether a given tweet is positive, negative or neutral according to its influence on the reputation of telecom or financial company. It is generally difficult to implement traditional sentiment analysis of user reviews since tweets collection could be noisy and each message is limited in length and could contain misspelling, slang and short forms of words. There have been a large number of research studies in the area of sentiment classification of short informal texts that are well described in (Martínez-Cámara, 2014). State-of-the-art papers have applied various feature sets from traditional text classification features (e.g., ngrams, part of speech tags, stems) to twitter-specific features (e.g., emoticons, hashtags, abbreviations) to handle the task in supervised manner (Kiritchenko et al., 2014). Since sentiment analysis in English has been explored in depth, there are not much research on sentiment classification of users' reviews in Russian. The recent works have focused on solving a task on sentiment analysis during ROMIP sentiment analysis tracks in 2011–2013 (Chetviorkin and Loukachevitch, 2013; Kotelnikov and Klekovkina, 2012; Blinov et al., 2013; Frolov et al., 2013).

In this study we report our submission to the SentiRuEval task. The approach is based on a Support Vector Machine model. The set of features includes term frequency features i.e. word ngrams, character ngrams; twitter-specific features and lexicon-based features. Since lexicon-based features are the most useful features for sentiment classification of tweets in English, we generated two types of sentiment lexicons. These two types are: manually created lexicons, constructed from *Pros* and *Cons* reviews in a particular domain; automatically generated lexicons, based on pointwise mutual information between unigrams in training set. We achieve 44.77% of macro-average F-measure of for tweets about telecommunications companies and 35.2% for banks domain, that give improvements of 26.54% and 22.53% in macro F1-measure over official baseline results, respectively.

The rest of the paper is organized as follows. In Section 2 we introduce related work on sentiment classification of short informal texts. In Section 3 we describe proposed classifiers with a set of text classification features and twitter-specific features. Section 4 presents results of experiments. Section 5 provides error analysis. Finally, in Section 6 we discuss the results and future extensions of our work.

2. Related Work

Extracting information from short informal texts, such as tweets or sms messages, has received much attention in sentiment analysis (Go, 2009; Kiritchenko et al., 2014; Sidorov et al., 2013), event detection (Sakaki et al., 2010), problem extraction (Gupta, 2013), sarcasm detection (Davidov et al., 2010) and public sentiment tracking (O'Connor et al., 2010). Traditional approaches of sentiment classification were based on the presence of words or emoticons that indicated positive or negative polarity (Turney, 2002; Taboada, 2010; O'Connor et al., 2010). State-of-the-art papers have implemented hybrid approaches based on the use of machine learning techniques and lexical resources such as sentiment lexicons (Mohammad et al., 2013; Zhu et al., 2014; Kiritchenko et al., 2014; Evert, 2014). Recent studies showed that important machine learning features are bag-of-words unigrams and bigrams, and the use of tweet syntax features (e.g., hashtags, retweets and links) can improve the classification results (Barbosa and Feng, 2010). In (Kiritchenko et al., 2014) authors showed the importance of determining the sentiment of words in the presence of negation. They used separate lexicons for terms in affirmative and negated contexts.

Much work in sentiment analysis involves the use of existing sentiment lexicons and generation of lexical resources capturing the sentiment of words (Martínez-Cámara, 2014). The generation of lexicons range from manual approaches of annotating lexicons to fully automated approaches. In (Evert, 2014) authors used manual extension of existing sentiment lexicons and dictionaries of emoticons and internet slang. In (Mohammad et al., 2013) authors created automatically generated hashtag lexicon estimating sentiment scores for terms based on pointwise mutual information between terms and tweets with polarities. Inspired by these works, that describe supervised methods top-ranked in the SemEval-2014 task about sentiment analysis of tweets in English, we decided to create sentiment lexicons in similar way.

Sentiment analysis of texts in Russian is less studied. In (Chetviorkin and Loukachevitch, 2013) authors describe the first open sentiment task about sentiment classification of users reviews in Russian. Supervised methods, based on SVM classifier in a combination of manual or automatic dictionaries or rule-based systems, are top-ranked for reviews about movies, books, and digital cameras in the task. In (Frolov et al., 2013) authors proposed an approach based on special dictionaries and fact semantic filters in sentiment analysis of user reviews about books. In (Blinov et al.,

2013) authors used manual emotional dictionaries for each of three domains and showed benefits of machine learning method over lexical approach for user reviews in Russian. They reported that it was difficult to select particular machine learning method with the best results in all review domains.

3. Twitter-based Sentiment Classification

The task determines whether each tweet about a telecommunication companies (ttk) or banks contains a positive, negative, or neutral sentiment. We applied a machine-learning approach, based on bag-of-words model and a set of twitter-specific, lexicon-based features that are described in section 3.3.

The following examples illustrate situations in which different types of classification features appear in a tweet. Tweets such as "Лучи дикой ненависти вашей организации, ГОРИТЕ В АДУ *бешусь*" ("Sending rays of wild hatred to your organization, BURN IN HELL *rage*") contain strong negative polarities with regards to words with all characters in upper case. Tweets such as "Почему у дебетовой карты списали деньги просто так?!" ("Why was money from my debit card taken out with no reason?!") and "Сеть прыгает из E в 3G и обратно каждые 5 минут ((" ("Network shifts from E to 3G every 5 minutes ((") do not contain any positive and negative words. Therefore, a human annotator detects negative sentiment in each tweet with regards to the context of the tweet and whether the last symbols are emoticons, exclamation or question marks. Emoticons indicate positive or negative sentiment in short tweets, e.g. "@ sberbank всё спасибо, готово :)" ("@sberbank thank you, it is done :)") and "сбербанк продлил рассмотрение дела до 160 дней :(" ("Sberbank has prolonged consideration of the case till 160 days :("). Complex sentiment analysis in tweets such as "Проехать полгорода и узнать, что карта в другом из банков. Всегда мечтал .__." ("Crossed half the city to hear that my card is in another bank. I have always dreamed .__.") shows that some emoticons present sarcasm, which means that the opposite polarity of the positive word *мечтал* (*dreamed*) is denoted in the tweet. Presence of twitter-specific features such as URL or a retweet indicate to neutral context of tweets about news or informal messages, e.g. "mts коннект драйвер для android http://t.co/J3I5SNZuKM" ("mts connect driver for android *URL*") and "RT @Anna_Anna29: в билайне как узнать свой номер http://t.co/FpDZtLbdMZ" ("RT @Anna_Anna2: how to know your number in Beeline *URL*").

In the following examples we consider the use of sentiment lexicons, created manually and automatically. Manually created sentiment lexicons have been successfully applied in sentiment analysis in traditional approaches that detect whether a message contains positive or negative sentiment (Turney, 2002). The tweets such as "хреновый интернет, отвратительная работа с клиентами. Никогда не связывайтесь с этой шайкой" ("the lousy Internet, disgusting operation with clients. Never communicate with this gang") and "МТС пожелали хорошего дня, даже не попытались ничего продать. Уверовал в добро" ("MTS wished good day to me, didn›t even try to sell anything. I have believed in good") contain mention of domain-independent sentiment words like *отвратительный (disgusting)* and *хороший* *(good)*. Many tweets require deeper sentiment analysis due to difficult context of messages, e.g. the negative tweets “к вашему интернету хочется приложить подорожник” (“there is a wish to put a plantain to your internet”) or “Билайн, отдай мне мой интернет” (“Beeline, give me my internet”). For these reasons, other sentiment lexicon is automatically created to cover such cases.

We tested three different learning algorithms: Naive Bayes, logistic regression (MaxEnt) and Support Vector Machine model (SVM). The squared euclidean norm L2 is selected as the standard regularizer for linear models. Based on the results obtained on the training sets we select SVM with default parameters[1] for tweet classification in banks domain.

3.1. Two Types of Sentiment Lexicons

We explore two main methods to construct sentiment lexicons: manual and automatic.

In the manual method we collected user rated reviews from otzovik.com: 3357 reviews about banks and 1928 reviews about telecom companies. To make corpus more accurate, we included only *Pros* reviews into positive corpus and *Cons* reviews into negative corpus. *Pros* (*Преимущества*) and *Cons* (*Недостатки*) are parts of a review that describe strong reasons why an author of the review likes or dislikes the product aspect, respectively. For each domain we selected the top K adverbs, adjectives, verbs, and nouns which have the highest frequencies in each corpus. Then we reduced noun words, expressing explicit aspects in a user review of particular domain due to neutral polarity of these aspects (e.g., *связь* (*connection*), *услуга* (*service*), *платеж* (*payment*), *скорость* (*speed*), *сотрудник* (*employee*)). In addition, we reduced the most common adjectives (e.g., *российский* (*russian*), *большой* (*big*), *абонентский* (*subscriber*)) and verbs expressing an action (e.g., *использовать* (*use*), *написать* (*write*), *подключать* (*connect*)). For each word we added other word forms. The dictionary consists of about 139 positive and 131 negative words in banks domain. The dictionary consists of about 68 positive and 168 negative words in telecom companies domain.

Following Mohammad et al. (2013) and other state-of-art approaches, automatically generated lexicons are based on sentiment score for each term w in the training test:

$$score\,(w) = PMI\,(w, pt) - PMI\,(w, nt)$$

$$PMI\,(w, pt) = log_2 \frac{p\,(w, pt)}{p\,(w) \times p\,(pt)}$$

where *PMI* is pointwise mutual information, *pt* denotes positive tweets, *nt* denotes negative tweets, $p\,(w)$, $p\,(pt)$, and $p\,(w, pt)$ are probabilities of *w* occurs in positive corpus. The words with strong sentiment polarities have statistically significant difference between $PMI\,(w, pt)$ and $PMI\,(w, nt)$ in contrast to neutral words. For example, the pair of values ($PMI\,(w, pt)$, $PMI\,(w, nt)$) computed over the tweets in banks domain

[1] We have used the scikit-learn library in Python.

equals (−0.8016, 0.1450) for the neural word *еда* (*food*); (−15.2438, 1.5649) for the negative word *ущерб* (*loss*) and (2.1839, −19.2026) for the positive word *выгодный* (*profitable*). Since tweets contain low-frequency noisy words, we ignored terms that occurred less than three times in the training set.

3.2. Preprocessing for Short Informal Texts

Since raw tweets are usually informal and very noisy, the following preprocessing steps are performed. User mentions are normalized to @username. The morpho-syntactic analyzer[2] is applied to replace the words in the tweet with the base forms. We define negated context as a part of tweet between a negation (e.g., a particle *не* (*no*), a predicative expression *нет* (*not*)) word and a punctuation mark. Words with related negations (the words after negations) are modified in conjunction with the negation tag "neg_". We identify emoticons and replace them with corresponding sentiment expressions[3] (e.g., we replace ':-)' with *happy*, 'o_0' with *surprise* and ' ;-]' with *wink*).

3.3. Classification Features for Sentiment Classification of Tweets

Each tweet is represented as a feature vector; brief descriptions of the features that we use are presented below:

- **word n-grams**: unigrams (single words) and bigrams (multiword expressions) extracted from a tweet are used as the features. Features with document frequency greater than two are selected.
- **character n-grams**: lowercased characters n-grams for $n = 2, \ldots, 4$ with document frequency greater than two were considered for feature selection.
- **all-caps words**: the feature counts the number of words which contain all capitalized characters. Abbreviations of companies (e.g., *МТС* (*MTS*), *ВТБ* (*VTB*)) are excluded.
- **punctuation**: the features count the number of marks in sequences of exclamation marks, question marks, or a combination of these marks and the number of marks in contiguous sequences of dots. Sequences that consisted of more than one mark are considered for feature selection.
- **last symbol**: a binary feature indicates whether the last symbol of a tweet is an exclamation mark or a bracket.
- **emoticons**: four features are extracted: the number of positive emoticons; the number of negative emoticons; two binary features that indicate whether a last symbol of a tweet is a positive or negative emoticon, respectively.
- **twitter-specific features**: three binary features that indicate whether a tweet contains mentions of a twitter user, a retweet, and a presence of URL.

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2 We have used Mystem tool, url: https://tech.yandex.ru/mystem/

3 We have used some sentiment expressions from http://en.wikipedia.org/wiki/List_of_emoticons

- **lexicon-based features:** for each of the two generated lexicons, the features are calculated as follows:
  - for the manual created lexicon we count the number of positive sentiment words, negative sentiment words. Sentiment words with negations change the sentiment polarity, e.g. a positive word with a negation suffix consider as a negative word.
  - for the automatically created lexicon four features are added: the count of words with non-zero scores; the sum of the words' sentiment scores normalized by words' count; the maximal sentiment score and minimum sentiment score in a tweet. Sentiment words with negations shift the sentiment score towards the opposite polarity.

4. Experimental Results

We used the training set of 5,000 annotated tweets for each domain provided for the SentiRuEval task. The final number of tweets in the testing collection is 4,549 tweets about banks and 3,845 tweets about telecom companies.

The official results obtained by our classifiers on the testing set are presented in Table 1. The table shows the official baseline results and the results of the method, ranked first according to macro-average F-measure as the main quality measure in the task (Loukachevitch et al., 2015). Macro-average F-measure is calculated as the average value between F-measure of the positive class and F-measure of the negative class. The classifier was trained to predict all three classes (positive, negative, and neutral), but this macro-averaged measure does not consider any correctly classifying neutral tweets. Our method is second among 7 teams with 14 runs in banks domain. The method is ranked fourth among 9 teams and fifth among 19 runs in telecom companies domain. The best approach has a 0.007% improvement in macro F1-measure over our approach in banks domain.

Table 1. Performance metrics in tweet classification task in two domains: telecom companies and banks

	telecom companies		**banks**	
	micro F	**macro F**	**micro F**	**macro F**
Best	0.536	0.488	0.343	0.359
Our approach	0.528	0.448	0.337	0.352
Official baseline	0.337	0.182	0.238	0.127

We also present feature ablation experiments on the testing set, removing one each individual feature category from the full set. Table 2 shows the results of the ablation experiments, each row shows macro-average precision, macro-average recall, and macro-average F-measure, calculated as the average value between corresponding measures of the positive and the negative classes. The most effective features are word n-grams for tweets about telecom companies. The most effective features are based on character n-grams and emoticons in banks domain. The method also archives an improvement of 0.021% in F-measure after reducing word n-grams in banks domain and an improvement of 0.041% in F-measure after reducing word automatic lexicons in ttk domain. These improvements could be caused by a dynamic context of tweet messages about companies. The tweets of the training set were published in 2014, the tweets of the testing set were written in 2013.

Table 2. Experimental Results for the ablation experiments in two domains

	telecom companies (ttk)			banks		
	macro P	macro R	macro F	macro P	macro R	macro F
All features	0.443	0.471	0.447	0.538	0.279	0.352
w/o character n-grams	0.447	0.413	0.405	0.444	0.233	0.301
w/o emoticons	0.413	0.450	0.406	0.489	0.274	0.335
w/o both lexicons	0.419	0.553	0.475	0.496	0.276	0.337
w/o last symbol	0.458	0.379	0.390	0.509	0.274	0.340
w/o lexicon (manual ver.)	0.379	0.505	0.432	0.516	0.270	0.340
w/o lexicon (automatic v.)	0.427	0.569	0.488	0.426	0.292	0.343
w/o all-caps words	0.446	0.447	0.436	0.498	0.293	0.349
w/o punctuation	0.429	0.429	0.412	0.522	0.286	0.350
w/o twitter syntax features	0.447	0.441	0.443	0.491	0.289	0.351
w/o word n-grams	0.390	0.412	0.373	0.507	0.316	0.373

We also analyzed the significance of SVM tuning to our method. After shifting SVM's regularized regression method to elastic net that linearly combines the L1 and L2 penalties and the regularization term's alpha to 0.0001, the classifier had the improvements of 4–5% in macro F1-measures over our results with SVM's default parameters in both domains. The tuned classifier achieves a macro-average F-measure of 39.46% for banks domain and of 50.6% for tweets about telecommunications companies. The results show that careful tuning of the machine learning algorithm could obtain much better results.

5. Error Analysis

After error analysis we identify the following types of most frequent errors in tweet classification:

- misspelling and difficulty with transliteration of English text into Russian
- multiple hashtags
- emotional discussion of neutral topics
- insufficient size of sentiment lexicons (presence of out-of-lexicon words in the testing set)

From Table 3 shows that most of the errors are caused by insufficient information about context in positive or negative tweets about companies.

Table 3. Error types distribution

	Misspelling and transliteration	Multiple hashtags	Emotional discussion	Insufficient size of sentiment lexicons
telecom companies	20.40%	8%	14.90%	43%
banks	9%	1%	11%	64%

Tweets such as “Билайну труба короче” (“Beeline›s game›s over”) contain hidden negative meaning like “game›s over” with the word “труба” (“a pipe”). Negative tweets such as “Самый безалаберный банк!” (“The most disorganized bank!”) are missclassified due to low-frequency words like “безалаберный” that are not contained in the training set nor created lexicons.

We haven›t applied error correlation for cases of orthographic errors like *ацтой* (*rubbish*) and *чорд* (*damn*), while the correct spellings of these words are included in manually created lexicons. Tweets such as “Билайн. Дисконнектинг пипл.” (“Beeline. Disconnecting people.”) with transliterated words with strong negative polarity in English were misclassified as neutral. The analysis shows that misspelling caused less errors to tweets than elongated, transliterated words, and presence of asterisk (star symbol) in foul language words.

Hashtags such as *#отстойсвязь* (*#yourconnectionsucks*), *#мтсумри* (*#mtsdie*), *#люблюего* (*#loveit*) contain strong sentiment orientation. 8% of errors in telecommunications would be eliminated by splitting hashtags into words and then calculated the sentiment scores of hashtags.

Fourth type the errors is related to neutral tweets about telecom companies or banks, that contain positive or negative polarity about other topics (e.g., tweets about a *company’s dress code,* friendly conversation or flirting with a company’s worker*). Other type of such tweets is* a tweet describing some daily company’s event: “Матч штаб-квартиры Вымпелком — Сибирь. Пока ведем!!! :)” (“Match of Vympelcom›s headquarters Vs Siberia. We›re winning!!! :)”). In all these cases the tweet about the company is neutral. Our classifiers haven›t considered such cases that affect up to 11% of errors about bank tweets, and 14.9% of errors in telecommunication tweets.

6. Conclusion

In this paper we described a supervised method for sentiment classification of financial or telecom twitter data with an emphasis on consumer experience. The proposed method exploits Support Vector Machines with term frequency features, twitter-specific features and lexicon-based features. Given a tweet the lexicon-based features were generated by checking whether a word is in sentiment lexicons, that were created both automatically and manually from user reviews. In order to produce an automatically created lexicon, we used pointwise mutual information to calculate sentiment score and associate each word from a training set with a proper sentiment class.

We demonstrated that by using these features, classification performance increases from a baseline macro-averaged F-measures of 0.265 to 0.447 for telecoms and of 0.225 to 0.352 for banks. We plan to create large corpora of positive and negative tweets for the sake of improvement of the classifiers with automatically created lexicons.

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